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Artificial Intelligence in Agriculture

Opportunities and Challenges

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Abstract

Artificial Intelligence (AI) is increasingly used in different parts of society for providing decision support in various activities. The agricultural sector is anticipated to benefit from an increased usage of AI and smart devices, a concept called smart farming technologies. Since the agricultural sector faces several simultaneous challenges, such as shrinking marginals, complicated pan-European regulations, and demands to mitigate the environmental footprint, there are great expectations that smart farming will benefit both individual farmers and industry stakeholders. However, most previous research focuses only on a small set of characteristics for implementing and optimising specific smart farming technologies, without considering all possible aspects and effects.

This thesis investigates both technical and non-technical opportunities and hurdles when implementing AI in Swedish agricultural businesses. Three sectors in agriculture are scrutinized: arable farming, milk production and beef production. As a foundation for the thesis, a literature review revises former research on smart farming. Thereafter, an interview study with 27 respondents both explores the susceptibility and maturity of smart farming technologies and provides examples of technical requirements of three chosen applications of AI in agriculture. Findings of the study include a diverse set of aspects that both enable and obstruct the transition. Main identified opportunities are the importance smart farming has on the strategic agendas of several industry stakeholders, the general trend towards software technology as a service through shared machinery, the vast amount of existing data, and the large interest from farmers towards new technology. Contrasting, the thesis identifies main hurdles as technical and legislative challenges to data ownership, potential cybersecurity threats, the need for a well-articulated business case, and the sometimes lacking technical knowledge within the sector. The thesis concludes that the macro trend points towards a smart farming transition but that the speed of the transformation will depend on the resolutions for the identified obstacles.

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Artificiell intelligens (AI) har under det senaste årtiondet utvecklats enormt, med ständigt nya användningsområden och tillämpningar. AI kan både automatisera vissa aktiviteter samt förse människor med datadrivna beslutsstöd till olika aktiviteter. Inom svenskt jordbruk används redan mycket avancerad teknik men de framtida användningsområdena för AI ser ut att vara näst intill obegränsade.

Samtidigt står det svenska jordbruket inför större utmaningar än någonsin, inklusive men inte begränsat till den låga lönsamheten på svenska gårdar, komplicerade direktiv från EU samt både interna och externa påtryckningar att minska jordbrukets belastning på miljön. Utifrån utmaningarna förväntas implementeringen av AI inom jordbruk, ett koncept som kallas ‘smart farming’-teknologier, kunna bidra med fördelar både till individuella lantbruk liksom andra intressenter inom sektorn. Trots detta är smart farming-teknologier ännu inte särskilt kommersiellt utbredda i Sverige idag. Denna studie syftar till att undersöka vilka möjligheter som kommer med att implementera AI inom jordbruk, samt vilka potentiella utmaningar som hindrar en utbredd användning av tekniken i den svenska jordbrukssektorn.

Resultaten i studien visar på en stor entusiasm bland både enskilda lantbrukare, forskare och företagare inom jordbrukssektorn för att implementera nya typer av teknologier. Samtidigt finns det en rad utmaningar som gör att övergången till ett datadrivet jordbruk fördröjs. Ett tekniskt problem, som huvudsakligen gäller växtodling, är att insamlad data är diskontinuerlig och att det tar lång tid att sluta en datacykel. I en snabb datacykel kan man korrigera och optimera en modells input-data för att nå önskade värden på den korresponderande output-datan. För att exemplifiera detta är datacykeln snabbare inom mjölkproduktion, där lantbrukare får ny information om hur mjölkkor mår varje dag då korna mjölkas och analyseras dagligen av mjölkningsrobotar. Genom dessa utförliga och dagliga insamlingar av data kan AI ge rekommendationer för, exempelvis, hur korna ska matas för att åstadkomma bästa möjliga mjölkkvalitet och volym. Växtodlare är mer begränsade till att använda sig av sensorer, manuella prover av grödor samt satellitbilder, som analyserar bland annat färg och så kallade vegetationsindex, för att ge underlag till fältets utveckling. Detta ger data med lägre kontinuitet vilket påverkar möjligheterna för AI att ta fram beslutsunderlag på goda grunder. Dessutom påverkas en åker av en lång rad ofrånkomliga och oförutsägbara faktorer, som väder och skadedjur, från det att ett frö sås på vårkanten till att grödan skördas på hösten. Detta i kontrast till mjölkproduktionen, där yttre påverkan går att minimera.

Ytterligare belyser studien hur svenskt jordbruk behöver förbättra delandet av data mellan olika typer av tekniska system. Idag fungerar sällan system från olika leverantörer tillsammans vilket hindrar innovation och försvårar användningen för lantbrukare. För att ett sådant datadelningssystem ska fungera krävs robust IT-säkerhet som skyddar den potentiellt nationellt kritiska informationen. Datadelning är dock inte möjligt utan större samverkan mellan olika jordbruksaktörer. Studien visar hur ökad samverkan för att snabba på digitaliseringen är på gång vilket bland annat visar sig genom att myndigheter överväger att ta ett större ansvar.

Just ansvarsfrågan för teknikomställningen är central för de icke-tekniska delarna av resultaten. Idag får lantbrukare själva finansiera ny teknik till lantbruken vilket ofta är svårt för gårdar med pressad lönsamhet. Dessutom är majoriteten av svenska lantbrukare i behov av utbildning och stöd för att ta till sig tekniken. Anledningen till detta är omtvistat, men resultatet i denna studie pekar på att det antingen beror på den höga medelåldern inom jordbrukssektorn eller att intresset för tekniken brister hos många. Samtidigt syns en trend inom sektorn att allt fler lantbrukare börjar dela på maskiner, eller hyra in dem som tjänster, vilket sänker tröskeln för att pröva tekniken. Många lantbrukare är nämligen optimistiska till ny teknik men upplever sig inte ha de ekonomiska musklerna att köpa helt nya tekniska lösningar. Höga ekonomiska risker leder också till att sociala aspekter kraftigt påverkar lantbrukares teknikinköp. Kan lantbrukaren få bevisat för sig att tekniken är lönsam, trovärdig, underlättande för vardagsarbetet och gärna rolig är sannolikheten stor att lantbrukaren kommer vilja använda den.

Studien använder sig av en tudelad metod för insamling av information och data. Inledningsvis genomfördes en strukturerad litteraturstudie för att kartlägga den vetenskapliga omgivningen och vilka typer av AI-drivna tekniker som har börjat implementeras inom jordbruk under de senaste åren. Därefter inleddes en omfattande intervjustudie med 27 intervjuer med personer från olika håll inom jordbrukssektorn. Respondenterna grupperades baserat på sin sysselsättning, nämligen lantbrukare, forskare, samt yrkesverksamma inom kommersiella företag och statliga myndigheter. Intervjuerna syftade dels till att undersöka vad nyttan med, och hindren för, AI inom jordbruk skulle kunna vara, men även att ge exempel på faktiska applikationsområden för AI inom mjölk-, kött- respektive växtproduktion. Vidare vägdes resultaten från intervjuerna samman med resultaten från litteraturstudien för att belysa likheter och skillnader mellan denna studie och de tidigare studierna inom området.

Slutsatserna från denna studie öppnar upp till intressanta nya frågeställningar. Då denna studie ger en överblick över det svenska jordbruket och dess olika typer av aktörer finns ett behov att vidare fördjupa sig med insikter inom var och en av sektorerna, samt mer fördjupade studier i var och ett av applikationsområdena och vad som krävs för att realisera dem. Vidare öppnar studien även upp för diskussioner på samhällsnivå för vad som skulle hända om vi hade ett mer digitalt styrt jordbruk. Hur kommer maktförhållandet mellan olika aktörer i jordbruket och livsmedelskedjan se ut då man med hjälp av AI kan förutspå produktionen under ett år? Vilka kommer att lockas av lantbruksyrket då det blir allt mer drivet av data och teknik? I och med att det inte verkar finnas några gränser för vad som är möjligt att göra med teknik inom jordbruk finns det likväl inga begränsningar för viktiga frågeställningar att undersöka under denna transformation.

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To our subject reviewer Vera van Zoest we would like to express our gratitude for the endless guidance, support, and expertise you have contributed to this thesis. We wish everyone would be so lucky as to have you as their subject reviewer.

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Table of Content

1. Introduction

Swedish agricultural businesses face a vast number of simultaneous challenges. Shrinking marginals, complicated pan-European regulations and external, as well as internal, demands to mitigate their environmental footprint are all examples of requirements to be met. As a response, several different techniques are proposed to meet the needs of farmers. Even though farming has been developing technologically for centuries, the 21st century offers a wide range of technological possibilities that could deeply affect the future of farming. One of them is Artificial Intelligence (AI).

Applying AI to agriculture is often referred to as ‘smart farming’. This term constitutes a wide scope and demanding expectations. Smart farming could enable increased yield volumes, mitigate the workload for farmers, contribute to climate change adaptation and future-proof farming for the coming centuries. With this in mind, smart farming is expected to affect several areas within the agricultural sector. To mention a few, some trained AI models are implemented to predict the optimal time for planting and harvesting crops, prevent nutrient deficiencies and the spread of diseases, and guarantee food safety (Liu, 2020). This master thesis will investigate how smart farming can be implemented in Swedish agricultural businesses.

Contrary to most earlier research, this thesis investigates technical aspects as well as non-technical aspects of smart farming in Sweden. Several earlier studies have scrutinized technical aspects such as optimal remote sensing picture resolution and important cybersecurity aspects to sensor systems. In this thesis, these aspects are considered but other essential, practical aspects such as data ownership and data sharing are also analysed. Furthermore, non-technical aspects to smart farming, for instance trust and profitability, are discussed with the interviewed respondents. By this interdisciplinary approach, new insights into the possible application of AI in Swedish agriculture are provided. Additionally, the wide scope allows for a comparison between three different agricultural sectors: arable farming, milk production and beef production. Thus, all stakeholders interested in a holistic understanding of the technological development of Swedish agriculture can use this thesis as a knowledge foundation.

1.1 Thesis Statement

This thesis aims to examine how AI in agriculture is deployed and may be developed in a Swedish context. It will provide different perspectives on smart farming by interviewing commercial enterprises, organisations, governmental authorities, and farmers in Swedish arable farming, milk production, and beef production. Both technical and non-technical factors that drive or hinder the development of smart farming will be analysed.

1.2 Research Question

The main research question that this thesis answers is:

- Which are the main opportunities and hurdles for applying AI to Swedish agricultural businesses?

Three sub questions are used to concretise the main research question:

- Which demands are there for AI in Swedish agriculture and what drives those demands?
- Which barriers are there that prevent the implementation and propagation of AI in Swedish agriculture?
- Which technical features are needed for the implementation of solutions meeting the identified demands?

1.3 Delimitations

To limit the scope of this study, only supervised AI models (see explanation in *2.2. Machine Learning*) are considered. Additionally, the thesis investigates three main agricultural sectors, namely arable farming, milk production and beef production. Thus, poultry farming, pig farming and other sectors are excluded to limit the scope. Furthermore, internal differences between, for instance, different crops in arable farming are only touched lightly upon, even if they in practice can differ significantly in their exact application. However, for a holistic understanding and comparison, the sectors are sufficiently specific to generate insights.

2. Theoretical Background and Key Concepts

In the following section the theoretical background and key concepts of the thesis are presented. Technical terms, such as ‘artificial intelligence’ and ‘smart farming technologies’ are defined and explained. Thereby, an introduction to the concepts, as well as a common ground and understanding for the coming sections of the thesis, are provided.

2.1 Introduction to Artificial Intelligence

Artificial Intelligence (AI) is a wide concept with many applications. Grosan and Abraham (2011, p.1) define AI as *“creating machines which solve problems in a way which, done by humans, require intelligence”*. In practice, AI is used in several applications, ranging from automatically interpreting and translating voice to text, to drawing conclusions out of enormous amounts of data. Still, Grosan and Abraham believe that society is just barely scratching the surface of the possible applications of AI in different areas (Grosan and Abraham, 2011, p.1-2).

Fundamentally, AI consists of three parts. First, it must run on a hardware that can process data in an efficient manner and store all data in a fast and efficient memory. Secondly, AI needs a software advanced enough to draw conclusions from the data. Often, AI software is made to simulate mechanisms from the human brain which has brought large advancements but is still not as complex as the human brain. Finally, the input data must be collected through for example sensors and cameras in a structured manner and result in an output relevant to the task it is meant to solve (Grosan and Abraham, 2011, p.2). This is referred to as input and output mechanisms.

2.2 Machine Learning

A subset of AI tasks is solved with an approach where the algorithm is learning to improve itself. This approach, called machine learning, is suitable for solving tasks that are characterised by either a fault of human expertise, an unexplainable knowledge area such as interpreting handwriting, an unpredictable environment such as the stock market, or a need for specific adaptations for every single user such as a spam-filter for email (Grosan and Abraham, 2011, p.261-263). To learn a machine learning model the system needs input data, a task to solve and an evaluation metric to assess its performance on the task (Grosan and Abraham, 2011, p.261-263).

Machine learning is divided into four main categories: reinforcement learning, supervised and unsupervised learning as well as active learning (Grosan and Abraham, 2011, p.266). Reinforcement learning-models are models where the system is affected by feedback from the actions taken in a previous stage (Grosan and Abraham, 2011, p.267). The supervised learning-model is learned on labelled input data. Labelled data regards for instance images or tabular data that a human manually has classified to the right class.

This tells the model how to predict an output when encountering a new but similar unlabelled data point. Unsupervised learning, on the other hand, discovers patterns and clusters in the data on its own without any human labelling (Grosan and Abraham, 2011, p.266-267). Active learning is similar to supervised learning in the sense that labelled data is used, but the system can also get direct input from the end-user to improve the model (Grosan and Abraham, 2011, p.267).

For supervised learning, which will mainly be discussed in this essay, Grosan and Abraham (2011) describe different machine learning types. Three of those types, relevant for agricultural applications, are summarised in table 2.1. First, its objective can be to predict an output based on historic data input divided into input and output pairs (Grosan and Abraham, 2011, p.265). In a smart farming context this could mean predicting the future yield based on factors impacting the previous yield. Secondly, a regression model is similar to a prediction model, but it takes one or many current variables and forms a function that estimates an output (Grosan and Abraham, 2011, p.265). A smart farming example would be to determine the amount of irrigation needed in a specific place given soil data from that location. Lastly, a classifier takes one or many input variables and classifies the output into a predetermined category (Grosan and Abraham, 2011, p.265). Farmers could use classification models to identify cattle with specific ID numbers based on their fur pattern.

Table 2.1. The three types of machine learning types referred to in this essay (Grosan and Abraham, 2011, p.265)

Machine Learning Type	Input data	Output data
Prediction	Input parameters different from output	Estimation of a future value based on previous pairs of input and output
Regression	One or many different variables	Estimation of a function from scattered data
Classifier	Object, could be data of different kinds	Predicts a predetermined class

In practice, the above stated machine learning types are solved through different types of machine learning algorithms or models. To mention an example, it can be a linear separator, which is often the case in regression problems. This algorithm draws one or many function lines and predicts the outcome. Another significant algorithm is the decision tree, which creates a tree model based on different “if”-statements and a function that makes each leaf as homogenous as possible. Furthermore, machine learning can use neural networks, a group of mathematical models aimed to mimic important parts of the brain, or several other algorithms to solve the mathematical task (Grosan and Abraham, 2011, p.266).

2.3 The Trade-off Between Bias and Variance

One important aspect of machine learning is the trade-off between bias and variance. Kopper et al. (2020) state that when selecting a model for a particular data set and for a certain purpose, it is important to understand how that trade-off works. The bias-variance trade-off is in short a balance between the complexity of a model and the predictive error. In a model, the complexity is constituted by how many layers of data, i.e. the amount of variables, that affect the model output. In contrast, the predictive error tells the difference between the prediction and the correct value (Kopper, et al., 2020).

Figure 2.1 illustrates the bias-variance trade-off. As the model complexity increases, one can see that the variance increases and the bias decreases. When variance increases, the model overfits to the training data, which means that it fails to generalise on unseen validation data (Kopper, et al., 2020). On the other hand, when the model complexity is low, the variance is also low, but the bias is high. Therefore, the model cannot detect the complexity of the data and learns very biasedly, implying that the model is too simple (Kopper, et al., 2020). As previously stated, the ideal point between bias and variance is a balance between the two, suited to the purpose of the algorithm. In the figure, the optimum model complexity is marked where the bias and variance graphs intersect. At this point, the total error is minimised, and therefore the ideal model is chosen.

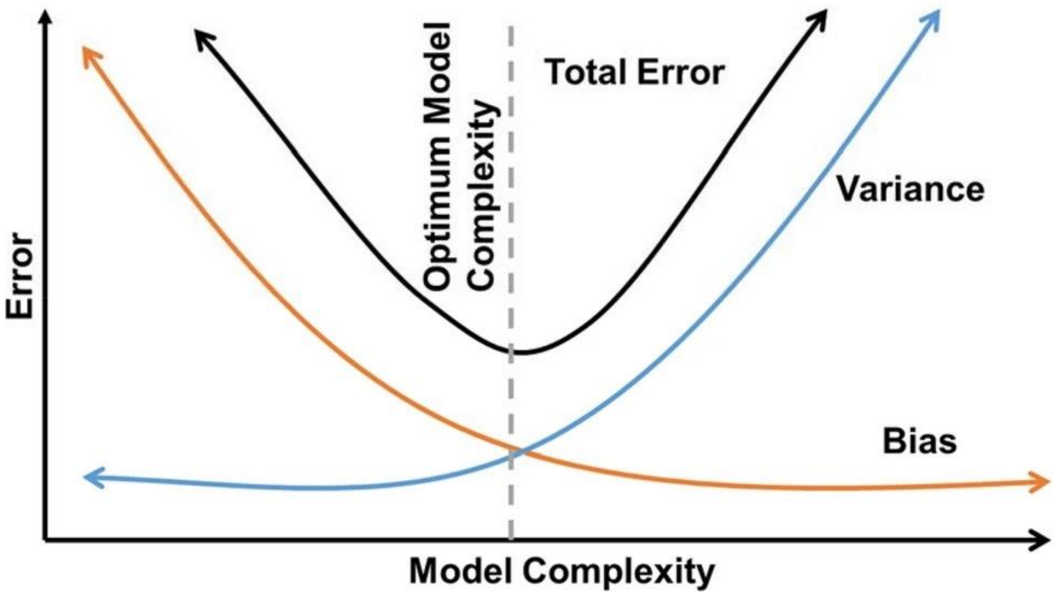

Figure 2.1: An illustration of the bias-variance trade-off. On the x-axis is the model complexity and on the y-axis is the predictive error. The optimal model complexity is found where the graphs for bias and variance intersects, as this is where the total error is minimised. Source: (Kopper, et al., 2020)

2.4 Definitions of the Main Smart Farming Concepts

Applying data-driven decision support and AI to farming is often referred to as smart farming. However, the definition of smart farming is wide and can contain everything from GPS-connected tractors to data visualisation of IoT sensors to extracting information from images. Even if smart farming as a general concept will be referred to repeatedly in this thesis, the two more specific subconcepts precision agriculture and precision livestock farming are defined below.

Implementing new and smart technologies to arable farming goes under the definition 'precision agriculture', described as following by The International Society for Precision Agriculture (ISPA):

> *"Precision Agriculture is a management strategy that gathers, processes and analyses temporal, spatial and individual 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, 2019 in Buller, et al., 2020)

On the other hand, smart farming technologies that enable real-time monitoring, data management, and decision support within livestock systems are called 'precision livestock farming'. While the activities in farms that hold animals might differ from arable farms, the concept of precision livestock farming is quite similar to precision agriculture. Both strategies require a sensing system for inputs and outputs, a mathematical model of input/output relationships, a target and trajectory for controlled processes, and a model-based controller with actuators for process inputs (Wathes, 2007 in Buller, et al., 2020, p.3).

With these definitions in mind, this thesis will henceforth use the concept of smart farming as a broader term that includes both precision agriculture and precision livestock farming. By such an approach, all types of initiatives and technology are included in one expression, avoiding exclusion based on agricultural sectors. Moreover, when discussing technology specifically related to either arable or livestock farming, the terms precision agriculture and precision livestock farming are used.

3. Agricultural Context in Sweden

In this section the industry context to Swedish agriculture is presented. Main macro-level statistics of the industry are displayed as well as important legislative and economic facts. In addition to the previous section *2. Theoretical Background and Key Concepts*, the context provides a foundation for understanding the implications of the smart farming transition in Sweden.

In 2016, the agricultural industry employed 171 400 people in Sweden accounting for approximately 1.7% of the total population (SCB, 2016). The total area of agricultural land is measured to 3 013 300 hectares (SCB, 2020). Out of the total revenue of agriculture in Sweden, the distribution between crop and animal output are divided roughly equally. Out of the total Swedish agricultural revenue in 2019, cattle beef constitutes 11.2%, milk 18.6%, and cereals, forage plants and potatoes together provide 36.3%. These statistics, together with the aggregated sectors not investigated closer in this thesis, are displayed in figure 3.1 (European Commission, 2020).

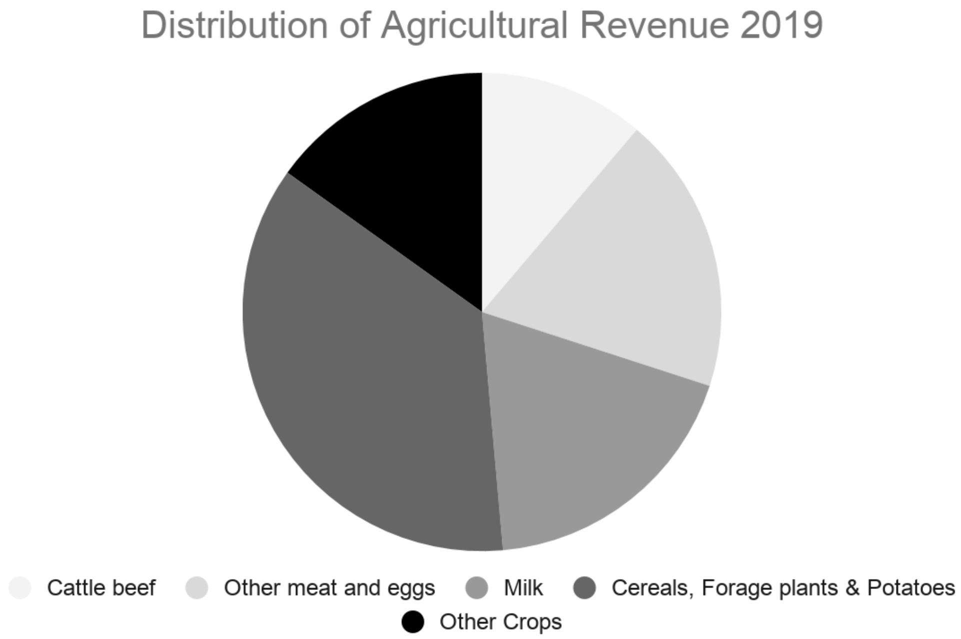

Figure 3.1: Diagram of the distribution of the agricultural revenue output in Sweden during 2019 (European Commission, 2020).

Agricultural activities are strongly dependent on the weather conditions. A period of bad weather can greatly damage the harvest for an entire season and thus affecting the revenue for an entire year. An example of such an effect from bad weather is shown at the year 2018 in figure 3.2. The figure displays the national income from agricultural activities for five different EU countries. In Sweden, the extremely warm and dry summer 2018 lead to reduced harvests for grains and forage plants. Thus, revenues were reduced but, most importantly, costs for producing forage increased drastically which damaged the net income for husbandry farmers. This, together with the global market prices for different resources, makes the income from agricultural activities highly volatile (Svensson, 2021).

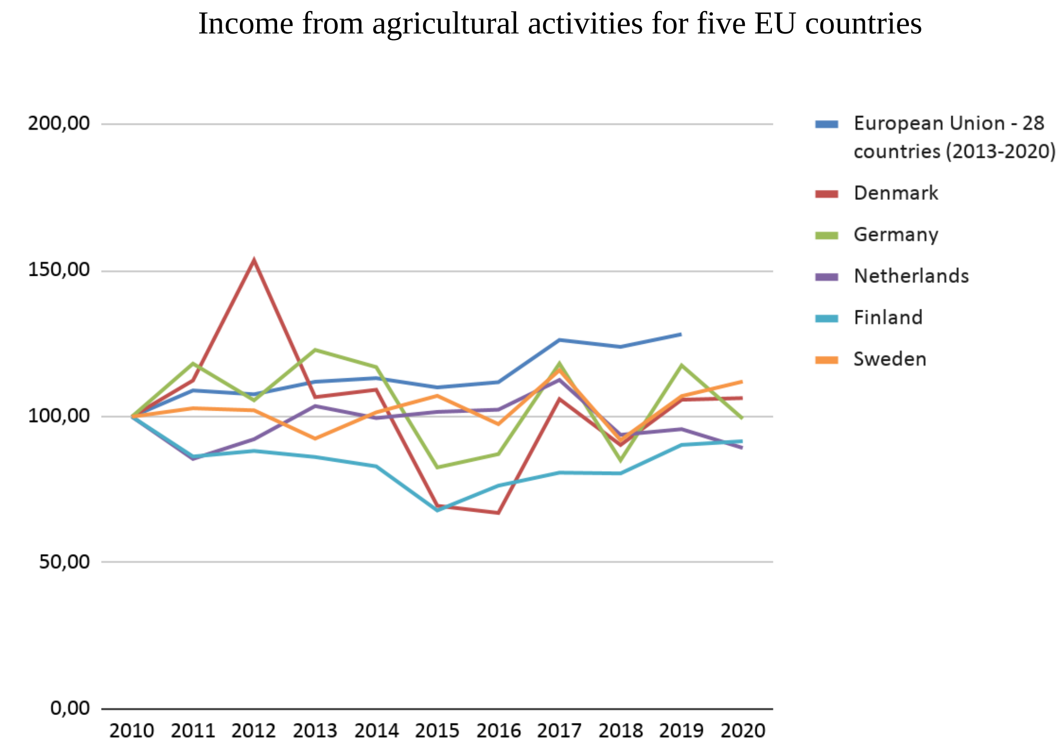

Figure 3.2. Indicator A, the deflated net value added of agriculture, per total annual work unit for different EU countries. Each country is indexed from 2010, thus the income is compared to the equivalent of 2010 (Eurostat, n.d.c).

The agricultural conditions in Sweden are partly specific for Sweden while also being regulated and shared with other EU states through the Common Agricultural Policy (CAP) from the European Commission. The common agricultural policy is a collection of laws that span all the member states (Jordbruksverket, n.d.). It is based on two ground pillars: one including direct aid to farmers and market measures and the other focusing on rural development. The goal of the common agricultural policy is to ensure foods of high quality to fair prices, a reasonable standard of living for farmers, to preserve and protect the environment as well as promote employment, growth, and development of rural areas (Jordbruksverket, n.d.).

Since CAP is a foundation for Swedish agriculture, and managed on a European level, the EU Commission has summarised extensive statistics on how Swedish agriculture compares with the average of the 27 European Union member states. Statistically, there are many similarities between Swedish and the aggregated EU-27 agriculture but also some important differences. Starting with similarities, the Swedish agricultural sector constitutes 1.6% of the national gross value added, a number slightly smaller than the EU-27 average of 1.8% (European Commission, 2020). Also, Swedish farmers have an age distribution similar to the EU-27 with around a third of the farm holders being more than

64 years old and only around 5% being less than 35 years old (European Commission, 2020).

On the other hand, there are some areas in which Swedish agriculture differentiates itself. To begin with, 84.3% of Swedish farm holders are men, compared to 68.8% on EU-27. In total, only 1.3% of the Swedish working population are employed within agriculture, compared to the EU-27 average which is more than three times higher (European Commission, 2020). Furthermore, the structure of the farms differs significantly. Average Swedish farms are about three times bigger than the average utilised agricultural area in the EU-27 (European Commission, 2020). This indicator displays similarities between Swedish agriculture and its neighbour Finland but also that other highly industrialised countries such as Denmark and Germany have considerably larger farms, as displayed in the three left columns in table 3.1. One obvious flaw with this comparison is that, for example, poultry farms require far less land usage than cattle which makes the agricultural composition in each country a key factor affecting the utilised agricultural area per holding. Since agriculture implies a broad variety of activities but often is generalised in statistics, the comparisons and average of farms may lack some precision when applied to individual farms.

Comparing the agricultural structure in different countries can, nevertheless, be done in different ways. Another way is to analyse how large the percentage of the total national agricultural revenue that is produced by holdings larger than 500 000€, as described in a blogpost by the Swedish Board of Agriculture (Karlsson, 2020). This indicates how large the agricultural consolidation is within a given country, i.e. the higher percentage a country has, the more its agricultural revenue is dominated by a few large farm holders. The column to the right in Table 3.1 displays this indicator.

Table 3.1. Agricultural holdings (single technical and economic unit producing agricultural products), utilised agricultural area (UAA - arable land, permanent grassland, permanent crops, and other agricultural land), and UAA divided by the number of agricultural holdings for five EU member countries in 2013 (Eurostat, n.d.a & Eurostat, n.d.b). In the bottom row, the percentage of the total national agricultural revenue that is produced by agricultural holdings with a revenue larger than 500 000€ in 2020 (Jordbruksverket, 2020).

Macro Statistics of Agricultural Structure in some EU countries

Country	Sweden	The Netherlands	Denmark	Finland	Germany	EU-28 average
Utilised Agricultural Area in 2013 (Eurostat, n.d.b) [unit: thousands of hectares]	3036.08	**1847**.60	2627.80	2258.60	16699.60	6369.57
Number of agricultural holdings in thousands in 2013 (Eurostat, n.d.a)	67.15	67.48	38.28	54.40	286.03	387.08
Utilised Agricultural Area per holding in 2013 [unit: hectares]	45.21	27.38	81.41	46.48	58.38	16.45
Percentage of total national agricultural revenue produced by holdings larger than 500 000€ (Karlsson, 2020)	46%	68%	79%	25%	48%	28%

Agricultural products are an important part of Swedish trade, making out 4.0% of the total export in 2019. However, Sweden imports more than double as many agricultural products as it exports with a negative trade balance for all categories (commodities, other primary products, processed products, food preparations and non-edible) except beverages (European Commission, 2020). Still, the index of the real income of factors in agriculture per annual work unit has been volatile in Sweden but is in 2020 slightly up from the indexed 2010 level, but still under the average EU-27 level (Eurostat, n.d.d).

4. Methodology

To delve into the thesis objectives and answer the research question, the thesis follows certain methodology steps. To begin with, a comprehensive literature review explores the agricultural sector, its agricultural technology initiatives, and former research about smart farming. Thereafter, data is collected qualitatively through a semi-structured interview study examining how different agricultural stakeholders regard smart farming technology. Consequently, three use cases for AI in agriculture are chosen out of the results from both the literature review and the initial results from the interview study. Additional interviews, with a focus on solely technical aspects of the three use cases, follow. Finally, all interviews, from both parts, are analysed. Thereafter, the findings from the analysis are discussed in relation to the literature review. In the following section of the report, the methodology will be further explained and accounted for.

4.1 Literature Review

A literature review is conducted with several purposes. It aims to identify which types of technology smart farming relies on, to map out some currently available implementations of smart farming technologies, and gain insight on the identified barriers in the literature that hinder the spread of smart farming technologies. The study uses a systematic review framework as proposed by Berrang-Ford et al. (2015). The literature review is conducted from peer-reviewed literature in the Web of Science-database. The chosen topic words in the search engine regards *"(("machine learning" OR "deep learning" OR "artificial intelligence" OR smart OR AI) AND ("precision farming" OR "precision agriculture" OR "precision livestock farming" OR farm* OR agricult*) AND (Sweden OR Scandinavia Or Europe))"* which render 87 results. Out of these, titles and abstracts are scanned to further narrow down the search to relevant literature. To methodically map the prevalence of smart farming technology-initiatives and actual usage, criteria for including or excluding studies in the literary review are set. The criteria are motivated by limiting the number of results of the search as well as only regarding the most relevant articles. For example, the scientific pace of AI in agriculture is fast, and therefore articles more than five years old may already be outdated, which motivates the third criteria. Table 4.1 shows the four criteria used in the search.

Table 4.1: Inclusion and exclusion criteria for literature selection

Inclusion criteria	Exclusion criteria
Either published as journal article, conference paper, review, or book chapter	Other publication type
Linked to the agricultural sector	Linked to other sectors
Published from 2015 to 2021	Published during other time periods
Abstract focused on individual farms or group of farms	Abstract focused on farming on a regional or country level

Out of the 87 results, all studies are marked as either relevant or irrelevant. 32 studies meet all inclusion criteria regarding AI and smart farming technologies in agriculture. These articles are reviewed completely, and their relevant findings are summarised in the thesis.

4.2 Interview study

The main data gathering for the thesis is conducted using a qualitative interview method. A qualitative method has few restrictions and is based on data collected from, for instance, texts and interviews. Compared to quantitative methods, qualitative methods differ regarding flexibility and fluidity of planning, where studies with qualitative methods often evolve over time (Graziano, et al., 2013). This type of method aims to understand the studied phenomena in-depth, rather than evaluating a predetermined hypothesis of an outcome (Taylor, et al., 2016, p.14). Thus, to thoroughly understand the underlying motivations and obstacles for AI-driven smart farming, which a quantitative survey would not be able to grasp, this thesis uses a qualitative interview methodology.

The interview study consists of 27 interviews and take place during week 6-14 in 2021. All interviews are conducted through digital media, such as Zoom or Google Meet (depending on the preference of the respondent), and last for approximately 60 to 90 minutes. Janghorban et al. (2014) state that online interviews benefit from not being limited to geographical places and that the respondents may choose a location they feel comfortable in. However, they describe some barriers that may affect the nature of the interview. These barriers include that it is crucial that all parties have access to high-speed Internet, are familiar with online communication as well as having so called 'digital literacy' (Janghorban, et al., 2014). Arguments aside, mainly motivating the online interviews is to minimise the spread of the virus Covid-19. Therefore, the method is deemed necessary, and all respondents agree to the terms.

Generally, there are three types of interview methods that originate from the level of structure and script of the interview (Taylor, et al., 2016). This thesis uses a semi-structured interview method, which enables the interviewer to adapt questions to the competence of the respondent or interest while still addressing the same themes (Kvale, et al., 2009). By using the same interview type, comparisons between interviews are facilitated. In a semi-structured interview, questions are often prepared beforehand, with different themes and types of questions (Kvale, et al., 2009, p.134-138). With the structure of questions as the base of the interview, Kvale et al. emphasise the importance of follow-up questions, in which the interviewer finds an interesting essence or detail in the respondents answer and ask further questions about that (Kvale, et al., 2009, p.139-140). This demands a certain level of flexibility and creativity from the interviewer but may lead to gathering of information that might otherwise be left unmentioned.

Some remaining interview technical characteristics must be stated. The initial contact with the respondents is through different approaches. Some respondents are contacted via email, some through telephone and some are introduced to us via 'word-of-mouth' by other respondents. 25 out of 27 interviews are recorded, with the explicit permission of each respondent. These recordings are only used to help the authors double-check the responses and will never be published. Additionally, all interviews are held in Swedish. This gives rise to a certain risk of mistranslation of the results in this report. However, opportunities to correct or clarify these kinds of mistakes are given to the respondents before the publishing of the report, which mitigates this risk.

4.2.1 Interviews with Two Objectives

To answer all the research questions of the thesis, the interview study focuses on different objectives: the initial 21 interviews focus on demands and barriers within smart farming, and the remaining 6 interviews scrutinise technical features of three identified use cases. The amount of interviews are determined by the amount of information gathered, and not set beforehand. However, the use case-oriented interviews are partly a result of the insights from the initial holistic interviews.

Although all interviews are semi-structured, the two types of interviews have some differentiating characteristics. To begin with, there are three different questionnaires used in the interview study. For the initial interviews, focusing on both technical- and non-technical aspects of smart farming, there are two questionnaires, one for farmers and another for organisations, commercial enterprises, authorities, and scientists (see Appendix A and Appendix B). Additionally, the questionnaire for farmers contains two trajectories to adapt the questions to the respondent's prior knowledge of smart farming. These questionnaires contain questions regarding the same themes, but with distinct emphasis adjusted to the two groups of respondents.

For the interviews that focus on the three use cases, there is less focus on receiving answers from respondents in every sub sector of the Swedish agricultural ecosystem. Instead, the interviews focus on how the use cases may technically be implemented. Thus, the deck of questions is more technical and the respondents, as described in the next subsection, are chosen for their technical understanding. Although the questions are identical for every respondent in this part of the interview study, the questions are more open to enable a discussion between respondents and interviewer (see questionnaire in Appendix C). Furthermore, as respondents are chosen for their specific technical understanding, not all the respondents answer questions about all use cases.

Another difference between the two interview segments is that all respondents in the initial part are anonymous meanwhile all respondents in the second part are published with their names. Motivating this divergent disclosure decision are the different purposes between the two interviews. In the first part of the interviews, the respondents are encouraged to openly display their personal views on technology and structures within the agricultural sector. To align with this purpose, all respondents are promised complete anonymity. However, for the second part of the interview study, the questions are strictly technical and therefore the need for anonymity decreases. Furthermore, the number of respondents for the second interview phase is significantly lower than the first part. Therefore, each answering respondent plays a significant role, leading to a greater need to disclose her or his background. A summary of the characteristics between the two types of interviews are seen in table 4.2.

Table 4.2. The main characteristics of the two types of interviews

	Holistic Interviews	**Use Case Interviews**
Number of conducted interviews	21	6
Type of interview	Semi-structured	Semi-structured
Purpose with the interviews	Identify both technical and non-technical opportunities and obstacles of implementing AI within the Swedish agricultural system	Analyse the three use cases technically
Deck of questions based on	Literature review	Holistic interviews & literature review
Length of interviews	60-90 minutes	60-90 minutes
Disclosure of respondents	Anonymous respondents	Respondents published with names

4.2.2 Selection of respondents

Since the implementation of smart farming is complex with different types of hindrances for different actors, the selection of respondents is of great importance for a representative study. The purpose of intentionally selecting respondents is to identify the participants that would contribute with relevant and valuable information fitting to the purpose of the study (Yin, 2011). In the holistic interviews, different stakeholders within the agricultural industry are interviewed. By the diverse respondents, commercial enterprises, advisor companies, research institutes and governmental authorities, and farmers with different kinds of specialisations, a comprehensive perspective on smart farming is attained. An overview of the respondents is provided in table 4.3.

Table 4.3: Respondents of the interview study distributed over categories.

		Meat	**Milk**	**Arable**	**Inter-disciplinary**
Farms	Large farms	F9	F2	F8	
	Medium /small farms	F6, F7	F4	F1, F3, F5, F10	
Organisations	Commercial Cooperatives	C6	C2	C1, C3, C8	C4, C5, C7
	Researchers	R6	R2, R3	R5	R1, R4, R7
	Authorities				A1, A2

Eleven of the respondents represent organisations within the agricultural sector. The backgrounds of these respondents vary, some come from a background of farming and others are more business- and technologically driven. In this portion of respondents, four out of eleven respondents are female. As for the remaining ten interviews, those respondents are farmers responsible for their own agricultural business. Out of these, only two farmer respondents come from a background other than from a farming family. Additionally, one out of ten farmer respondents are female. See more detailed information about the farmers in Table 4.4.

Table 4.4: Farmer respondents with their respective reference number, sector, method of farming, the (generalised) size of the farm and their location in Sweden.

Farmer ID	Sector	Method	Size of farm	Location
F1	Crop	Organic	<100 ha	Gotland
F2	Milk	Conventional	>500 ha & >500 animals	Uppland
F3	Crop	Conventional	>100 ha	Småland
F4	Milk	Organic	>100 animals	Uppland
F5	Crop	Conventional	<100 ha	Dalarna
F6	Meat	Conventional	<100 animals	Uppland
F7	Meat	Conventional	>100 ha & <100 animals	Halland
F8	Crop	Conventional	>500 ha	Skåne
F9	Meat	Organic	>400 animals	Uppland
F10	Crop	Organic	<100 ha	Västergötland

In the six interviews focused on the technical features of the three use cases, five of the respondents are from researcher backgrounds. The sixth respondent has a background in an agricultural tech-company. All but one respondent are male. In table 4.5 the names and organisations of the respondents are presented, as well as the date of the interview.

Table 4.5. Respondents in the use case-oriented interviews

ID	NAME	ORGANISATION	DATE
R3	Tomas Klingström	SLU	2021-03-23
R4	Jonas Engström	RISE	2021-03-25
R5	Bengt-Ove Rustas	SLU	2021-03-29
R6	Susanne Eriksson	SLU	2021-03-29
C8	Johan Martinsson	Dataväxt	2021-04-07
R7	Mikhail Popov	RISE	2021-04-07

4.3 Analysis

The analysis of the holistic-oriented interviews is conducted by identifying the answers of respondents connected to the different themes of the questionnaire. Each theme is mapped out by noting all responses to the related questions. Answers are then aggregated where they correlate and patterns where answers differ between respondent groups are noted. Thereafter, a combined analysis on the demands and barriers to smart farming in Swedish agriculture is compiled.

Furthermore, three use cases in the holistic interview segment are selected to exemplify innovations in each studied agricultural sector. These use cases are selected on basis of a couple criteria. First, the three use cases should represent technological innovations within arable farming, milk production and beef production. Secondly, each use case should be one of obvious interest for the relevant interviewed respondents in the first parts of the interviews. Lastly, if possible, the use case should be reflected in the literature review. Table 4.6 displays how each of the three use cases matches these criteria.

Table 4.6. The three use cases and the selection criteria.

	Predict the quality of the yield	**Indicators for the health status of cows**	**Optimise the time for slaughter of beef cows**
Type of food	Arable farming	Milk production	Beef production
Interested respondents	C1, F1	C4, C6, C7	C4, F4
Mentioned in the literature review	Griffiths et al., 2020; Khanal et al., 2020; Viljanen et al., 2018	Caja, et al., 2020; Buller, et al., 2020	None mentioned

The interviews focused on the use cases are summarised and their answers compared. As these respondents are experts in their own agricultural sector, the respondents only contribute to the use cases in which they are working. In the cases where respondents have insights or opinions on use cases outside their expertise, the answers are added only if they are in line with what the other respondents state. All respondents have the opportunity to discard questions or subjects that they feel are not within their competence or knowledge.

5. Results of the Literature Review

In the following section the previous research on data-driven technology in the agricultural sector is presented. Below, the result of the literature review is displayed, aiming to account for the present techniques and initiatives of smart farming technology. The section is divided into two parts: the initial one regards different techniques for data gathering. Thereafter, a section with applied initiatives for different agricultural sectors are presented.

5.1 Different Techniques for Data Gathering

To be able to conduct analyses and smart decision support in agriculture it is fundamental that some data exist to base the analysis on. Regarding the gathering of data, different techniques may be adopted. The techniques used for gathering different types of data depend on what type of data that is requested. Below, two data gathering techniques are presented, categorised by remote sensing technologies and Internet of Things.

5.1.1 Remote Sensing Technologies

Remote sensing is one of the ground pillars in precision agriculture, enabling detection and monitoring of physical characteristics of the earth's surface (USGS, n.d.). Remote sensing data is collected from a distance, commonly from satellites and drones. The three most common properties of remote sensing data are spatial, spectral, and temporal resolutions (Khanal et al., 2020, p.6; Meier, et al., 2020, p.2).

Spatial resolution is the pixel size of an image, a property that affects the ability to detect objects through imagery. Differently, spectral resolution refers to the spectral sampling intervals size and number which affect the ability of the sensors to detect objects in electromagnetic regions. The temporal resolution regards the frequency of acquired data (Khanal, et al., 2020, p.6). A practical consideration when gathering remote sensing data is the risk that clouds or fog cover the photographed area. As this data is collected discreetly, often with days in between each photograph, such bad weather can drastically reduce the usability of the collected data (Heidler, 2019, p.7306).

The availability and economics of using remote sensing data collection is addressed by Khanal et al. (2020), which present remote sensing technology alternatives both open-accessed (e.g., NASA's Landsat, the European Space Agency's Sentinel satellite series) and for some cost (e.g., RapidEye, GeoEye-1) (Khanal, et al., 2020, p.18). However, the resolution of the data varies, where the trend is that medium-resolution data (≥10 m pixel size) is free whereas the prices for high- (≤5 m) and very high (≤1 m) resolution data increase in proportion to their increasing quality (Khanal, et al., 2020, p.18).

Regarding data resolution, Meier et al. (2020, p.9) opine that site-specific smart farming depends on high resolution, as detection of anomalies are impossible or insipid with too large pixel sizes. According to Meier et al. (2020, p.5) it is desired to have at least 50 pure pixels per field to determine a spatial distribution of crop growth conditions, wherein site-specific actions can be taken. Of course, depending on what kind of analysis the data aims to contribute to, the need for resolution varies. For example, predicting the crop yield within a field can accomplish a high accuracy despite a coarse resolution (Khanal, et al., 2020, p.15) while detection of plant diseases through hyperspectral imaging requires a detailed resolution (Torai, et al., 2020, p.1515). Generally, the application of remote sensing technologies in the selected literature focus on detecting drought (Heidler, 2019; Crocetti, et al., 2020), predicting yield (Griffiths, et al., 2020; Khanal, et al., 2020; Viljanen, et al., 2018) and detecting diseases (Torai, et al., 2020).

5.1.2 Internet of Things

Internet of Things (IoT) is a collective concept for things with incorporated electronics and connections that enable remote control and information sharing over the Internet. It has developed over time to include several different technologies and data. Today, the concept of IoT can cover everything from everyday objects, buildings, vehicles, and machines, to name a few. In agriculture, IoT is mainly used for collecting data through different types of sensors. By further data analysis, valuable information can be derived as decision support, e.g. for farmers (Atzori, et al., 2016). Examples of applications of IoT in agriculture will be further disclosed in this section.

Kamienski et al. de (2019) define four main challenges for IoT development in smart farming. First, the IoT system must have a high level of *adaptability*. Since the needs of farmers often significantly vary, the IoT system must be customisable to local circumstances but still not increase the required work for the farmer. Secondly, the IoT *deployment* must be efficient. As Kamienski et al. (2019, p.17) write, “there is no ‘one size fits all’ in IoT systems”. Thus, each system needs to be configured, the Internet connection and farm infrastructure must be reliable, and the farmer must deploy enough human and economic resources into this process. Furthermore, the *scalability* is affected by the previous factors but also depends on if the system, and the models learned, are supposed to work for just one farm or entire agricultural consortiums. Lastly, the *complexity* of the IoT system can be interpreted as a trade-off between making the middleware broker complex and the software application simple, or the reverse (Kamienski, et al., 2019, p.17-18).

Another aspect to IoT in smart farming is security. Since the data often is valuable for the farmer and is regarded as a business secret, Kleinschmidt et al. (2019) describe the need for end-to-end encrypted communication from the sensor to the application. In practice, this means that the IoT sensor network must have a synced security strategy to the cloud database and the potential fog computing network (Kleinschmidt, 2019).

By ensuring four properties, the IoT system can be regarded as secure. First, it needs to ensure *confidentiality*, i.e. that data is encrypted and not viewable by other parties between the sender to the receiver. Then data *integrity* is crucial. This means that no data is unwillingly modified, and that the data source is authentic. Additionally, the data must be accessible by the user at all times, a property referred to as *availability*. Lastly, IoT systems need to provide an *authentication* solution, so that a user needs to verify its identity with a password before accessing the data (Kleinschmidt, 2019).

By ensuring security, the probability that the farmer trusts the IoT system increases. Still, trust in IoT systems does not just depend on security but also on the precision of the sensors. Without ensuring that there are no systematic measurement errors in the sensors, few farmers would trust the learned model or the real-time data (Herhem, 2017).

5.2 Smart Farming Technologies Applied to Agricultural Sectors

Agriculture is a heterogenous industry with sectors in need of a diverse set of technologies. Since the gathered data differs between the sectors, certain data types are more common in some sectors than others. Below, recent research and current initiatives on smart farming are presented divided by type of agricultural activity: livestock farming and arable farming. Furthermore, this section includes previous research of barriers for propagating smart farming technologies as well as research on business models linked to smart farming.

5.2.1 Livestock Farming

The potential of smart farming in animal husbandry, such as dairy-, beef- and fur production, is largely constituted by increasing productivity and profitability by streamlining and automating tasks and information (Buller, et al., 2020). In this following section, the most recent literature regarding precision livestock farming is presented.

A macrotrend in livestock farming is the consolidation of farms, resulting in a reduced husbandry staff to animal ratio. Larger farms sometimes entail less attention to individual animals, as most care practices become group oriented (Caja, et al., 2020, p.34). The consolidation is mainly driven by large-scale benefits, limited labour availability and increased costs. Caja et al. (2020, p.34) state that the reduced ratio between staff and animals might compromise production, health, and welfare practices. As a counterreaction to these negative effects, the study investigates technology that can monitor livestock both on an individual and group basis. Findings show sensors divided into two categories: wearable and non-wearable. The wearable devices, attached to collars, ears, or injectable devices to name a few, need to be wireless, small, and compact as well as robust and resistant to different types of environments (Caja, et al., 2020, p.37-43). The non-wearable devices include weather and environment monitoring, infrared cameras, automatic gates and weighing scales as well as 3D cameras for body condition scoring (Caja, et al., 2020, p.43-44). Thus, precision livestock farming may be achieved through both remote sensing and small sensor technologies.

One example of precision livestock farming involving non-wearable devices is the identification of cattle using deep learning. Using AI for this process has the potential to replace traditional ear-tags and collar IDs which suffer from loss of tags, fading of labels, and physical damage to the ID tags. Bhole et al. (2019) describe a hands-on approach on how specific Holstein cows are recognised using a side-angle thermal and colour (RGB) camera. By these temperature distribution and photographic features, a convolutional neural network is learned which can identify individual cows with a high accuracy. The authors also use an extensive data pre-processing structure, involving segmenting the cows from the background and inpainting missing or blocked parts with another convolutional neural network, to increase the accuracy of the output (Bhole, et al., 2019).

Not only the trained model is important in precision livestock farming, but also how the data is presented. A study by Herhem, et al. (2017) emphasises the need of the farmers for a visualisation tool displaying the data. Their system takes real-time continuous data from IoT devices and automatically displays it in an app accessible for the farmer. In this specific application, the farmer detects respiratory problems and diseases for pigs by automatically identifying pig coughs by microphones on the farm. Herhem et al. conclude that farmers who receive training in how to understand and act on the data are more likely to use the tool (Herhem, et al., 2017, p.2-9).

Another dimension of precision livestock farming is presented by Buller et al. who argue that precision livestock farming technology has the potential of detecting and measuring animal welfare in a new way (Buller, et al., 2020). The data derived from precision livestock farming-technology can be combined to create complex welfare indicators, which in turn can be turned into holistic, continuous, and standardised welfare assessment for farm animals (Buller, et al., 2020, p.3). A few examples of precision livestock farming approaches to some identified welfare criteria are provided by the authors, but as welfare amongst animals is difficult to define, they stress the importance of further studies on this application area (Buller, et al., 2020, p.7).

5.2.2 Arable Farming

One challenge for Northern European arable farmers is to predict the yield biomass and quality of ley that grow during a year. Ley, the main nutrient for meat and dairy cows in Northern Europe, is harvested around three times a year and often continuously applied fertilizers. By predicting the yield, it is possible to determine farm management practices and security precaution measures in advance to maximise the probability of a successful harvest (Feng, et al., 2020).

Viljanen, et al. (2018) train a machine learning model aimed to optimise the “balance between the highest possible yield quantity and an adequately high digestibility for feeding” (Viljanen, et al., 2018, p.2). By using an inexpensive drone system that can get multispectral data from an RGB camera and an infrared camera, traditional physical tools for predicting ley yield can be replaced by smart machine-learned models with higher accuracy (Viljanen, et al., 2018, p.20). Viljanen and the research group use an infrared camera in line with the method used to calculate the vegetation index, since vegetation often has high reflectance in the near-infrared wavelengths. The method is effective for indicating the amount of live biomass, which is useful when predicting yield (Viljanen, et al., 2018). Furthermore, the research of predicting yield and quality of silage can also be accomplished through satellite data, as presented by Griffiths et al. (2020). The study shows that it is possible to detect mowing events of grasslands, and therefore characterise the land-use intensity by looking at satellite imagery (Griffiths, et al., 2020).

Staying on the topic of predicting yield, Feng et al. (2020) stress the importance of incorporating biophysical characteristics of the crop in machine learning algorithms. This means that to learn a model with high precision, it is important to simulate the growing process of the crop to ensure that the model learns the crop characteristics in different stages of the growing process. Feng et al. use both remote sensing data as well as IoT sensors while training the model. Common methods for yield forecasting are field surveys, dynamic process-based crop simulation models and statistical regression-based models (Feng, et al., 2020). However, the study combines the dynamic process-based approach with a statistical regression model, resulting in a more accurate forecasting model (Feng, et al., 2020).

On the topic of biophysical characteristics included in the machine learning model, Matos-Moreira et al. (2017) uses manual soil samples to further improve their model. By including manual soil sampling and analysis with a variety of existing data sources one may learn a model to predict the concentration of phosphorus at a given place and time. This is important since phosphorus often is unequally scattered throughout the farmland. Its complexity stems from the number of factors impacting its distribution, such as climate, agricultural practices, and topography to name a few (Matos-Moreira, et al., 2017, p.282). After a complex data pre-processing, they applied linear regression models and other machine learning algorithms to deliver estimations of high accuracy (Matos-Moreira, et al., 2017, p.287-293).

In Southern Europe, one of the largest identified demands for smart farming is precision irrigation, which can be accomplished through IoT-sensors. Kamienski et al. (2019) describe that if successfully launched, precision irrigation could help mitigate the risk of over-irrigating or under-irrigating fields. By learning a model and automatically predicting the exact needs for fresh-water at a given time and place, precision farming has the power to radically change fresh-water-intense agribusinesses (Kamienski et al., 2019, p.2-3). However, the scientists describe that most systems for precision irrigation are still in a scientific phase “with limited proof of concept experiences” (Kamienski, et al., 2019, p.3). Furthermore, the authors singled out the cloud servers to be the “key bottleneck” of the system since they overloaded and finally crashed when the amount of sensors were increased from 10 000 to 15 000 (Kamienski, et al., 2019, p.17).

Another application of precision farming is to detect sickness or pests among crops. Torai et al. (2020) research how diseases can be detected in crops by classifying, or labelling, areas in pictures as “healthy”, “infected”, “diseased” or “aged”. Thereafter, methods such as hyperspectral imaging, Bayesian networks, and an analysis through probabilistic latent semantics are applied to detect the diseases (Torai, et al., 2020). This study is a good example of a remote sensing technology applied to agriculture which needs a very high resolution of data, preferably on a scale of centimetres.

Khanal et al. (2020, p.6-17) have researched a broad variety of implementations of remote sensing in agriculture which stretches from preseason planning to post-harvest treatment. The application of remote sensing in preseason planning mostly involves topography mapping of fields meanwhile the field preparation-stage covers soil moisture, temperature mapping and soil compaction assessment. Identifying emerging crops and densities within the fields together with in-season crop health monitoring are possible implementations in the planting stage. In the harvest, yield forecasting and grain quality assessment are possible to perform. Finally, the post-harvest applications cover crop residue assessment and soil health (Khanal, et al., 2020).

Besides identifying possible applications of the technology in agriculture, Khanal, et al. (2020) argue that methods within machine learning and AI require decision support tools that visualise the data in comprehensive ways (Khanal, et al., 2020, p.19). Best practice for remote sensing data applications, according to the authors, include three steps. First ‘known unknowns’ and ‘unknown unknowns’ are identified by modelling large volumes of data. Secondly, these results are used to create insights for decision-support, which are, in the third step, presented through reports and interactive dashboards (Khanal, et al., 2020, p.19).

Lastly, a dilemma when applying artificial intelligence to arable challenges is how to use the different types of available data. Kerkow et al. (2019) use fuzzy mathematical modelling to solve this problem. In practice, fuzzy mathematics means translating numeric terms to linguistic ones, e.g. the wind speed is “comfortable”. This approach allows for mixing machine learned climate models with wind data and expert knowledge of the landscapes to build models of how a specific type of mosquito is spread throughout German farms (Kerkow, et al., 2019, p.12-17).

5.2.3 Applying and Implementing Smart Farming Technologies

Medvedev et al. (2019) highlight both theoretical and practical knowledge of smart farming as requirements for successful implementation. Regardless of the accelerating technological advancements, smart farming will not bear fruit “if farmers will possess insufficient knowledge level and practical skills” (Medvedev, et al., 2019, p.1883). Unfortunately, seldom farmers have either the economic resources or the time to attend longer educations within the subject. Furthermore, age is described as another hurdle. Only 6% of European farmers under 35 years old and a majority are more than 55 years old (Medvedev, et al., 2019, p.1884).

To meet the lack of technical education within smart farming, Medvedev et al. propose five smaller model-based courses that would benefit students of agriculture academic programs, students of computer science and electrical engineering, and farmers belonging to small- and medium-sized farms. The modular courses would cover technical, economic and management aspects to smart farming. A crucial part of the education is that the courses are on-demand, i.e. busy farmers can access it whenever it suits them (Medvedev, et al., 2019, p.1883-1886).

Particularly business models for smart farming and climate-smart agriculture have been described in literature by Long, et al. (2016). They see an adequate choice of business model as a "critical component" for sustainable farming (Long, et al., 2016, p.6). To them, a business model consists of defining how revenue will be created, segmenting main customers, modelling how to build relationships with customers, and pinpointing key activities, resources, and partners. From their interviews with farmers regarding climate-smart agriculture, they find that farmers regard the risk of investing in new technology as high and therefore are not inclined to accelerate the transition process. Also, they quote farmers that consider proven return of investment as the key factor trying out new agrotechnology. Additionally, some farmers are described to primarily want technology that is easy to comprehend and helpful for the everyday operations at the farm, and secondarily high-level goals such as mitigating climate change (Long, et al., 2016, p.7-17).

Long et al. (2019) also discuss the driving force towards diffusing smart farming. They argue that sustainable entrepreneurs face difficulties in implementing the initiatives and new technologies that are available. The main barriers are categorised as economic, institutional, behavioural, and organisational factors (Long, et al., 2019, p.993). Another group of researchers, Fusco et al. (2020), additionally identify market factors as barriers. Long et al. (2019, p.994) further state that it is hard for an individual entrepreneur to solve and suggest that inter-firm and firm-to-government relations are likely to play a critical role when solving these barriers. Furthermore, they identify social and moral drivers to play a key role in terms of creating a societal demand for smart farming. Without the support from society at large, innovations will not be adopted by key actors, they conclude (Long, et al., 2019, p.1001).

Other research aims to map the barriers to implementing and diffusing smart farming technologies. Kernecker et al. (2020) describe that farmers approach smart farming technologies differently given how much smart farming technologies the farmers have already adopted. The so-called *adopters* perceive the barriers to adopt smart farming technology as high investment costs, a difficulty in interpreting data, a lack of interoperability or precision in devices, that farmers cannot see the added value of the new technology or the relative advantage of the system, as well as a lack of neutral advice from advisors and other actors (Kernecker, et al., 2020, p.44). The *non-adopters* also perceive high investment costs and unclear added value as barriers. Additionally, they regard too demanding complexity of use, that the technology is not appropriate for their context or farm size, as well as a lack of access to proof of concept from a neutral point of view, as obstacles (Kernecker, et al., 2020, p.44).

6. Results of the Interview Study

In the following section the results of the interview study are presented. They are structured into four parts. First, an introductory subsection in which general knowledge of smart farming and opinions regarding its role in agriculture are compiled. In the second subsection, technological aspects of smart farming technologies, through the eyes of the respondents, are presented. This subsection also contains three examples of use cases for future smart farming. Thereafter, the third subsection encloses non-technical aspects that influence how AI and smart farming technologies are spread in the agricultural sector. Included in the third subsection are the economic and political structures that may affect the susceptibility of new technologies, as well as social factors and the knowledge base in the sector. Finally, the fourth subsection summarises the results. Answers from the interviews are referenced by noting the respondent ID, to maintain anonymity of the respondents. See more information about the respondents in the method section, and the full list of interview respondents in Appendix F.

6.1 General Interest in Smart Farming

Among the respondents in the interview study, there is a general interest in, and positive view on, technological developments and digitalisation in the agricultural sector. One respondent at a governmental authority states that digitalisation is a natural development, and the next logical step in developing agriculture as well as society at large (int. A2). Another respondent, working at a Swedish agricultural enterprise, says that he sees an enormous long-term potential in applying AI in agriculture because the agricultural sector is affected by many interconnected random factors such as wildlife, weather, and climate. Therefore, AI could be helpful to predict and prevent the possible negative consequences that these non-controllable factors have on agriculture (int. C3). Farmers, too, are curious about new technology incorporated in the sector. Most of them see technological development as a must to be competitive on the market in the future, but a lot of them also see new technologies as something fun and interesting that would benefit the farm several ways (int. F1, F2, F4, F6, F8, F10).

All respondents, except for two farmers (int. F3, F7), understand the main concepts within smart farming, precision agriculture and precision livestock farming. When asked to define the concepts, the provided definitions of the respondents highlight how the technologies are expected to increase the efficiency in agriculture and therefore increase revenue per activity. Many also define smart farming and precision agriculture as technologies that optimise the input resources needed in agricultural productions, mitigating excessive usage of inputs (int. C1, C2, C5, C6, F1, F5). In this way, the respondents claim that the technologies are helpful both environmentally, because resources are not wasted, and economically, since inputs generally are large expenses for farmers (int. C2, A1, F7). One governmental employee describes the relation between economy and smart farming:

> "*Small modifications [in input resources and agricultural activities] that increase profit in a sector where returns are decreasing.*" (int. A2).

However, there is not a uniform view on smart farming as something new and modern. In an interview with a commercial enterprise, the respondent describes how agricultural technology for decades has been described as revolutionary when it has developed (int. C5). An example of former revolutionary innovation is the introduction of GPS steering to tractors. When the GPS was introduced, farmers could decrease the plough overlap and its related fuel costs, leading to increased profitability and output. With the example, the respondent argues that it is not the technology in itself that is relevant but how it is implemented by the farmer using it (int. C5). For a responding farmer, the introduction of threshing machines in the middle of the 1990s constitutes the inauguration of smart farming in Sweden. After their market introduction, electronics have continuously been added to machines, leading to the smarter agricultural machines of today (F8). Respondent A1, an employee at a governmental authority, argues that agriculture has innovated and adapted to new technological tools for decades:

> *"There is a habit of incorporating new tools and new technologies in the agricultural sector that stands out compared to other business sectors."* (int. A1).

Nevertheless, this view is not shared by all respondents, not even all respondents who are farmers. While some of the respondent farmers see themselves as very technologically driven and in the forefront of technical implementations, others do not. While some see the agricultural sector as a fast-paced and tech-driven part of society, others tend to think of it as an old and inert industry for technological implementations. With the following quote from farmer F10, we conclude this introductory section and dive into the technical aspects of implementing AI in agriculture:

> *"There is enormous potential in technology but there are also enormous barriers that you must overcome. Many of the barriers are not only technical, but some are also social."* (int. F10).

6.2 Technical Aspects

In this section the technical aspects of implementing smart farming technologies are presented, as discussed with respondents during interviews. Of course, when implementing and developing a technical system there are several factors that one needs to keep in mind. The section includes subsections in which the respondents' views on what types of systems are beneficial in the agricultural sector, a technical description of what is needed practically to implement three chosen use cases, as well as a subsection that includes all topics regarding data.

6.2.1 Different Circumstances Within Different Sectors

Applying AI to the agricultural sector is not a homogenous challenge since the sector varies substantially. One pattern, stated by a farmer respondent, is that farmers of different agricultural sectors almost always believe that the implementation of smart farming technologies has come further in other sectors than in their own (int. F4). The agricultural sector that most farmers highlight as currently the most technologically advanced is the milk production. Milk robots were introduced to the commercial market decades ago. These provide cows with high-energy fodder, milk them automatically, sample the milk and analyse the nutrition values of the milk. Hence, the fodder of an individual cow can be customised, increasing its health status and production capacity. Due to the milk robots, the dairy industry is regarded notably data driven (C4).

One important aspect to consider when evaluating the success of the milk robots is the short feedback loop. Since cows are both fed and milked daily, the machines can adjust quickly depending on the latest input (int. C4). Furthermore, Swedish dairy farmers have a long history of collecting data by being part of the so-called *Kokontrollen*, a cow data collection application owned by Växa Sverige. Even if *Kokontrollen* today is web-based, Swedish dairy farmers have been reporting to it for more than 100 years. Previously, all data was collected manually but today almost all data connected to milk production is automatically gathered by the milking robots (int. C6).

However, not all farmers believe that the technologies themselves, such as milking robots, have been particularly prominent to the spread of smart farming techniques in milk production. Two crop farmers believe that milk farmers have come the furthest in the usages of precision farming techniques in farmlands since milk farmers, in addition to husbandry of milk cows, produce their own ley. Ley is the main fodder for cows in Sweden and is harvested several times a year. Compared to other crops, ley production requires less machines which the crop farmers believe allows the milk farmers to invest in more expensive and advanced machines (int. F1, F3). Contrasting, arable farming is diverse with different crops requiring distinct machines and technologies. Hence, a single successful machine is difficult to implement for the entire arable farming sector, making its technological development more complex. However, it is possible to create effective technology for specific crops. As a rule of thumb, crops with high manual work, such as vegetables, use lots of technology since they operate on small, more controlled areas (int. C3). In such environments, as in green houses, the feedback loop is faster and there are less uncontrollable factors, such as weather or wild hogs, which makes the application of new technology and AI easier (int. C3, F3, R5).

If farmers grow many different crops, the possibilities to implement precision farming are higher for the more expensive crops. One farmer mentions potatoes as being the crop with the highest cost per hectare. If a new technology could help him better control the usage of input resources for the potatoes meanwhile maintaining a high, even quality, buying such technology would be interesting (int. F1). Another benefit with implementing smart farming techniques in arable farming, compared to agricultural sectors connected to animal husbandry, is the lack of animals. From a risk perspective, innovative smart farming techniques related to arable farming are described by a researcher to be easier to implement and scale. This stems from the lack of animals which allow for higher risks and experimenting (int. R1).

Of the three agricultural sectors compared in this thesis, beef production is described as the least technologically developed. Nevertheless, one respondent at a major company believes that meat production will have a central role in the development of the Swedish primary food production (int. C4). The list of possible innovations includes making the value chain digital, automatically transferring information to the slaughterhouses regarding characteristics of the animals they will receive. By mandatory RFID tags for all cattle, the respondent argues there is an enormous potential, since the development of the animals could be followed in real time throughout the value chain. With such a system, the slaughterhouse could, far in advance plan, for incoming meat quality and volume. In that case, a grocery store could send data to the farmers regarding which meat that currently is popular, enabling the farmers to adjust their production to the current consumer behaviour (int. C4). Furthermore, if one could autonomously and automatically weigh the cattle, their growth curves can be predicted which would enable optimisation of the timing for sending animals to slaughter. By this optimisation, one could avoid having full-grown animals that both drain economical resources and emit environmentally damaging methane gas (int. C4).

Another way of differentiating farms is by dividing their production in organic and conventional farming. In Sweden, most organic farms are certified by KRAV, which ensures that the certified farmers are following the EU-regulation for organic production and the standard KRAV has set up. However, one respondent that works at KRAV states that she does not think that the use of technology differs much between conventional and organic farms. She says that the main factor that determines if the farm can implement some technological systems are economical, and not the production form itself (int. C7). With that said, two respondents state that some precision agriculture technologies are redundant for organic farmers since they never use pesticides or other chemicals, the products that precision agriculture technologies often aim to optimise (int. F4, C7).

6.2.2 Use Cases and Applications of Smart Farming

In the interview study, all respondents were asked to themselves come up with new potential smart farming applications. Additionally, the respondents were asked to give their input on one or several use cases commonly appearing in the literature review. As described in the methodology section, one use case from each farming sector is analysed in this section.

As most use cases discussed in the interviews are not analysed in detail in this section, their potential should still be commented. Predicting the spread of vermin or weeds in arable farming is one use case with interesting potential. One major Swedish agricultural consultancy firm launched in February 2021 an AI application which detects crop diseases, lack of nutrition and the spread of vermin. A respondent from that firm describes the application as a way to provide their consultants with a platform for more data-driven analysis (int. C5). As previously mentioned, one organic farmer states that detecting the spread of vermin would not provide too much value since they are not using any pesticides. However, he believes predicting where weeds are spreading could be useful if these could be removed manually (int. F1). Another use case that already is quite developed is the prediction of the amount of water, pesticides, or other inputs needed in a specific place. Both respondents C1 and F2 regard these technologies as important but that their potentials to further improve are quite limited (C1, F2).

In the livestock sector, the possibility to identify cattle through cameras, using pattern recognition technologies, divides the respondents. Most cows in Sweden are marked with RFID ear tags or collars which makes the additional added value of using cameras small, according to a researcher respondent (int. R1). However, three interviewed livestock farmers agree that having a way of monitoring the interaction of a herd, how the cattle behave together and how their internal hierarchy is organised, would be useful (int. F6, F7, F9). Another dairy farmer instead states that the most important feature is that the identification system they use is compatible with the milking robot which is of utmost importance for the farm (F2).

In the following three subsections, each use case is presented separately. After a brief introduction, the necessary input data, corresponding output, and possible models to solve the problem are presented. Thereafter, some ways of evaluating the model as well as the practical considerations of the solutions are suggested.

6.2.2.1 Use Case 1: Predicting the Quality of Ley for Silage

In Sweden, most cattle eat predominantly silage, i.e. grass and clover that has been fermented and stored, also called ley. Differentiating from most grains, silage is harvested several times a year. Depending on where the farmland is situated in Sweden, the number of harvests differs. In southern Sweden, the ley is harvested up to four times while it is often only harvested twice a year in the most northern parts (int. F5). However, since the whole crop is harvested, the timing of the first harvest is critical, as its success affects future harvests the entire growth season. Therefore, there is a need to predict how the quality of the crop will develop over time so that the timing of the harvest can be optimal (int. R5). Additionally, predicting the quality can help to decide how much fertilizer to add the last time before harvest or to separate the high-quality forage from the lower quality forage (int. C8). This use case is discussed in the literature by Griffiths et al. (2020), Khanal et al. (2020) and Viljanen et al. (2018). The topic is also examined in the interviews, where many respondents that produce ley and other crops state that this kind of application would benefit the economy and workload on an arable farm, which is discussed in section *6.3.2 Economic and Political Structures* and *6.3.4.3 Workload* respectively (int. C1, C5, F1, F2, F7). Below, the technical aspects of a model that predicts quality of the harvest of ley is further inspected.

INPUT

There are several potential input data that can help predict the quality of the ley. Some practices are already in place. One visual parameter that farmers already consider is the botanical development of the crop, where harvesting when the ear of the grass emerges is a common goal. Additionally, farmers can take samples for lab analysis to get an indication of nutritional status. By doing this a couple of times per week during certain periods, farmers receive some data on the growth speed of the ley (int. R5).

In an AI application these samples could still be used. However, they would primarily work as a calibration of the AI model (int. R5, C8). The model would instead primarily use remote sensing data such as satellite or drone photos (int. R4, C8). Additionally, the model could use several time- and location-specific parameters such as temperature, hours of sunlight, and precipitation. Also, data generated by machines or added manually such as the nutritional values in the soil or the amount of fertilizers added could improve the model (int. R5). If the number of fertilizers added could be compared to the percentage of fertilizers that is absorbed into the ley it would add extra value. In any case, building a model requires the data to be consistent during several years and include the relevant output parameters such as protein percentage and perhaps also carbon emissions (int. C8).

OUTPUT

The most relevant output parameter for a farmer would be a recommended harvest date given a desired ley quality. This is important since the need for a specific quality depends on the type of cattle that should eat the silage. Dairy cows need silage that has been harvested early, suckler cows require a later harvest quality, and horses yet another type (int. R5). However, a way of increasing the trust to the system would be to provide different dates based on e.g. three different weather scenarios. Then the farmers could act based on how they expect the weather to behave (int. R4).

MODEL

The type of mathematical model to predict the quality of the silage is difficult to determine. It could both be a multiclass classification model, which predicts the output into a given set of quality types, or a regression model, predicting linearly the growth over time. Respondent R5 suggests that the model should be dynamic, and that the type of model depends on the complexity and the input data. One respondent (int. R7) states that he thinks that the model in an initial state should be built on a few simple parameters. Thereafter, the developer can include one additional parameter at a time to increase the complexity of the model. He means that it is important to tune each parameter to the model, and that if one works with too many variables at the same time it is impossible to determine the actual consequences of a change (int. R7). However, this reasoning applies to all use cases presented in this thesis, not only use case 1.

EVALUATION METRICS

When evaluating either a classification model or a regression model, there are several adequate evaluation metrics. For classification, the two main evaluation metrics are accuracy and precision. Accuracy shows the amount of correctly classified ley quality predictions divided by all predictions. Precision differs by dividing all true positives, i.e. ley data points adequately classified to a certain ley quality class, by the total number of ley samples classified to that class. Combined, optimising for both accuracy and precision often work well. Conversely, when evaluating a regression model, one rather regards errors by calculating, for example, the mean squared error (MSE). Thereafter one may perform a model selection based on comparisons of the errors of different regression models.

According to respondent R5, the first spring harvest must be very precise, due to the fast but variable development of the crop and hence change in feed quality. He describes a miscalculation of one week to be devastating to the entire harvest and affecting the timing of coming harvests.

PRACTICAL CONSIDERATIONS

One aspect to consider regarding this use case is the practical cost of sampling. Even if the cost is quite low, a couple of hundred SEK, it requires time from the farmer and is therefore not always considered worth the investment if the farmer is not particularly interested in the technique. Furthermore, since the lead time for postal services is important for how fast the farmer can get back and use the sample information, the interest in remote sensing techniques grows in inverse proportion to the stated increasingly sparse mail deliveries (int. R5). Still, by using new machines that by themselves can take some of these soil samples, the data will be refined and improved (int. C8). Today, scientists at universities are best at this process of gathering specific data that is continuous over time. They will play an important role when developing these prediction models further (int. C8).

6.2.2.2 Use Case 2: Detecting Health Anomalies amongst Dairy Cows

Animal care is a sensitive subject in agriculture and society at large. Sweden has one of the strictest regulations for livestock care and health in the world (int. C2, C6, C7). One researcher respondent claims that the development of health indicating systems stems from the need to show external stakeholders, as authorities, that the animal welfare is as good as the farmers are convinced that it is (int. A1). Farmer respondents state that this kind of solution would be valuable to a farm since continuous monitoring could potentially detect diseases among livestock in an early stage, either before the disease takes hold or before the disease spreads to other animals (int. C6, C7, F6, F7, F9). Also described in the article by Buller et al. (2020), an AI-model could be learned to monitor animal health and give indicators to farmers when it detects some anomalies. This use case aims to explore which technical features such a model would require.

INPUT

There are four main categories of input data that are of interest in this particular use case: temperature data, behavioural patterns, feed intake and milk samples (int. R6). Milking robots detect the feed intake of high-energy fodder as well as milk samples from every cow (int. R5). The needed temperature data come from sensors on each cow (int. R6). Lastly, behavioural patterns are monitored from cameras in the barn (int. R6) as well as activity sensors on the cows (int. R3). All these types of data are possible to gather today or in the near future. Respondent R3 states that a lot of the data, such as milk yield, milk composition and data about sicknesses and rut, is already compiled in *Kokontrollen*, the management system by Växa Sverige. There, veterinarians also report on the health status of individual animals that might be useful for the model.

OUTPUT

A dashboard that continuously keeps track of daily data would be a good way of presenting the result of the analysis. Two respondents believe that the system should be able to give some kind of warning or a notification when the system detects anomalies in the health status of some animal (int. R3, R6). The output should produce warning messages such as “look this up, check on this cow” rather than determining a diagnosis.

MODEL

There is no consensus about what type of mathematical model that would be optimal for this type of solution (int. R3). Respondent R3 states that linear regression models are often used to make predictions and detections. However, he adds that motivating this is the lacking knowledge of the conditional relations between the variables. Non-linear models, respondent R3 states, also require more data but could in the end provide better analysis. For this particular case, one would likely need a model that would be able to combine several types of data, both tabular and streamed data in the form of videos (int. R7). Behavioural patterns and detection of anomalies could be detected through algorithms based on photographs or videos, respondent R7 states. Cameras could furthermore be helpful in identifying each animal and connecting them with their ID-number (int. R6), which is possible by using, for instance, a convolutional neural network (int. R7).

EVALUATION METRICS

The evaluation of the model will probably be inclined to minimise the ‘false negative rate’ without overburdening the farmer with a lot of false positives. By optimising in this way, the number of animals that incorrectly are detected as healthy are optimised to be as close to zero as possible. By plotting a ROC curve the desired optimum can be identified (int. R6). Respondent R3 states that in the case of automating the monitoring of health indicators, one would preferably want a system that is more inclined to detect some cases that turn out to be false than missing some of the cases that turn out to be true. He states that farmers are more likely to want to check up on their animals a few extra times rather than not noticing if someone becomes ill (int. R3). However, both respondents state that determining an evaluation system for a model should be a process involving farmers, so that they can try out the system and determine what measurements have the best results (int. R3, R6).

PRACTICAL CONSIDERATIONS

As for the practical considerations, a dimension that connects to the evaluation measurements is that the false alarms of health anomalies cost a lot of time and resources for the farmer. If an animal would falsely be detected as sick, the farmers would be obligated to call on a veterinarian or keep a close eye on the animal, which could become costly (int. R6). Another practical consideration is that the physical hardware, in terms of cameras and sensors, would need to be compatible with the rest of the systems, particularly with the milking robots and other data gathering equipment (int. R3, R6). Since the solution would require input data from multiple sources the data transmission and compilation would need to be seamless and automatic. Otherwise, it would be far too time-consuming for the farmer to maintain the solution, since it would involve such huge amounts of data every day (int. R3). One last practical consideration is that it is hard to design anything general that can be applied to all dairy farms, as every farm uses different machines and combinations of them.

6.2.2.3 Use Case 3: Optimising and Predicting the Time for Slaughter of Beef

One possible use case in precision livestock farming is prediction and optimisation of the slaughter time for beef cattle. Roughly, more than one third of the Swedish heifers, i.e. female cows that never have had calves, are kept for specialised calf production and not for production of milk for human consumption. These suckler cows for beef production are purebred beef breed cows, crossbreds, or dairy cows that in different ways are not fit for milk production. The remaining calves used for beef production are bred from dairy cows and often bought directly by meat production farms (int. R6). These growing cattle are kept and brought up for the purpose of producing meat. When they are ready for slaughter, after approximately 12 to 16 months, it is most efficient both economically and timewise to send them to slaughter as soon as possible. When their growth has stagnated, they keep taking up space and eating expensive fodder without adding value to the end-product, which motivates the optimisation of timing (int. R5, R6). Therefore, a model for optimising the time for slaughter is further explored below.

INPUT

The necessary input data for such a model includes a frequent weight measurement of each animal. As of today, weight is only measured a few times during the lifetime of a beef cattle. However, should the weight frequency increase and relate to how much the animal feeds, one would be able to predict a growth curve (int. R5, R6). Of course, there already exist some systems for automatic weighing, e.g. where the cattle are weighed when walking through an enclosed path, that give continuous monitoring of weight development (int. R5). Furthermore, farmers would be interested in how different fodders respond with the cattle, i.e. how the weight gain of the cows corresponds to a certain fodder (int. R5). It is also important to be able to estimate the flesh composition, which is possible by using cameras for body scoring (int. R5). Lastly, one would need input in the form of previous samples of data from carcasses, such as the weight, amount of fat and the conformation class of the beef (int. R6). In summary, the input data should be mostly tabular data but also include image analysis.

OUTPUT

The output can be regarded in two ways: either the system should give output as a date for optimal time for slaughter, or the date for slaughter should be an input and the system should give decision support on how to optimise the growth of the animal until that date. Indicators on how to best feed the animal to follow the growth curve could also be provided by the system (int. R5). Another idea is that the model regards the quality of the beef and suggests time for slaughter according to the economical revenue the meat would give (int. R7). Common for both these responses, however, is that the model produces a saturation curve, in which the growth of the animal is compared to the economic cost it grants while alive.

MODEL

There is no consensus of which mathematical model would be sufficient to use in this case. Should the output be a date for slaughter, the model could be a classifier that states with some certainty the date or a period when the cattle is of a certain quality, and thereby ready for slaughter or not. Alternatively, should the output be how the farmer should feed the cattle to make them ready for slaughter by a specific date, one would rather look for regression models to solve the problem. Respondent R7 states that the best way of solving the problem is to use several models and evaluate how well they work.

EVALUATION METRICS

When evaluating the solution, it is important to keep in mind that the predictions are probably not binary, i.e. the answer is not "yes" or "no" if the date is optimal, it is rather that one wants to be as close to the optimum as possible. Evaluation should therefore illustrate the distribution around a desired value in a real turn-out (int. R6). It might also be valuable to evaluate the economic aspects, such as how much profits increase by following such a model for the beef production (int. R7).

PRACTICAL CONSIDERATIONS

The practical considerations, to this type of solution, are mostly focused on the lack of data. There is simply not enough data collected on an individual basis in beef production as of now (int. R3). However, as seen in the dairy production, it is possible to collect a lot of data with the technology that exists today. Gathering the data requires money and effort for farmers, especially in an initial stage if no current data gathering processes are in place. Nevertheless, after the initial investments are paid, a time and resource saving model has potential of being long-term beneficial for the farm (int. R3). Another challenge is that there are several production models in meat production that set different goals for how quickly the animals should be ready for slaughter (int. R6). As it is hard to measure how much an animal feeds while pasturing outside, it is today more plausible to implement this predicting solution on farms that keep their beef cattle inside the barn (int. R6).

6.2.3 Data Gathering and Management

Applications of AI are useless without data sets of sufficient quantity and quality (int. A2). This means that it is of highest importance that relevant data is gathered and stored in a structured manner, otherwise AI and machine learning models will not be able to produce anything of value. Therefore, the following section brings up the topics discussed in the interviews regarding data: what data is being gathered now, how the data is currently used, what technical considerations that data gathering and model constructions imply, as well as respondents' general thoughts of how they want technology to serve them.

6.2.3.1 Existing Data

Regarding data and the activity of collecting data, the responses from the interviews reflect different realities within the agricultural sector. On the one hand, some respondents say that farmers generally are positive towards gathering data on their farm (int. C3, F6, F8). On the other hand, some responding farmers state that they collect almost no data on their farms, although they say that they understand that data could add value to them (F1, F3, F5). There in between is a spectrum of attitudes towards data gathering and implementation of technology in the farms.

Some respondents from the larger companies and cooperatives suggest that the attitudes might be affected by the perceived inconvenience that data gathering causes. They all believe that more farmers would have a positive view on it if it were made easier for them to collect it. However, there is also a sense that the data is not used optimally, partly because it is saved in different databases that are not interconnected (int. C3, C4, C5).

One aspect to data sharing is that different stakeholders often require the same data. Actors such as the Jordbruksverket (Swedish Board of Agriculture), other governmental authorities, regional governments, and municipalities, often ask for the same type of data. Since this data is reported several times, the data already exists in some other system. Collecting and sharing the data is, as of now, very time consuming. By sharing data between authorities, the farmers would have more time to spend on their farm according to a consultant respondent. Some farmers feel they manually need to manage up to ten web pages with different data at the same time, and then merge them into something consistent for it to provide value to the farm (int. C5). Limiting the time spent on compiling and arranging as well as distributing data could free up time for farmers to do what they want to do: manage their farm. A responding researcher states that a reduced, or perhaps automated, administration could be instrumental in making farms more profitable and climate neutral (int. R2).

> *"There is a lot of paperwork connected to animal husbandry. [...] Technology could reduce administration and create an incentive to make environmentally friendly measures that are not profitable today."* (int. R2)

Regarding the value of the data, most respondents believe that their data is of high value, and increasingly so (F5, F8). Two farmers independently envision a problematic scenario in which a certain large and popular international machine manufacturer would own a large portion of the agricultural data in Sweden (int. F5, F8). Since a corporation of that sort would be able to gather data with their machines, they could also aggregate it into enormous datasets. From this, they could create valuable systems, for example by benchmarking farms to each other. However, such a scenario requires that farmers share their data with the corporations for free, which the farmers are hesitant to do (int. F5, F8). This becomes an important strategic question. If not for the individual farmer, then for the aggregated farmer brigade in Sweden (int. F5). One farmer explicitly states that *"One of the prime resources that are produced in the farms will probably be the gathered data, and we should not just give it away."* (int. F5). This connects to the discussion of ownership of data which is further discussed under *6.2.3.5 Data sharing and data ownership*.

Hence, what type of data is being gathered today? One respondent from a Swedish authority calls the data that is being gathered "a blissful mixture" since there is so much different data collected from different kinds of sources, such as satellite images and sensor data (int. A2). He further states that the major challenge going forward is to come up with an answer to the question *"how do we extract something valuable out of so many different kinds of data?"* (int. A2). The hardware used to extract data that most respondents can name are satellites capturing images, milking robots registering milk data, different kinds of large machinery, installed cameras in barns, drones equipped with cameras, and a wide range of sensors. Depending on the source the data types vary, but most data come in the form of tabular data, images, and real time data. Even if different data is needed for different applications, it is possible to see special value in some data types. The previously mentioned governmental respondent believes that the 'high value data sets' are the ones that describe which crops are being grown where on a field, i.e. geospatial data. These data sets are valuable since they can calculate the utility of different crops at specific land masses (int. A2).

Finally, the responses from the respondents indicate that data is being gathered differently depending on the agricultural sector. For instance, many respondents in the dairy section state that there is a lot of data gathered, to a high degree on an individual level, on the farm animals (int. C6, F2). In contrast, arable farmers also collect data on almost all farms, but that data is not always as detailed. An arable farmer may collect remote sensing satellite data on its farm, but sometimes not with a resolution of square meters, but rather on a field level or even farm level (int. F1). One arable farmer states that the data that is gathered on the farm is what he would define as ‘output’ from the business. The inputs, i.e. the resources added to the soil, are what would be interesting for him to get decision support on, if one could see a beneficial correlation between input and output (int. F4).

With a continued positive attitude and some easier way of gathering data, most respondents see no problems or limitations to what new kinds of data could be collected in the future (int. C4, C5, F4, F8). One respondent with a macro perspective to agriculture says that he thinks it is hard to know what types of data will be interesting in the future, that the development of new sensors will ultimately decide what types of data will be created and collected in the future. Also, the main challenge going forward will still be to predict weather more precisely and for longer intervals, and therefore it becomes increasingly important to gather more data from local weather stations and interconnect them (int. C4).

6.2.3.2 The Usage of Data in Agriculture

Several respondents report that the data collected for arable farming is used momentarily, i.e. utilised in the moment that it is created (int. F1, F3, F8). In precision agriculture, momentary data is used when a farmer fertilizes or adds nutrients to the soil exactly where the sensors detect they are needed. Such an approach creates some problems. One farmer states that the data he uses on his farm is not aggregated and continuous, and therefore he cannot form knowledge over time through the data (int. F3). Another farmer confirms this problem by describing that although he uses tools like the agricultural satellite images program CropSAT, only the most recent insights from the tools are used. Instead, he believes that such a system has the potential to be used more long-term, taking historic data into account for future decisions (int. F8). Nevertheless, some simple historic comparisons are possible to perform though, but those are built on discontinuous discrete data, i.e. simple samples of data from different points in time (int. F4).

For dairy farmers, the data usage differs. One farmer active in livestock management says that their data, from fodder distribution and milking robots, is collected daily, and that the data is compiled in a farming management system (int. F2). With these systems in place, the data is aggregated, continuous and used daily which distinguishes dairy farmers from meat- and arable farmers. The production cycle of dairy farms is quicker than other farmers, that only get their output a few times a year, compared to a milking cow that produces milk every day. Consequently, arable farmers and meat production farmers are more prone to use data momentarily.

On this topic of using data, one responding farmer with previous experience from the tech industry, believes that the problem with applying AI to arable farming is the lacking volume of interconnected data (int. F10). The whole data chain is not connected today, he states. In practice, the input data taken during, for example, arable seeding is not properly connected to the output of the harvest. Additionally, the insights from the harvest are not used as a decision basis for the next seeding. Thus, the data loop is not closed, which it would need to be for AI to be efficient (int. F10). In addition to confirming this theory, a respondent working in the agricultural technology industry believes this data gap combined with the large amount of uncertainty factors, such as unpredictable weather, is a technical hindrance to the learning of AI models (int. C8).

6.2.3.3 Technical Considerations

In the field of AI and machine learning, there is an important trade-off between bias and variance. In the interviews, the respondents have had different opinions on the matter. As shown entirely in Appendix A and Appendix B, bias and variance are in this thesis discussed in terms of 'precision' and 'generalisability' instead of the original technical terms. With that said, the terms are not considered exactly equal to bias and variance, but the concept of a trade-off between models that are narrow or generic is considered quite similar. Introducing these interview questions, all respondents were given a brief explanation of the trade-off, stating that a model might either generate a higher precision or be more generalisable and scalable to more farms. With these, for many often new, concepts in mind, the preferences for either model bias or variance vary. Some respondents say that precision is extremely important since a technical solution that only predicts or detects something half of the time is useless (A1, C6, R2, R6). At the same time, other respondents say that as long as the predictions are slightly better than human predictions or detections then the model can be as general as one wants. In fact, many respondents claim that there is a much larger market for standardised models than the ones that are too adapted after local needs (C4, F4, F5, F8).

There is a tendency among arable farmers and corporations that they tolerate a higher degree of generalisability while livestock farmers need more precision (int. C1, C4, C6, F4, F5, F8). A respondent in the livestock farming sector claims that a farm would never really benefit from a technical solution that could only detect rut amongst the animals one out of three times. She further underscores the need for precise models dealing with biology and living animals (int. C6). On this topic, a researcher states that:

> "*For arable farming generalised solutions work well. There you can use for instance CropSAT, which provides satellite images with models that can be applied for basically all of Sweden. But for livestock farming it is more difficult. For almost all AI or machine learning applied to livestock farming, you need to solve a classification problem [...] and then you can go ahead and do more precise analysis and solutions. This means that you need to have a relatively high degree of model adaptation to fit the individuals or farms*" (R2)

However, this is somewhat contradicted in another interview, where a dairy farmer states that too precise machines "are a curse as well" (int. F2). He says that high precision requires a lot of time and effort from the user to calibrate the machines properly. Therefore, he opines that too precise machines can only be used by those who are specifically interested in technology (int. F2).

Despite the tendency of slightly different answers depending on the sector, many respondents can be interpreted as they require a balance between variance and bias, precision, and generalisability (int. C3, C5, F4, F5, F8). One respondent from a Swedish governmental authority says that both types of models are relevant if they can come to use for someone (int. A1). A model cannot be too applied because then it is not useful to enough farmers, and therefore not economically plausible to develop, but neither too general because then it does not benefit the user (int. C3, C5). According to a respondent from an agricultural enterprise, a generalisable model probably has more impact and is more likely to succeed on the market, but it must have some possibility of customizability to be able to benefit each farm (int. C4).

Speaking of customizability, identifying how farmers want their technical tools and machines to be designed, and how they want them to assist on the farm, is key. Among the farmer respondents, only one specifically says that he would like for smart farming technologies to completely automate activities on the farm (int. F10). Instead, a large share of farmers is prone to either having technologies that recommend a course of action out of the collected data (int. F1, F5, F6), or that the technology only presents data so that the farmer may make decisions on their own (int. F2, F4, F9). Decision support and assessments based on compiled data already exist to a certain degree but may be used more often and efficiently should the data become more accessible and of better quality. A responding dairy farmer says that although the system provides some recommendations from the continuous and aggregated data, his decisions on the farm are still only based on the raw data (int. F2).

Another aspect of a general versus narrow models is the economic cost. Generally, a narrower and more applied model to a local environment will be more expensive, partly because of the customised set-up and that the model might be trained on local data. A more general model could be usable for more customers and could therefore be cheaper. One respondent states *'a cheaper model is generally less precise'* and that this is not likely to change (int. A2). Higher precision will always be available for a higher price, but all types of solutions are constantly developed, the respondent argues (int. A2). One farmer says that if he feels like he needs to invest in smart farming technology, he will happily pay a little more and get an accurate system rather than a cheaper one that does not benefit him as much. He believes the more expensive system would pay off anyway because it would render a better return (int. F7).

6.2.3.4 End User Demands and Needs
Even though there is a clear general interest in smart farming, the driving forces towards increased data usage and applied AI in agriculture vary. Furthermore, there are some pressing barriers and needs to overcome. One increasingly urgent is how to facilitate data collecting and data structuring for the farmers. Many respondents agree that there is a huge potential in smart farming, if data can increase its continuity and aggregation (int. C3, C6, F4, R1). Specifically, most benefits from the collected data going forward will lie in the value created from systems that are aggregating and combining data over space and time (int. C3, C6, R1). One respondent from a commercial enterprise says that geo-marked data can derive a differentiated overview of required input resources (int. C3).

Continuous data allows for detecting changes as soon as they happen. A livestock farmer explains a scenario where this type of technology could lead to large savings, and therefore an increased profitability: if they could see through continuous data that some fodder works more efficiently for a specific animal at a specific time than the one they currently use, then they could rapidly switch to that fodder the next day. With these instant changes, instead of evaluating the fodder on a monthly or bimonthly basis, they could benefit from cheaper nutrition. Additionally, they might not need to consult an advisor (int. F4).

> *"The milking cows constitute 75% of our revenue and if we are able to lower the costs [by optimising their food] 2 [SEK] per cow per day this could lead to big changes in the end."* (int. F4)

Hence, end users demand easier gathering of continuous data. Consequently, the data both must increase in density but also be interconnected between systems (int. C4). One farmer argues that all data must be in the same system so that it is understandable and manageable (int. F3). Details of how data can be connected between different platforms is scrutinized in the next subsection *6.2.3.5 Data Sharing and Data Ownership.* Nevertheless, no matter how the data sharing problem is solved, many respondents believe that the consequence of increased data sharing will be an increased mix of different data allowing for new analyses and knowledge extraction (int. C1, C4, F1, F8, F10, R2).

Not only the varying data itself constitutes a problem for smart farming, making data easy to understand for farmers is by many described as the most important challenge for smart farming (int. C1, C3, C5, C6, F6, F8). This can be done in several ways. Some farmers want to understand all the steps behind the output generated by a software. I.e., just seeing the final number or recommendation is not enough but they want to have some transparency and the possibility of grasping how the program works. This is especially important in situations where two different programs perform the same task and deliver slightly different results (int. F1, C6). On this theme, a farmer says:

> *"There is nothing that says that what you do yourself is better [than an algorithm] but it is nice to critically review what the computer bases its decisions on."* (int. F1)

Another way of achieving a transparent and understandable system would be to present different recommendations with quantified probabilities or confidence intervals. Accompanied by an explanation stating that a given scenario is this likely given these uncertain parameters, the farmer would be able to better handle the recommendation and keep the feeling of operating freedom. In practice, this could mean that a farmer inputs data and receives a handful scenarios with different outcomes above, on, or below average, depending on adjustable parameters such as temperature or precipitation (int. R4).

6.2.3.5 Data Sharing and Data Ownership
One key concern for the development of smart farming technologies is ownership of the data. Most smart farming systems are created as closed technological ecosystems, with limited possibilities of sharing data in between each other. This technological segregation hinders the systems to share data with each other and is thereby an obstacle to the interconnection between systems. Descending from the rivalry between the major transnational agricultural technology companies, including the quest to both pin the users to their specific technological ecosystems and avoid giving their rivals a chance to create competitive technology, this structure is difficult to change (int. C3, F10). With that said, two respondents (int. C4, F10) note a tendency for transnational agricultural technology companies to move away from technology that ensnares the user to their ecosystem, to more open data flow. Such open data flow is believed to create more value for the businesses and their users. Consequently, a higher degree of data is expected to be on open standards (int. C4, F10).

Even if the companies providing the technology make some progress towards open data sharing, a couple of projects are created to facilitate the data sharing compatibility. *GigaCow*, a research project by the agricultural university SLU on data for dairy farms, aims to enable data sharing by automatically exporting the data from different milk robots over time. Such initiatives are welcome to most farmers. However, this is a third-party work-around solution and not as straight-forward as if all machines would automatically be open for data sharing (int. R2). Today, even the real technologically enthusiastic farmers have headaches over the incompatible technological systems. One such enthusiast complains:

> *"They say that you have a standard today, but it works poorly. [...]. The day that data sharing works, [smart farming technology] will be used much, much more."* (int. F8)

It is not as simple as that all farmers want to share their data. One responding farmer says he knows that his data is worth much to others. Thus, digitalisation of agriculture is seen as a further risk that someone will make money out of data that farmers are collecting without getting economically compensated (int. F4). Nevertheless, another farmer states the opposite and prefers that the companies take advantage of his data for the technological development to accelerate (int. F10).

To nuance the dichotomy between giving away data or not, agricultural product development is not as simple as just identifying a need that can be solved through technology. There are several reasons why. First, if a technology demands a very modern machinery, or that an entire series from one company is required to buy a new component, some farmers may feel this is an obstacle (int. F5). Product development is said to often be done with entrepreneurs regarding only their own products and ignoring the holistic needs. This causes problems since a farmer can end up with several different systems that overlap and perform the same tasks. Furthermore, some systems that operate the same tasks may interrupt each other, damaging the overall performance (int. C6, F5). Secondly, the size of the farm matters. One farmer says that even though smaller farms often are in a bigger need of new technology, the newest agricultural technology is often developed towards the larger farms (int. F5).

Another identified dilemma is overselling. In practice, many machine manufacturers are described to demonstrate optimised versions of the benefits of the technology as bait for buying it. Then, when the technology is sold, few farmers know how to use it as effectively as in the demonstration resulting in worse results (int. F8). Adding to that, one respondent from a governmental agency thinks that, to a certain degree, farmers are 'forced' into using smart farming technology (int. A1). She does not necessarily mean that it is a problem, but that it is almost impossible to buy a new tool that does not have some sort of smart farming technology applied to it. Since the interest in the technology varies, it is more problematic that farmers are not informed about how to use the technology they have paid for (int. A1). There are few structured venues where agricultural technology can be discussed and knowledge can be shared. This creates scepticism towards some new technologies (int. F8).

Some things are described to be working very well with agricultural technology though. Smart farming applications that are easily available through different platforms are really appreciated by the farmers. In practice, a farmer can monitor data over the farm meanwhile she or he is in the tractor which saves the farmer a lot of time (int. C6). Worth noting is that such accessibility only is possible if the data is stored in cloud-servers and that there is a functional IT infrastructure. Almost all interviews have stated that the IT and communications infrastructure in Sweden is well developed for agriculture today. This facilitates for farmers to adapt to new technology without having to think much of the underlying technical conditions (int. C7).

6.2.3.6 Cybersecurity

Some respondents lift the potential threat towards online IT systems as a risk when implementing new smart farming technology (int. A1, C4, C5, F1, F2, F8). The risk of being hacked poses a threat both to farmers and to society at large. Focusing on society at large, a respondent from a governmental agency describes cyber security as a particularly important aspect of digitalisation in agriculture. *"IT-security is vital [...], if a common data platform would become national it would become a key to the security of the nation."* (int. A2). He believes that such a data platform probably would be classified with an extremely high security and secrecy label and be managed by the Swedish Security Service SÄPO. Therefore, he believes that this is a clear barrier for the development process of a common data platform. Nevertheless, the respondent adds that it might be better if potential cyber-threats were aimed towards a national platform rather than directly at farmers, since people would be managing and looking after the platform to a much higher degree than farmers currently are securing their data (int. A2).

To exemplify what cybersecurity threats the respondents imagine, two respondents mention examples of autonomous systems, such as a water treatment plant, that were hacked in the USA during February 2021 (int. C4, C5). Another respondent mentions the Swedish Transport Administration (Trafikverket) that received major media attention in 2017 for their lacking data-security (int. A1). Additionally, a described threat for farmers is the amount of sensitive data that would cause a lot of trouble if it should be spread to, for instance, animal rights organisations (R6).

Even though these issues are mostly raised by the larger organisations and authorities, the threat is also acknowledged by some farmers. Connected data platforms with weak security make the farm quite vulnerable to threats they believe (int. F1, F2, F8). However, one farmer commented that *"it is not worse than having all money in a bank account, and that I trust today."* (int. F1). Other respondents, both governmental agencies and farmers, recognise the IT systems as possibly vulnerable but are not necessarily worried. Instead, they reject the belief that lacking cybersecurity would pose a greater threat to agriculture than to any other sector in society (int. A2, F5, F10).

6.3 Non-Technical Aspects

In the following section, the non-technical aspects of implementing smart farming technologies are presented. The non-technical aspects include all aspects found in the interviews that do not have a specifically technical basis, but rather conditions that facilitates or obstructs the implementations of smart farming on a social level. In this section, subsections are included which describe the respondents view on AI in their strategic agenda, the knowledge and education in technology within the agricultural sector, the political and economic structures that influence technological implementations, as well as social factors that affect the views on new technologies.

6.3.1 Strategy and Cooperation for Different Stakeholders

How farmers and organisations in the agricultural sector regard, and plan for, the future may be considered an important aspect of spreading new technologies in agriculture. In the following subsection, the views of the respondents on future application of smart farming technologies and AI are presented.

6.3.1.1 Strategic Agenda

AI and smart farming technologies play an important role on the strategic agenda of most interviewed agricultural organisations and cooperatives (int. A1, C1, C2, C4, C5). For one major Swedish agricultural company, AI is considered one of the most important tools to achieve a more sustainable farming while increasing the yield (int. C1). Another respondent from a Swedish agricultural enterprise, states that their take on digitalisation of the agricultural sector will be to invest in software integration of different tools to facilitate smart farming technologies for farmers, so that they can monitor their farm and make correct decisions (int. C2). Digitalisation and optimising the data usage are prioritised over investing in new hardware, such as server halls. By prioritising software, they believe they benefit the farmers more directly (int. C2, C4).

However, these strategic agendas are set in a context where the organisations assume and act on the account of their members. In other words, the organisations estimate what the members need, and thereafter the strategic agenda is set based on those estimations. Thus, the organisations cannot force the farmers into using more AI in their agricultural businesses (int. C1, C2, C4, C5, A1). No farmer respondents in the interview study have expressed that they feel pressured to implement any new technology from organisations and cooperatives that they are members in. Transforming into a ‘smart farm’ is viewed as a free choice, but one farmer states that he knows that the topic is of high interest for the organisations and that some of them conduct research on it (int. F1). Another farmer regards the view from organisations on smart farming as inspiration. Although, he agrees that there are cases where technological systems that the organisations offer facilitate for farmers (int. F9). Even though he could probably perform the same tasks manually, it would require more time and effort and bind the farmers to a commercial management system, for instance (int. F9).

Although most farmers do not feel pressure to implement smart farming technologies, one farmer worries that the County Administrative Board, that oversees administrative and control functions for agriculture, will leverage smart farming data to control the farmers (int. F8). The respondent claims that such a development would be devastating, since the County Administrative Board will never have the same knowledge of the local circumstances as a farmer, and thus might risk implementing micromanaging rules. Implementing these hypothetical smart control mechanisms would, according to the farmer, facilitate for the controller from the County Administrative Board but not really benefit farmers (int. F8).

Not only authorities and companies require more data, but the respondents from research institutes express the same need. A part of the strategic agenda of the interviewed research institutions is to involve themselves in projects that gather and structure data on some platform that several actors can get access to (int. R1, R2). In this way, researchers will not have to collect data, but rather order it from the platforms, which would shorten the research time and is overall estimated to contribute to better research (int. R2). Also, some initiatives exist where research funding is implemented on test farms, thereby farmers get access to new technology with investments from research institutes (int. R1, R2).

6.3.1.2 Nationwide Interests

When it comes to digitalisation of such a fundamental societal system such as the agricultural sector, many strategic decisions are of nationwide interest. Some of the interviewed respondents from organisations and a governmental agency believe that there is a wide interest that the agricultural sector becomes smarter (int. A1, A2, C7). However, farmers are themselves accountable for making this technological transition. Two respondents argue that there is a lack of initiatives from the state or from the large organisations to drive the propagation of digitalisation forward in a structured manner (int. A1, C7).

> *"Everything is governed by the market's willingness to pay [for smart farming technologies]."* (int. C7)

One respondent, working at a governmental authority, addresses the topic of nationwide interest in digitalising the agricultural sector (int. A2). He states that AI in agriculture is a natural step moving forward. The respondent says that there are a lot of internal discussions in governmental agencies regarding if and how they should take a more active leadership role in the digitalisation of Swedish agriculture. For farmers to be competitive, he continues, there might be a need to assist the ones that definitely are not 'front runners' when implementing smart farming technologies and AI in their businesses. In that way, the so-called 'conservative farmers' could be able to implement more expensive and precise AI than they would otherwise do, and therefore become more competitive on the market (int. A2).

> *"Jordbruksverket [Swedish Board of Agriculture] is standing at a crossroads regarding our role in the development of the agricultural sector. Historically, Jordbruksverket has been reactive and only listens to the demand of the farmers. Now there is an idea about potentially driving the development further and working more proactive for the farmers to be competitive and economically sustainable."* (int. A2)

The governmental official thinks that Sweden nationally is behind with its digital development compared to other countries with weaker economic conditions and budgets for agriculture (int. A2). A natural first step, he believes, is to create a common national data platform for all agricultural data to be compiled on. Therefore, the agency has carried out an investigation, following a governmental order, resulting in recommendations about how such a platform can be structured. Behind this initiative lies a national need to be competitive on the global markets, which forces the Swedish agriculture to readjust the strategy towards increased digital innovation. One of the resulting initiatives from these recommendations are is the common agricultural data platform Agronod. Still, respondent A2 sees no clear political ambition driving this change. Such a political decision would, according to him, speed up the digital transition tremendously. Although there is no wish to 'force' farmers into using agricultural technology and digitalising their businesses, this is what may happen if there is a nationwide and political interest in going in that direction (int. A2).

Furthermore, if competitiveness on the world market is one motivator towards an increased productivity and efficiency in agriculture, another one might be the aspect of a national self-supply of food. One respondent, from the same governmental authority, says national agricultural self-supply is an interesting perspective to agriculture, especially in the light of international conflicts and other situations that might affect the market (int. A1).

> *"It is a very important question of preparedness if a war or crisis occurs. What do we do then? Today, we are only self-sufficient on cereals, carrots and sugar [...] but we have potential to become self-sufficient on more crops."* (int. A1)

She states that self-supply of food is not a factor that plays a great role today when investing in and propagating smart farming technologies, but that it is part of the overall national food strategy to increase the food production (int. A1). On a similar topic, a respondent identifies a trade-off when choosing between international technological solutions and domestic ones. Often the international ones are better but in an insecure world there might be a need for self-supply of both food and technology (int. C4). Furthermore, several respondents bring up the fact that if all agriculture is smart and connected, then the entire national food supply might be damaged if an IT-attack happens. This is further discussed in section *6.2.3.6 Cybersecurity*.

6.3.1.3 Sustainable Business

Although many respondents bring up the keyword 'sustainable' when describing what they believe smart farming could result in (int. C4, C5, F5, F7), few are concrete in how smart farming practically can contribute to a more sustainable business. One company representative states that they offer a program to farmers where they get compensated for their efforts if they can prove that they emit 20% less carbon dioxide emissions than average. The respondent believes that this business model could be more profitable in the future, if it is further developed, as they believe that economy is the most pressing matter for farmers. As a tool for increased resource efficiency, smart farming technologies could help farmers that aim to produce these carbon-sparse products (int. C1). Even so, farmers seldom feel direct pressure in being sustainable from companies and organisations, but state that the motivation for being environmentally friendly originates from their own will to be sustainable (int. F1).

6.3.2 Economic and Political Structures

Technological implementations are often in many ways driven by and limited by economic forces. The market demands and businesses supply of new technologies oftentimes drive innovations, but the implementation and propagation of these might also be limited by economic factors. Furthermore, the political structures in society propel the development of the agricultural sector and its technological implementations to a high degree. In the following subsection the economic and political structures connected to technological implementations, as the respondents of the interview study view them, are presented.

6.3.2.1 The Business Case for Smart Farming

As in any other industry, the agricultural sector is driven by the quest for increased profit. Money is a motivator, not only for larger agricultural enterprises but also for farmers (int. F3, F5). Therefore, the general low profitability in Swedish agriculture is a major problem for farmers. Optimisation plays an important role for the often unprofitable Swedish agricultural farms to be competitive on the world market (int. A2, F3). Even though there are lots of subsidies connected to food in the European agricultural system, no farmer respondents recognise any subsidies for investments in new technologies at a farm-level. Instead, the technological transition that is supposed to lead to more sustainable food production or larger output is financed by the individual farmer (int. R2).

Investments in new technology are by most respondents seen as keys to increased profitability. The decisions to implement a specific new technology is by one farmer described to be affected by three factors: "*interest, experience, and profitability*" (int. F3). Even though the first two factors play an important role, that is regarded in the section *6.3.4 Social Factors*, new investments are paid for by the prospects of increasing the return revenues per product and mitigating costs such as diesel consumption (int. A1, C5, F3, F7). Improving crucial key performance indicators are important from an economic point of view but also affect other conditions. If one earlier can identify that a cow is in rut (ready for insemination) or is suffering from some health conditions using some technology, then the tool works as *"an extra employee that is only working with supervising the animals"* (int. C6).

Another problem with investing to mitigate costs is that investments in new technology are, as one farmer describes them, "very tiresome" (int. F2). Although almost all respondents share a positive attitude towards new technology, to three farmers new technologies are expensive. To them, avoiding the risk connected to being one of the first to implement some technology is the wisest and most reasonable choice (int. F2, F5, F7). At the same time, one farmer regards this economic blow as an act of solidarity with the rest of the farming community in the sense that he, as an early adopter to new technology, takes the largest economic risk and hit. Concurrently, he means that smart farming techniques can only be a source of increased revenue if successfully implemented as one of the first farmers. Since he believes that the only way of making money in the agricultural sector is by cutting costs and "being slightly sharper than my neighbour" he also regards being a frontrunner technological development as a necessary risk to increase profitability (int. F2).

6.3.2.2 Structural Economic Factors

Different farmers have distinct economic incentives to implement smart farming technologies in their work. Generally, there is one group of farmers that have less reason to care about implementing new technologies since they will have structures in place to reach their revenue in any case. This group often owns their own property and farmland. On the other hand, there are farmers that lease their farmland and therefore constantly must become more and more effective (int. C3, F4, F5). As one respondent formulates it: *"Not everyone needs to push themselves to succeed."* (int. C3).

It is not only a matter of farm ownership though, also the size of the farm affects the probability that smart farming technologies will increase profitability. With a small farm, farmer respondents believe it is difficult to profit from smart farming techniques (int. F1, F5). A farmer with a small farm describes that he cannot afford buying new equipment, such as a new tractor, himself. Upgrading the machine park is necessary for smart farming technologies to gather enough useful data. Since these costs are estimated too expensive for the farmer, the responding farmer manually tries to mimic the tasks that a smart tractor would perform. In practice, he lets a company manually ground control his entire soil to get samples of the nutrition levels at different places. Then, he input the data into diagrams and GPS coordinates for the tractor. Currently, the farm is 85 hectares but if he expands to a farmland of twice the size, he believes a tractor that automatically can soil map would pay back the extra cost (int. F1).

A major macro trend for farms in Sweden is consolidation. Basically, this means that smaller farms cannot afford to compete with the larger ones that can use their competitive advantages of being larger. There is simply not enough profit in managing most small farms, a problem which forces many farmers to merge with neighbouring farms (int. C7, F4). However, this does not imply that all farmers strive to increase the farm size. One dairy farmer sees his farm size to be adequate to his needs:

> *"In our case it feels like the size of our crew of milking cows is quite accustomed after our capacity on the farm, how much time we have and our dedication to each cow*." (int. F4).

Another structural factor impacting the economic possibilities for farmers is the dependency on subsidies and regulations. As described in section 3. Agricultural Context in Sweden, the Common Agricultural Policy in the EU determines a lot of the legal and economic possibilities for European farmers. Nevertheless, some responding farmers are not positive towards this system. One farmer, who previously has had vast experience of driving other businesses in other industries, specifically says that she does not believe in a business that is dependent on grants and financial support (int. F6). A researcher respondent aims his critique towards the specific regulations from the state. As he puts it: *"The state can make decisions that can increase costs [of products] but not decisions that can increase the income [for farmers]."* (int. R2).

6.3.2.3 From Hardware to Services

Another megatrend that impacts the agricultural sector is how technologies are sold and distributed. Today, most technology is bought as a hardware which is often a huge expense for the farmer. However, slowly things are changing. There is a transition happening towards services being bought as 'Software as a Service' (SaaS) solutions. This allows for business models in which the sold hardware is much cheaper than today or to no cost, but that the farmer must pay a fee or subscribe for using the set of hardware and software. One respondent from an agricultural cooperative foresees that this change will have major implications and wonders if, in ten years from now, tractors will be sold solely as a rental service instead of as a product. To enable this, an enormous amount of data will be needed (int. C4).

This change towards SaaS solutions is recognised by the interviewed companies and organisations as important in the transition towards smart farming. Earlier, before cloud solutions existed, one had to invest in private server halls and private technical solutions (int. C2). Today, less energy and resources are wasted on technological development since these services are provided by well-functioning and cheap larger companies. Thus, the Swedish companies can instead put more effort on the development of services for the farmers (int. C2).

Farmers also reckon this change as important. One farmer means that when investing in a new technology or a new tool, the threshold to adding for instance one more sensor is becoming increasingly small (int. F8), which is further confirmed by a respondent from a governmental agency (int. A1). The reduced investment cost facilitates the capability for an individual farmer to try out smart farming technologies that they otherwise would be able to afford (F1, F7).

For the larger investments, such as a tractor or a threshing machine, the investments can still feel cumbersome. Usually, these large machines are only used a few times per season or year. This connects to the return of investment. An expensive investment that can cut operational costs several times a year is considered more reasonable to invest in than a tool that only can be used once or twice a year (int. A1). Nevertheless, a way of facilitating for these investments to pay off is to rent their machines, or drive them themselves, to other farmers. Several farmers claim they are willing to buy services from others that they cannot afford to have inhouse themselves (int. F1, F7). One farmer describes it as: *"a win-win to avoid having machines that condition fixed costs."* (int. F7).

However, not all farmers agree. For one farmer, that describes that he has almost all new technologies on his farm, renting or lending equipment to other farmers is not a real option (int. F10). He describes himself to be incredibly careful and pedantic with his tools and is afraid that someone using it would not have the adequate understanding or feeling for the technology to be used properly and safely. Additionally, he believes investments in hardware to be essential. Without a proper machine park or sensor park he argues that a farm will not have the adequate input data to allow for AI applications (int. F10).

6.3.2.4 Consumer Habits and Markets Demands

One aspect of investing in new farming technologies, that worries some of the respondents, is the potential reaction from the consumers. This concern stems from the notion that a lot of the profitability is anchored in consumer habits and market demands. If there is a demand for certain products with specific standards, certifications, or production styles, then there is likely profitability in producing them. However, some respondents mistrust the consumers and feel that they simply do not care enough (int. R2, C7).

Exemplifying the mistrust towards the consumers, one researcher respondent divides consumers into three categories. First, the 'cheap' customers that only buy the cheapest products regardless of origin and quality. Then there are the 'conscious' customers (or ‘food nationalists’) that are rational and willing to pay more for the benefit of Swedish animal welfare or other added values. Lastly, there are the ‘trendy’ customers that are willing to pay a lot more but are unpredictable as they tend to quickly hop from one trend to another (int. R2). The respondent argues that:

> *“The biggest losers of the vegan-trend are the organic farmers since they have invested in a more expensive production. Then, when a new trend comes along, the ‘trendy’ consumers stop buying organic meat products and start to buy imported highly processed vegan alternatives. This implies that the most ‘emotionally engaged’ customers are also the most short-term.”* (int. R2)

Consequently, he argues that many farmers are hesitant to invest in new technology or to serve the needs of the ‘trendy’ consumers as there is an apparent risk for the demands to quickly diminish (int. R2).

Another described contradiction is how many consumers desire ‘natural’ food production. According to one respondent from an organisation in the agricultural sector, many consumers do not fully understand how food is produced and base their beliefs on different marketing instead. She exemplifies with a major Swedish butter brand that markets itself with beautiful cows on a green field with children playing and a constant sun. With that image in mind, she worries that consumers may oppose products that are produced with a lot of technical and automated tools. These kinds of products get a very ‘dystopian’ impression, but they may be of better quality and provide a better animal health (int. C7). She goes on saying that:

> *“For the animals it is much better when every activity is done in the exact same way every day. A milking robot always milk the cow in the same way whereas one person (or several persons) [may differ in their technique from day to day]. A machine would never do that. In that way it is better for the animals, but I believe that some consumers may think that ‘only machines, no one can see these animals...’. But ideally, I would think that if you have the machines, you’d still be there.”* (int. C7).

6.3.3 Knowledge and Education

How much knowledge about smart farming technologies is there in the Swedish agricultural sector? What are the possibilities of acquiring that kind of knowledge? These questions are discussed in the following subsection.

6.3.3.1 Perception About Knowledge on a Structural Level

There are a wide range of opinions regarding both which knowledge is necessary to be successful in farming and how knowledgeable most Swedish farmers are regarding smart farming technology. All but two of the interviewed farmers have grown up on their farms and have learned a lot of the craft from working with their parents (int. F1, F2, F3, F4, F5, F7, F8, F9). Additionally, most of them have also completed an agricultural education that is equivalent to a high school degree, and a few on university level. According to several interviewed farmers, this education has been quite broad and covered general basics of different agricultural sectors. Thus, topics related to digitalisation or technical development have not been covered (int. F1, F8).

The lack of technical education is interesting as technical skills are regarded as necessary for modern farmers. Most farmers agree that the role of a farmer today can technically be incredibly demanding. One farmer describes the farming profession as combining the work of an electrician and an engineer meanwhile also taking care of the biological elements of the farm (int. F2).

This demanding role raises the question if there is a "polarisation of tech-use" between farmers with different technical expertise, i.e. that the different technological skill sets enhance divides between different production types. In such a scenario, different production types could generate different profitability. However, one respondent, who works at a Swedish governmental agency, does not see this as a large concern since farmers generally are nifty in their businesses, making themselves more profitable and competitive (int. A2). However, ensuring a basic knowledge level and technological education among farmers, and Swedish citizens at large, is a hot topic for several stakeholders in the Swedish society. Therefore, the governmental respondent believes it is important that the current debate regarding raising IT knowledge in society also gets applied to the agricultural industry (int. A2).

6.3.3.2 Knowledge for Individual Farmers

To obtain insights and develop the agricultural skillset, many farmers are helped by experts and consultants. An individual farmer can take help from consultancy firms to perform difficult tasks such as analysing all the data a tractor generates. In the case with the data, farmers often understand some of the data themselves but want to perform more in-depth statistical analyses and do not know how to use all data in a proper way (int. C5). Still, consultants themselves regard many farmers as curious entrepreneurs who, in many cases, know more than the consultants. This knowledge is acquired through industry magazines and exhibitions but also through search engines like Google (int. C5, C6). Additionally, the global Covid-19 pandemic has benefited the technological understanding of farmers since everyone now is used to both having meetings and receiving technical support through internet-based applications such as TeamViewer (int. C6).

Of course, there are differences in how technologically driven different farmers are. Some are cutting edge whereas others are less inclined to be the first to implement or invest in some new technology. One respondent from an organisation claims that the farmers who are lagging have a 'knowledge journey' ahead that they need to go through (int. C4). The respondent means that larger corporations have an important role to play in this knowledge transfer, so that the usage of technology can be increased (int. C4).

Out of the existing systems often used by Swedish farmers today, some farmers state that they think the interfaces of the systems are good and understandable (int. F3, F5). The Swedish agricultural technology company Dataväxt is an interesting example of a well-functioning interface, since it was started by individual farmers trying to solve their own problems with data. Even though the examples vary, several respondents believe that this process of including end-users in the design process elevates the probability that the data will be presented in an understandable and meaningful manner (int. C1, C3, C5, C6, F4, F6, F8, R1).

6.3.3.3 Gap between Academia and Every-day Farming

Similar to the need to involve users in the design process, one hurdle for initiatives and research projects to reach the market is that their concepts are not based on agricultural market demands (int. C6, R1, R2). Three respondents argue that this might be a result of researchers and developers not being in contact with end users and not doing proper market research to identify which demands there are needs to develop solutions for. Instead, they believe that agricultural technology is often developed for the sake of the 'coolness' of the technology itself (int. C6, R2, A1).

During the interviews, several examples of how the lack of practical farming knowledge within research contexts have resulted in unnecessary technology, are raised. One example of a failed innovation that was heavily researched are the circular carousels for milking cows. Even though lots of money was invested in researching and developing the milk carousels, the market had a much higher demand for milk robots, which today dominate dairy farms (int. R2). Another farmer doubts that any complex and heavily researched technology would be able to benefit him. He says that a single field of 100 hectares is too big and complex to optimise using only one machine. No matter how complex the machine is, there are too many crops, too many layers and nuances for using a single smart farming machine. Therefore, the respondent believes agricultural technology innovations would be more useful if they were smaller and cheaper instead of complex machines trying to fix a myriad of tasks simultaneously (int. F8).

The barrier between agricultural universities and the demands of the farmers is described to stem from the lack of technical focus in the agricultural academia. One researcher describes that, for several years, Swedish academia actively focused on other parts of agriculture than technology (int. R2). However, during the last decade, Swedish universities have started to understand the importance of new technologies in farming and allocated resources to the field. The change did not happen top-down but derived from initiatives from several persons (int. R2). A researching respondent describes that:

> *"A university is far from a uniform entity; it is more like a swarm of individuals with more or less similar interests. [The change] started with enough researchers realising that this is important and works as 'early adopters' to then spread the realisation throughout the institution."* (int. R2).

6.3.4 Social Factors

During the interviews, it becomes clear that there are some intangible aspects that matter and influence the technical implementations within agriculture. These aspects are in this section called 'social factors', and regards the concerns about, views on, inspiration from and limitations of factors that influence use of technology.

6.3.4.1 Dependency on Technology

One communicated and discussed concern about implementation of smart farming technologies is the dependency it might create towards technology. Dependency on technology refers to a system that relies on automated or semi-automated activities based on often incomprehensible software, a constant power supply or Internet-access. The system itself is not problematic to any of the respondents. However, there are some concerns regarding the cases when this type of system fails. One respondent, from an organisation, states that the usefulness of the system would be compromised if the communication infrastructure would somehow break (int. C6). The concern is expressed in different ways and with different urgency.

On that note, there is a particular concern for dependency on technology within livestock farming. One respondent means that since practically all activities in a livestock farm revolves around the animals - live creatures - a development towards a dependency to technology can be extra sensitive for these types of farms (int. C5). A farmer exemplifies this through his dairy production. In his farm, milking robots have replaced a substantial amount of manual work, which also determines the capacity of the farm and consequently the size of the herd. If the milking robot would stop working, the milking would have to be done manually, he states. The question is whether the farm would have the capacity to do this, or if they have developed a dependency on technology that operates continuously (int. F2). Respondent C5 argues that there must be a high reliability to the system. However, the Swedish law forces all farmers within animal husbandry to have backup electricity through, for instance, diesel generators. Thus, even if natural disasters such as storms occur, milking machines and other equipment can continue to operate for a few days (int. F2).

When it comes to dependency on technology, another aspect that several respondents mention is that some practical knowledge among farmers and advisors might be forgotten (int. A1, F1). One responding farmer believes that if he applies too much technology to his farm he would risk losing some of the local, tacit knowledge of the farm. Particularly, some local variations of the farmland he finds difficult to represent correctly with data. Since there are a vast number of connected parameters affecting how a crop at a specific place will grow, he fears that a program could miss some critical aspects (int. F1). Technology might become too influential in the every-day farming business, or as one farmer says:

> *"You do not want to drive away too far from your cultivation either, a lot [in agriculture] is pure instinct and you do not want to become a slave under the technology."* (int. F1)

6.3.4.2 Trust Towards New Technology

The thought of technology not working may not be the sole reason for scepticism towards technology, but it seems to be part of it. Several farmers in the interview study raise the topic of trusting, or not trusting, new technology (int. F1, F4, F8). A common theme that permeates all interviews is that investments in new technology in agriculture are crucial since they affect the farm to a high degree. Therefore, it is important that the investments are 'successful' or beneficial from the start. Some respondents opine that new technologies are not fully developed when they enter the market, and hence not trustworthy (int. F4). Therefore, they say that it is better to wait and let others try out the new technologies before they would invest in it themselves, despite the fact that they think that some technologies have potential of benefiting the farms both economically and through improving their work environment (int. F4, F9).

The topic of trust towards technology also takes shape during the interviews in the form of farmers double checking that their technological solutions work as they should. One farmer describes how he usually does not trust technology. He states that he has had too many bad experiences with salespersons overselling technology that he believes the salespersons themselves have no clue how it works (int. F8). For that reason, a lot of time and resources are spent overlooking new automated or semi-automated activities on a farm, so that they do not make any errors (int. F1, F4).

Precision farming sensors that can keep track of, for example, water levels on fields are examples of technologies that can raise trust issues. Both a farmer and a company representative claim that if such sensors would fail then the crops on that field would be damaged (C5, F8). Furthermore, this type of failure is particularly sensitive to activities that are seldom performed, for example sensors detecting pests. If the sensor fails, it is hard to detect and it might lead to the entire field getting infected with the pest. Mitigating this risk, these types of systems often have warning symbols aiming to prevent such situations (int. F8). However, scepticism and lack of trust towards technology is not a general trait amongst farmers. Respondent F10 claims these tendencies are symptoms of a lack of education.

6.3.4.3 Workload

As stated before, there is a general positive attitude towards smart farming and what it could mean, to agriculture generally and farmers specifically. Incorporating smart farming technologies could mean that time or costs for activities, such as irrigation and manure, are reduced. Therefore, farmers can better manage their time when using well-functioning new technology (int. C3, C5, C6, F7, F8, R2). One positive side effect of this is an improved work environment for the employees (int. F8). With that in mind, researcher respondent R2 states that farmers are generally bad at valuing their time spent compared to the economic return. Agricultural farms are extremely pressed to get a rewarding return on their investments which leads to, at times of the year with high workload, farmers not getting much sleep at all (int. R2). This is confirmed by a farmer who says that since he works so much, some hours are nearly unpaid (int. F7).

From an economical point of view, there are more aspects to the notion of reduced agricultural workload. Jobs that earlier were manual and did not require any specific competences, are now in need of educated personnel. Thus, even though the farms may need less employees, parts of the economic benefits are reduced by the need to pay the higher salaries necessary to obtain educated staff (int. F2). Another consequence is that farms will no longer function as a place where people who are lacking education can easily get employed. This might have implications both for the individuals but also for the society (int. F2).

6.3.4.4 Amusement Account

One dimension of investments and implementation of new technology in agriculture, is that investments in smart farming are not always viewed as necessary by farmers but rather something neat and trendy. Thus, such investments are described to be paid by the "amusement account" (int. C3, F5). This is confirmed by a farmer that states that most of the technological investments made on his farm are motivated by his interest and fascination with technology (int. F8). Respondent C4 says that a lot of farmers gladly spend money on new and exciting tools and machines, for instance new tractors. But when it comes to things that are not noticed in the same manner, for example implementing an IoT communication network, then it must be presented with a crystal-clear business case (int. C4). With that said, the respondent adds that most farmers are curious entrepreneurs and strive to make their farms better all the time (int. C4). The so-called "amusement account" is mentioned by four respondents (C4, F5, F9, F10), who mean that it is important not to look down on those types of investments.

> *"One should not despise or ridicule the happiness that those investments bring. The alternative might be that some lose interest in farming and decide to do something else. These kinds of investments are something that makes the job more fun and gives it a lot of freedom."* (int. F5)

From this, it seems like many think that the charm of running an agricultural business is to be able to tailor and adapt the farm according to one's liking. While some respondents like doing things very manually (int. F9) others like to develop their way of working consistently with new types of technology (int. F10).

6.3.4.5 Generational Gap

When talking to farmers and organisations within the agricultural sector about technological implementations and changing work habits, the most frequent response is that the biggest obstacle for change are old habits. This is further narrowed down into two aspects that seem to hinder digital spread: the generational gap and the educational backgrounds in the farmer community.

The generational gap refers to the high average age amongst farmers. Many respondents believe that the age of a farmer, in most cases, correlates to their tech-savviness and the inclination to invest in new technology (int. F1, F2, F10). Some farmer respondents argue the agricultural sector is lagging in digitalisation because a large portion of the Swedish farmers are quite old compared to other sectors. This, they mean, does not imply that they are generally resistant to technology, but that the threshold to implement new technology is higher if one has been working in the same pattern for several decades (int. F1, F2). However, one researcher respondent clearly rejects this theory, meaning that it is the prior knowledge and technological interest that is the main differentiator, not age (int. R1). This being said, these two factors could be correlated and affect each other.

On that note, it seems like the background of farmers matter when trying to implement new technology in agriculture. Not only do the farmers need to have some education on the matter (see section *6.3.3 Knowledge and Education*) but also some interest and enthusiasm about new technology. Additionally, one organisational respondent states that farmers often come from families where the parents are farmers, inheriting their farms. This is an aspect which, despite the constant generational shifts, diminishes the amount of 'new blood' in agriculture (int. C7). The respondent claims that this is largely because it is so expensive and difficult to start a new farm. 'New blood' in agriculture could potentially nurture the interest of diffusing smart farming and come up with new solutions that could help drive the technology, and agriculture, further (int. C7).

6.3.4.6 Comparisons and Benchmarking

There are a lot of preconceptions about farmers, and one of them is that farmers are very behind when it comes to digitalisation and incorporating new technologies. However, farmers have a long history of being open to new technology (int. A1, F4). One farmer states that agriculture is one of the most tech-driven sectors there is (int. F4). A lot of innovations come from the military and then they are incorporated in agriculture before the rest of society even knows about them. As an example of this, the respondent mentions how the GPS was incorporated into farming tractors far before they were used extensively in traffic (int. F4).

Nevertheless, two respondents are farmers but come from completely different backgrounds than growing up on a farm. They state clearly that they see themselves more as entrepreneurs than farmers, and that they therefore might look at themselves, and the agricultural industry, differently than other farmers (int. F6, F10). These respondents may be examples of the previously mentioned 'new blood' in agriculture since they have not had a clear or 'destined' path into agriculture. They describe their view on using technology in agriculture as very positive. Respondents F6 and F10 tend to view the agricultural sector as very inert, that it is reactive rather than proactive, when it comes to technological innovations. This stands in contrast to the interviewed farmers with a long family history of farming, where they tend to think of the agricultural sector as very advanced and at the forefront regarding technological innovations and the spread of those (int. F1, F2, F3, F4, F5, F7, F8, F9).

When investing in new technology, the interviews clearly show that comparisons between farmers and experiences from other farmers influence decisions on what technology to choose. Some respondents say that many farmers compare themselves with their neighbours and want to use technology that is already proven to work (int. C3, C4, F1). As an example of social factors, one respondent from an organisation remembers how a farmer he had contact with installed an iron pole on top of his tractor for no other reason than to mock his neighbours into thinking that he had some new secret technology (int. C3).

On a larger scale though, benchmarking farms at a national level is claimed to be important for Sweden and agricultural agencies (int. C1, C4, A2). One farmer respondent, however, claims that benchmarks and comparisons between farmers key figures are useless and redundant in many cases (int. F4). The respondent states that since the farm conditions vary so much it becomes irrelevant to compare so much between farms. However, he means that it is still interesting to benchmark against previous years at his own farm to see how they stand towards other years or months (int. F4). Furthermore, another farmer would appreciate if the Swedish systems could connect better with international databases so that, for example, data on animals could be compared to animals in other countries (int. F7).

6.4 Summary of Results by Respondent Group

To summarise the results of this interview study, the themes and topics are divided into what appears to be the demands or opportunities for AI in agriculture, as well as the barriers or hurdles that hinder the use of it. Furthermore, based on the contrastive responses and views of different groups of respondents, the demands and barriers are differentiated by the respondent groups that all have distinct roles in the agricultural sector.

To begin with, the responses from farmer respondents show that there are many opportunities linked to the usage of AI and smart farming technologies in agriculture. Most importantly, according to them, new smart farming technologies have the potential of increasing their profitability, either by contributing to higher revenues or freeing time spent on some tedious tasks. On the other hand, the large initial costs to set up the technologies are identified as a barrier. However, if economical means allow for investing in such solutions, farmers believe that the investments will pay off in terms of profitability and competitiveness. Other factors that act as demands for smart farming technologies are their potential to be more sustainable and that they make farming more fun. Further barriers according to farmers are the complex solutions and lack of interoperability, as well as the poor prerequisites and opportunities of continuous education regarding technology in agriculture. Also, the fickle market makes smart farming risky to invest in for farmers.

From a commercial enterprise point of view, there are many opportunities connected to smart farming, but also some critical barriers to overcome. The respondents of this group see potential in increased cooperation between companies as well as with farmers, business cases in providing software as a service and additionally to streamline logistics connected to agriculture. Nevertheless, data sharing and cybersecurity are seen as large hurdles to the use of these technologies.

Respondents from research institutes also express a positive view on accelerated use of AI in agriculture. They believe such a development would result in more data collected by the farmers, which would decrease the time researchers themselves spend on gathering data. This would, according to the researcher respondents, lead to a faster and better research on agriculture. However, data sharing hinders, once again, the scientific development since high-paced research is hard to conduct without proper access to data from different sources. An additional identified barrier for smart farming is the mistrust from farmers that the scientifically developed solutions mirror a real agricultural demand and are not just developed for the sake of technology.

Finally, the respondents from governmental agencies claim that there is a great interest and demand for propagating smart farming technologies for national competitiveness as well as other economic reasons. Still, they are not sure how to position themselves in this transition, which slows down the process of digitising the agricultural sector. This respondent group also views cybersecurity and data sharing as critical barriers to overcome. In table 6.1 the results are summarised and illustrated for each respondent group, showing the identified opportunities and hurdles brought up during the interviews.

Table 6.1: Illustration of the results, i.e. the demands for and hurdles against implementation of smart farming technologies, divided by different respondent groups.

	DEMANDS/ OPPORTUNITIES	**BARRIERS/ HURDLES**
Farmers	▪ Increased profitability ▪ Improved work environment (time and comfort) ▪ Sustainability ▪ Social factors ▪ Amusement factor	▪ Too expensive investments ▪ Lack of technical education ▪ Technical systems not connected ▪ Difficulties understanding and acting on data ▪ Unpredictable consumer market
Companies	▪ Increased cooperation ▪ Involving end users in development process ▪ Transition towards SaaS ▪ Streamline logistics	▪ Data ownership is unclear ▪ Lacking cybersecurity
Research Institutes	▪ Faster and 'better' research ▪ Data sharing (e.g. GigaCow)	▪ Research not matching market demand
Governmental Authorities	▪ Improved competitiveness on world market ▪ Can provide EU subsidies for innovation	▪ Unclear role in transition ▪ Lacking cybersecurity

7. Discussion

In the following section the result and analysis of the previous chapters is discussed. Here, the interview study is compared to the literature review, identifying similarities and differences between the findings of this thesis and previous research. Furthermore, this section also discusses the validity of the results and proposes subjects to further studies related to AI in agriculture.

7.1 Data as an Enabler and Obstacle for Smart Farming

Several of the articles in the literature review discuss technical aspects of how to optimise smart farming techniques such as remote sensing. Khanal et al. (2020), Meier, et al. (2020), Heidler (2019), and Torai, et al. (2020) review aspects such as the most adequate spectral resolution to analyse e.g. crop growth conditions and the accessibility of different satellite systems. Still, as Kamienski, et al. state, many of the newest precision farming applications, such as predicting the volume and quality of a yield, are still mostly in a scientific stage, not yet commercial (2019).

In this thesis, several limiting factors to smart farming applications that limit their commercial application are identified. One dominating factor is the wide variety of data existing at different farms. Since all farms have different machine parks and have a varying level of interest for data gathering, the collected data is quite heterogeneous. Additionally, even though many farmers are eager to collect data and keep up with the newest technology, the legal and technical obstacles connected to data sharing hinder easy access of all data. Thus, it is difficult to practically access all existing data which could have benefited smart farming applications. Adding to that, some farmers do not see enough value in gathering data which diminishes their will to actively dedicate time and resources to connect the different data sets. Therefore, smart farming models, developed by scientists, that require specific types and amounts of data will most probably encounter problems when entering the market. To overcome the scientific stage, data models should be flexible for different types of input data and tested on different farmers within the same agricultural sector.

Another obstacle for smart farming technologies, especially within arable farming, is the difficulty with connecting the input seeding data to the output harvest data. Researchers such as Matos-Moreira, et al. (2017) use soil samples and regression models to predict the phosphorus concentration ahead of time. However, due to the many uncertainty factors, such as weather and vermin, it is difficult for a farmer to distinguish which factors in the end determine the harvest outcome. Compared to the dairy industry, which daily generates huge continuous datasets, the arable industry lacks sufficient data to recognise which factors led to the harvest. Therefore, most data are today used momentaneous. But if larger datasets were created, the possibilities of developing decision support models would increase. Hence, one conclusion from this thesis is that the arable farming sector needs to develop its datasets, connecting the input and output data on a large scale.

Aggregating large volumes of agricultural data also comes with its challenges though. Both Kleinschmidt, et al. (2019) and Herhem, et al. (2017) write how cybersecurity is essential to ensure safe application of smart farming technologies. As Kleinschmidt, et al. state, cybersecurity in smart farming may be achieved by regarding confidentiality, data integrity and availability, as well as user authentication. All categories of respondents in this study also regard connected agricultural systems to be vulnerable. The cloud-based data-sharing platforms that currently are developing have the potential to provide lots of value for farmers and companies, but they might also become a national security threat. Therefore, an agricultural smart system with high scalability, a factor described by Kamienski, et al. (2019), will first need to ensure an adequate cybersecurity level. Hence, there is a consensus from scientists, farmers, authorities, and agricultural enterprises that data sharing platforms must be developed with a high cybersecurity standard from the beginning.

Out of the existing smart farming technologies, most arable farmers use remote sensing techniques that are free. These satellite images have a lower resolution than the ones used by Torai, et al. (2020) when classifying crop diseases. However, predicting diseases in crops requires higher spatial resolution, probably a resolution of <1 m, since the diseases need to be identified on a crop-level. Furthermore, the temporal resolution might also need to increase to gain a more continuous data set (Khanal, et al., 2020). This implicates that future smart arable farming applications may be technically more similar to the applications used in dairy farming. As the usages become increasingly similar in their need for precision, the trade-off between bias and variance can also be expected to converge between the two sectors. Hence, the result stating that arable farmers tolerate a higher degree of generalisability is true for current crop applications but not necessarily for future purposes that require higher precision.

To implement such high precision supervised AI models to agriculture, the data must be classified. Depending on the application, this pre-processing can differ in complexity and time consumption. The pre-processing by Bhole, et al. (2019) contains both inpainting algorithms and convolutional neural networks. Such pre-processing would be far too time-consuming and complex for most farmers interviewed in this study. Instead, the software provider must either make data classification quick and simple, or pre-process the training data by professionals on large generalisable data sets. Otherwise, the system will not be sufficiently scalable, as classification will linger the implementation, or adaptable if no local data sets are used in the training.

As a final technical point, this thesis reaches no consensus on which level of automation or decision support a system should provide. As with Herhem, et al. (2017) and Khanal, et al. (2020), most respondents agree that the visualisation of the data is crucial for it to be properly understood. However, as the competences and interests of the farmers vary tremendously, a system that is adaptable to the different groups would probably render the largest success. Great smart farming systems should come with great opportunities to personalise the interface and output.

7.2 Economic Factors as Facilitating and Hindering Forces

Highlighted in the interviews, one key aspect of implementing new technologies in agriculture is profitability. Profit and economical assets are said to be both facilitating and hindering in the sense that smart farming technologies are expected to contribute to higher revenues and therefore an increased profitability, while at the same time require exceptionally large initial investments. In the literature review of this thesis, the economic aspects are brought up a few times. Long et al. (2016), Fusco et al. (2020) and Kernecker et al. (2020) all describe the economic dimensions as influential when it comes to implementing new technologies in agriculture. Although this theme is shared between both the previous research and the findings in this thesis, we feel that the reasons why the economy is so influential in this transition may be more nuanced than simply stating that the initial costs are high.

Long et al. (2016) conclude that the economic risks of investing in certain new technologies are notably high, resulting in slower propagation of these novel products. The risk is also expressed by the respondents in this thesis, for instance through the concern of market instabilities. This is also brought up in literature, as Fusco et al. (2020) identifies the market as a barrier towards the propagation of smart farming technologies. It seems that fickle consumers set the tone on the market, and that trends in the food chain makes the primary production sensitive when it comes to investments. Therefore, investments in new technologies connected to specific producing approaches are connected to high risk. Predominantly, the risk consists of uncertainty for not getting a return on the investment if the market demand for this production style changes and the products lose value.

Another aspect of profitability and the inclination for farmers to invest in new technologies is the tendency for farms to consolidate. Swedish farm sizes increase by small farms merging with other small farms or by smaller farms being bought by economically more powerful neighbours. It is simply not profitable enough to manage small farms today. Also, when regarding the responses from farmers on how they view investments in smart farming technologies, there is a certain trend that respondents from smaller farms are theoretically interested in using new technology, but do not have the economical, and therefore practical, means to invest in them. From the interview study, it seems that larger farms generally are more prone to investing in smart farming technology, but mostly because their financial status allows for it. At the same time, some respondents state that smaller farms are the ones that might benefit from these kinds of technologies the most, since they would make them more competitive. The general positive attitude towards new technology among respondents seems promising for the smart farming transition. Notwithstanding, one key question remains: will farmers see enough value to really pay for the necessary investments?

Furthermore, an interesting aspect related to the trend towards consolidation of farms, accentuated in the interviews, is that small farms tend to collaborate and invest collectively in smart farming technologies. As many farmers face the reality of not being able to own all the machines that they use during a year, many rent or provide services with their machines and get services in return. A shared machine park in some farmer collective is often more profitable as the farmers do not have to bind their money to expensive tools which are only used a few times each year. Furthermore, this might facilitate a broader customer group for modern machinery, which in many cases is a condition for using smart farming technologies.

Clearly, both the literature review and the interview study highlight structural economic factors and profitability as important for implementing and spreading smart farming technology. However, our sense is that the economic factors are of such a high importance for this matter that it becomes unavailing to simply cluster them as one. The articles in the literature review do not stress the importance of profitability with the same urgence as the respondents in this thesis. This is an interesting finding and might be connected to the poor profitability in Swedish agriculture.

Lastly, as smart farming technologies are expected to increase revenue and make farmers more competitive on the world market, it stands to accentuate that there are almost no incitements and financial aids available for farmers that want to invest in smart farming technology. Every farmer is individually responsible for all technological investments, which may further slow the transition towards a digitalised agriculture. The relation between state and the farmer stab is further discussed in the following subsection.

7.3 Societal Demands on the Shoulders of Individual Farmers

In the literature review, the article by Long et al. (2019) argues that the propagation of smart farming technologies depends on the support from society at large. Without that support, they state, innovations will not be adopted by key actors. This connects to the discussion amongst the respondents from the governmental authority regarding its role in the technological transition. These respondents state that there is no consensus on what role their governmental authority should take in the question of digitalising the agricultural sector. Although they state that there is a wide interest in society for increased agricultural productivity meanwhile minimising the strains on the environment, the authority is, as of now, supporting the transition but not driving it. In line with the theory of Long et al. (2019), a governmental agency could take a key role in creating a societal demand for smart farming. Therefore, the transition to a digitalised agriculture and the spread of smart farming technologies would accelerate if the authority took a more proactive role than today.

Additionally, what concluded the previous subsection is that although there is a wide interest of making the transition towards a more data-driven agriculture, the ones that are responsible for making this change are individual farmers. In contrast, both governmental agencies and commercial enterprises take a passive role in the transition towards a digitalised agriculture, despite their expressed interest in it. Such passivity is remarkable, as there clearly are demands to reform the technology usage in the agricultural sector, but the transition is left only in the hands of farmers. One could ask if this external interest is, as of now, even tangible, or just an abstract goal? To really form a more data-driven agricultural industry, more initiatives that facilitate tech-driven farming are needed. The results in this thesis state that Swedish farmers are open to using more smart farming technology, but the main motivator is to increase profitability. Therefore, if the societal demand is motivated by some other driving force, for example to mitigate climate change, then other actors should take on an active role and pressure and encourage actors in that direction during the transition.

One aspect that is also brought up in the literature review is the trust that the end users hold towards the technology. Kernecker et al. (2020) state that both adopters of smart farming technologies and non-adopters feel they lack neutral advice from advisors regarding investments in new technology. The non-adopters also perceive a scarcity of access to proof of concepts and live demonstrations of the technology they might invest in. Similar topics are also discussed in this thesis, where respondents describe that they seldom believe that salesmen and developers of the technology have the farmers best interest in mind. They state that they are briefly shown by the salespersons some technological features, but that these technologies are not always used in practice. Furthermore, the technologies that are available on the market are not always seen as useful by the end users. Hence, some mistrust exists towards new technologies, and towards those who develop and sell them.

Since not all farmers trust the developers of technology, would farmers trust technology that automatically manages agricultural activities for them? From the interviews, it seems that there is some concern about how an increasingly data-driven and a digitalised agriculture could lead to technological dependency. In practice, the farmers worry that if a technological system suddenly stops working, a farm would have trouble managing all the tasks that the machines usually would do for them. This is addressed in the literature review by Herhem et al. (2017), who says that security in IoT systems is tightly connected to the trust farmers hold in the system. However, the trust is also anchored in the precision of the technology. Herhem et al. (2017) mean that with too large measurement errors in sensors and technologies, there is no reason for any user to trust it, and therefore no reason to use it. This connects to the respondents expressed need of double checking the technology. Furthermore, the dependency on technology would increase if humans lost the tacit knowledge gained from the activity that technology replaces. In the reviewed literature, this aspect of implementing smart farming technologies is not identified.

7.4 Life-long Learning Adapted to all types of Farmers

Knowledge of how to properly work with smart farming systems has been highlighted in the literature review by both Medvedev (2019) and Herhem et al. (2017). Both reports argue that training in how to understand and act upon agricultural data is necessary for successful implementation. In this thesis, most interviewed farmers and other respondents have been able to correctly define smart farming and precision agriculture.

The respondents have displayed a need to properly understand and coordinate all data generated by the, often vast, machine parks. With that said, many farmers have stated that they can get advice in technological implementations both from consultants and from searching the internet. However, many respondents strongly believe that the agricultural education provided by universities needs to improve. Unsurprisingly therefore, this change has already been initiated with SLU offering more courses in IT. Still, most farmers already work around the clock and have limited possibilities to attend longer university courses which makes time a major constraint.

Smart farming can be one way of reducing that time constraint. As Caja, et al. (2020) describe in their article, new technology leads to more effective farms with less need of manual labour and processes in animal husbandry on a group-level instead of individual level. Results from this thesis shows, though, that even if time is saved with the new smart farming techniques, more time must instead be invested in finding and retaining employees with enough competence to handle the diverse technologies in the often big farms. Although in the end, all farmers must be knowledgeable enough to handle the equipment themselves which makes education crucial.

Since education is traditionally received in the beginning of a career, the age factor, described by Medvedev (2019), is interesting to analyse. Most farmers are indeed quite old, but this thesis finds conflicting opinions if age really affects the adoption rate to new technologies. Many interviewed farmers are born on the farm they run today but run them in a completely different fashion compared to how it was during their childhood, meanwhile others have started farming later in life and see themselves as entrepreneurs. In any case, a lowest common denominator is that all believe they need to constantly improve. Therefore, the idea about on-demand courses, instead of lengthy programs at a university, presented by Medvedev (2019) seems relevant to all farmers regardless of age and background. For a transition towards smart farming, an educational system open for effective life-long learning seems needed.

Learning is a process that must be adapted to the currently possessed knowledge level. Even if the age factor is disputed, it is certain that different farmers have substantially distinct expertise and interest in smart farming and their courses would therefore have to be differentiated. In the same spirit, the transparency levels of the smart farming technologies should preferably be easily adaptable so that the farmers looking for an in-depth explanation can understand the underlying calculations, and the farmers just interested in the output easily can manage the system. This is in line with the idea of avoiding a one size fits all IoT-system presented in the literature review by Kamienski et al. (2019). Combined with the identified aspiration to involve farmers in the design process, such transparency levels could be adequately developed.

7.5 Use Cases that Apply AI to Agricultural Activities

By presenting three concrete use cases in the arable, dairy and beef sectors, some insights in how to operationalise smart farming are provided. Still, these three use cases are just some of the potential agricultural technologies that have potential of being implemented soon. From the interviews and the literature review, other potential use cases could also have been selected. Nonetheless, there are some conclusions that can be drawn based on these use cases. One common theme in all three use cases is that they would require several different data types as input. Since the use cases currently are not implemented, there is no correct answer to what input data that is optimal for the use cases. As earlier concluded, the input data will probably have to differ between different farms due to their different conditions and starting points regarding machinery and data gathering. Then when each model is developed, the lesson from respondent R7, to test different mathematical models and start with few variables in the implementation, is well worth considering.

Another important conclusion from the use cases is that, depending on its purpose, different AI applications need distinct evaluating metrics. However, all use cases share a need for the output to be precise since the decision support affects core parts of the business. A failed harvest due to an imprecise prediction of the yield quality would damage months of arable work, and a model failing to detect health anomalies among dairy cows could lead to extra veterinary costs for the farmer and suffering for the cattle. Optimising the slaughter time of beef is probably the use case where errors are less impactful. This is at least true if the error is inclined to allow for the cattle to live slightly longer, i.e. if the error never causes a not-ready-to-be-slaughtered cow to be slaughtered. Nonetheless, if the measurement errors are too large then the gains from the use case would diminish and would probably not be used.

Throughout all interviews, there have been large interests for new smart farming technology. Compared to some farmer demands that are probably more difficult to implement, such as high-accuracy long-term weather prognosis, these three use cases build mostly on data that already exist in many farms. Additionally, as shown in the literature review, lots of research is being conducted on how these models can be optimised which strengthens their possibilities of soon being implemented. Still, other factors that have been discussed throughout this thesis, such as involving farmers in the design process, ensuring that farmers trust the system and presenting a clear business case, are just as important for these use cases to be implemented on a larger scale in Sweden.

7.6 Old and New Findings on Smart Farming Barriers

Concluding the literature review is Kernecker et al. (2020) overview of the implementations of smart farming technologies in agriculture. In the article barriers that hinder the implementation and propagation of smart farming technologies are identified and presented. Two examples of findings in this thesis that are not highlighted by

Kernecker et al. (2020), are cybersecurity and data ownership, which many respondents in this thesis state are large concerns. Also, the sometimes lacking technical education and the broad knowledge base of AI in agriculture are considered as hurdles. Although the barriers to some extent are similar to the findings of Kernecker et al. (2020) and articles of other researchers, some findings are new or brought into light from a new perspective as of this thesis.

Furthermore, though the barriers identified by Kernecker et al. (2020) are somewhat like the ones identified in this thesis, a substantial difference between the two research projects is the scope and the distribution of respondents. Kernecker et al. (2020) focus their research on the arable farming sector and group the respondents according to their main activity in four different types of crops. This thesis, however, deliberatively has a wider scope as it looks at arable farming as well as both dairy and beef production in livestock farming. Motivating this is both the aim to gain a holistic view of the sector and to explore technical implementations in different types of environments. One conclusion that can be drawn from this thesis is that it is difficult to aggregate several agricultural challenges into one, since the different sectors are very unlike each other. However, there are some similarities such as the usage of remote sensing techniques and IoT-sensors.

Additionally, the grouping of the results in this thesis stems from the backgrounds of the respondents. In the interview study, several groups of respondents were identified based on their occupation: farmers, researchers, commercial enterprise representatives and people working at governmental authorities. The results of the interview study are grouped by the type of respondents, which gives a full picture of what different actors in the agricultural sector think of smart farming technologies. Kernecker et al. (2020) rather groups their results on the division between adopters and non-adopters of smart farming technologies.

In brief, the methodology and scope of this thesis aims to acquire new knowledge that ranges over several production sectors in agriculture, as well as over several kinds of organisations that in some way work with agriculture. By contrasting responses from different respondent groups, new dimensions of hurdles and opportunities may be discovered. We believe this could be a great complement to Kernecker et al. (2020), and similar projects, with their more detailed investigation of a single sector. This leads us into a more in-depth discussion about the methodology of this thesis.

7.7 Methodology Review

As discussed in the previous subsection, the scope and focus of this thesis generates both strengths and weaknesses to the results. The aim of the thesis is to analyse the agricultural sector from a holistic point of view as well as to dive deeper into the technical requirements of a few selected use cases. A problem with choosing a wide scope is partly that some details in each sector might be lost in the results due to generalisability, partly that the results are not inclusive to all sectors, as we did not regard forestry, fishing, poultry, and pig farms, to name a few. This is motivated in the *1.3 Delimitations*, but stands to be commented on here as well. By comparing the responses from different groups in the agricultural sector, new dimensions and aspects are brought into light in this thesis. In the following two subsections, the methodology and the potential response bias of this study are discussed. With this section, we hope that future research projects will pick up the main methodological strengths as well as mitigate some risks related to the methodology.

7.7.1 Choice of methodology

In the literature review, there is a significant overweight of articles that scrutinize arable farming. Therefore, the majority of results from the literature review are based on technologies implemented in different types of crop farming. However, this thesis includes a large portion of respondents from livestock farming as well. Therefore, one can question whether the literature review is a proper foundation for the results from livestock farming respondents? Although the literature review contains some articles about smart farming technologies applied in livestock farming environments, the proportion of livestock related articles remains weighted unequally compared to the results from the interviews.

Two potential reasons for the unequal distribution are probable. Either the overweight of arable farming in the literature shows that arable farming simply is more investigated than livestock farming. In that case, the overweight towards literature on crop farming would be logical and mirror the scientific environment. A possible hypothesis for explaining this unequal scientific distribution is that a lot of research in dairy production is conducted in corporate environments, as most data in this sector is collected through, for instance, milking robots. The other likely reason for the distorted distribution of literature is simply that the chosen search terms and criteria in the literature review did not sufficiently cover the livestock farming sector. Choosing relevant search terms is, of course, crucial for the findings of a structured literature review. We are humble in the face of the possibility that we might have had insufficient search terms that ultimately caused, or amplified, this distorted distribution of literature.

7.7.2 Response Bias

To limit the spread of the global pandemic virus Covid-19, all interviews were conducted digitally. Although some respondents were accustomed to digital meetings as it had become a part of their daily business, other respondents were not as experienced with digital meetings. Overall, the data gathering of this study can be considered relatively unaffected by the circumstances around the interviews and in the world. One shortcoming of online interviews is that a headshot of the respondent may take away some of the body language that can be valuable for the interviewer to observe. All these barriers have been considered when planning the interviews, but still there might exist some possible loss of information due to this reason. However, when having online-based interviews one can argue that the threshold is lowered in terms of recording the interview. To go back and replay sequences of interviews has enabled us to clarify and extract more information than we probably would have if the interviews were held in person.

Furthermore, an aspect that is stated but left uncommented, is the distribution of respondents in this study. Specifically, the number of women respondents is a facet that is interesting in this study. Out of the 27 interviews conducted, only six of the respondents are female. Also, only one out of ten farmer respondents are female. This constitutes a slightly lower part than the 15.7% women in the Swedish agricultural sector, as stated in section *3. Agricultural Context in Sweden*. The sex distribution was achieved despite the intentional search for female respondents. In fact, several contacts with farmer respondents started as conversations with women, but when asked to participate in an interview, most of them referred to their spouses. Despite the male domination in the agricultural sector, one possible conclusion from this is that the topic of technology still poses the greatest barrier to women participating in this study. Of course, there is no way of knowing how this response bias might have affected the result, but we think the tendency is worth considering.

7.8 Future studies

This thesis lays a foundation for understanding the main opportunities and obstacles for applying AI to the Swedish arable farming, milk production and beef production. Future studies could similarly investigate how qualified other agricultural sectors, such as poultry farming and pig farming, are for applying AI. Additionally, there is a need to investigate in more detail different use cases and applications for one single sector. In particular, investigating how the output data in arable farming can be related to the input data and all the random factors throughout the year, is an interesting topic to research. Such sector specific studies could also open for scrutinizing how unsupervised learning models could be applied to agriculture, a type of learning models that this study excluded.

From a non-technical perspective, there are other interesting aspects to investigate further. One finding in this thesis is that almost all respondents ask for new smart farming technology but simultaneously are not always willing to pay for them if there is no clear business case. Researching how to best structure such a business case, considering the long-term trend towards SaaS systems, is a topic well worth investigating. Furthermore, analysing how the essential question of data ownership and data sharing can be solved economically and legally is no doubt a subject for future studies.

As a final note, conditioned that most of the current smart farming developments are practically implemented, there are several larger considerations that need to be analysed. What will happen to the crop prices when the quantity and quality of the yield can be predicted by AI on a national level? Will such predictions affect the power dynamics between farmers and agricultural enterprises, reducing the profitability for the individual farmer additionally? Which groups will manage, and want, to be farmers when more and more tasks requiring farming experience and hard work are replaced by decision support and automatic machines? Since agricultural technological development seems to have no limits, there are neither limits to the research questions that can be analysed in the future.

8. Conclusion

This thesis answers the research question *Which are the main opportunities and hurdles for applying AI to Swedish agricultural businesses?*. By conducting a structured literature review and an interview study with 27 respondents from various parts of the agricultural industry, data has been gathered to get a holistic view on technological use in agriculture. The scope of the thesis is deliberately wide, focusing on three agricultural sectors: namely arable farming, milk production and beef production. Furthermore, the respondents are categorised by their role in the sector, ranging from governmental authorities, commercial enterprises, researchers as well as farmers. Motivating the methodology is the aim to acquire knowledge that ranges over several production sectors, as well as over several kinds of organisations that in some way works with agriculture.

Most stakeholders interviewed in this thesis share a demand for applying AI to Swedish agriculture. Driving the farmers towards smart farming technologies are the needs for increased profitability, reduced workload and often a genuine curiosity for new technology. However, profitability stands out as the most influential factor which makes a clear business case an essential requirement connected to the propagation of smart farming technologies. Since more and more agricultural products become service-based, allowing for sharing and renting equipment, the business case is changing for both farmers and machine producers, opening new possibilities. Nevertheless, for smart farming to really transform the Swedish agricultural sector, governmental agencies and commercial enterprises might need to take a more active role in the transition. Such aspirations are especially important to ensure that the governmental and societal demand for reduced emissions and increased sustainability is met in the technological shift.

For the transformation to be successful, it is essential that the structures, allowing farmers to apply the smart farming technologies, are modern. One key requirement is that farmers have continuous and easy ways to acquire up-to-date knowledge of how to apply smart farming. Therefore ensuring that technical, agricultural education is easily accessible through for example flexible, on-demand courses are needed. Additionally, the smart farming techniques need to be modifiable to match the varying transparency and adaptability demands that different farmers have.

Regarding how implementation and propagation of AI in agriculture might be hindered, this study identifies some factors that act as barriers. The most prominent one is how data is managed, which can be further specified to data sharing and ownership as well as cybersecurity. This is a complex question that as of now do not have a clear solution, either technically or legally. However, there is a consensus amongst respondents that to transition the agricultural sector into a more data-driven and digital environment, the technical infrastructure must be secure. The solution must be able to guarantee that sensitive data is not available for intruders while at the same time guaranteeing access for the intended users. Furthermore, for the end users to be able to benefit from the digitalising transition of the sector, the data models require a high degree of flexibility.

This stems from the wide variety of machinery at farms as well as the varying level of technological interest and knowledge among the farmers.

Moreover, an important aspect that slows down the process of implementing smart farming technologies and AI in agriculture is the economical dimension expressed by the respondents. A large part of this are of course the high investment costs, but other economic aspects also play a part in this barrier. For example, the fickle market demands, the general low profitability in Swedish agriculture as well as the trend towards consolidation of farms all contribute to making investments full of risk. Other identified barriers that hinder the spread of AI in agriculture are some social factors, for example the concerns about technological over-dependency and insufficient end user trust towards technology. The lacking trust seems to stem from over-selling from developers of technology as well as a gap between the technology that is developed and the real market demands.

As for the technical solutions that could potentially solve the demand for AI and smart farming technologies, there are many possible ways. In this thesis, three use cases are explored, and findings show that a lot of the data and sensors types already exist. The problem that remains to be solved is to connect the input data to the output data by developing the datasets, and thereby close the data cycle. Thereafter, one can build models and evaluate which one of them performs best with some specified evaluating metrics. Additionally, the results show the importance of 'starting small' when building the models, i.e. using few input variables to begin with and then tune the model adding only one more variable at a time.

It is also evident that all use cases and technical solutions demand a high precision for classification model output as well as low prediction errors for regression models. Decision support in agriculture manages and affects core parts of the agricultural business, and therefore it is important that estimations and predictions are accurate. Interestingly, respondents from the arable sector express that they, as of now, accept higher levels of total error in the model. However, for future purposes and solutions with increased complexity, the total error must decrease which is likely to affect the bias-variance trade-off. A requirement for achieving precise supervised machine learning models, adapted to the local farm, will be easy pre-processing of the data. Thus, the data labelling process must either be simplified by developers or offered to the farmers as a service by consultants.

Technologically, Swedish agricultural businesses have developed for decades, but the shift towards smart farming techniques and data-driven agriculture might be one of the greatest transitions yet. Applied AI in agriculture has the potential to, months in advance, predict the quality of the yield in arable farming, determine the health status of cows, optimise the time for slaughter of beef and allow for several other use cases. By data-driven decision support, and even tasks performed completely automatically, farmers hope to improve their output both in terms of quantity and quality, mitigate carbon emissions, clear work time, and increase profits. For commercial enterprises and governmental agencies, the transition allows for updated supply chains and planning models, improving the agricultural industry on a macro-level. Still, several challenges remain unsolved, jeopardising the speed of the transition. Nevertheless, with such strong incentives, the long-term trend towards increased usage of AI in agriculture is clear. The question is no longer *if* smart farming will continue to develop, but *how* the hurdles will be resolved, and which stakeholders will benefit from its radical transformative effects.

References

Atzori, L., Iera, A., Morabito, G., 2016. Understanding the Internet of Things: definition, potentials, and societal role of a fast evolving paradigm. *Ad Hoc Networks,* [PDF]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-11].

Berrang-Ford, L.; Pearce, T.; Ford, J.D. 2015. Systematic review approaches for climate change adaptation research. Reg. Environ. Chang. 2015, 15, 755–769.

Bhole, A., Falzon, O., Biehl, M., Azzopardi, G., 2019. A Computer Vision Pipeline that Uses Thermal and RGB Images for the Recognition of Holstein Cattle. In: CAIP. *International Conference on Computer Analysis of Images and Patterns*.

Buller, H., Blokhuis, H., Lokhorst, K., Silberberg, M., Veissier, I., 2020. Animal Welfare Management in a Digital World. ANIMALS [Journal] 10/1779. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-11].

Caja, G., Castro-Costa, A., Salama, A., Oliver, J., Baratta, M., Ferrer, C., Knight, C, 2020. Sensing solutions for improving the performance, health, and wellbeing of small ruminants. Journal of Dairy Research [Journal] 87. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-11].

Crocetti, L, Forkel, M., Fischer, M., Jurečka, F., Grlj, A., Salentinig, A., Trnka, M., Anderson, M., Ng, W., Kokalj, Z., Bucur, A., Dorigo, W., 2020. Earth observation for agricultural drought monitoring in the Pannonian Basin: current state and future direction. Regional Environmental Change. 20/123. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-11].

European Commission, 2020. *Statistical factsheet Sweden*. [PDF]. Available at:

<https://ec.europa.eu/info/sites/info/files/food-farming-fisheries/farming/documents/agri-statistical-factsheet-se_en.pdf> [Accessed 2021-02-18].

Eurostat, n.d.a. Agricultural holdings by agricultural area. [Online]. Available through: <https://ec.europa.eu/eurostat/databrowser/view/tag00001/default/table?lang=en> [Accessed 2021-02-18].

Eurostat, n.d.b. Utilised agricultural area by categories. Available through: <https://ec.europa.eu/eurostat/databrowser/view/tag00025/default/table?lang=en> [Accessed 2021-04-26].

Eurostat, n.d.c. Indicator A of the income from agricultural activity. Available through: <https://ec.europa.eu/eurostat/databrowser/view/tag00057/default/table?lang=en> [Accessed 2021-02-18].

Eurostat, n.d.d. Economic accounts for agriculture - agricultural income (indicators A, B, C) [Online]. Available through: <https://appsso.eurostat.ec.europa.eu/nui/show.do?dataset=aact_eaa06&lang=en> [Accessed 2021-02-18].

Feng, P., Wang, B., Liu, L., Waters, C., Xiao, D., Shi, L., Yu, Q., 2020. Dynamic wheat yield forecasts are improved by a hybrid approach using a biophysical model and machine learning technique. Agricultural and Forest Meteorology. [Journal]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Fusco, G., Melgiovanni, M., Porrini, D., Ricciardo, T., 2020. How to improve the diffusion of climate-smart agriculture: What the literature tells us. *Sustainability*. [PDF]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Graziano, A.M., Raulin, M.L., 2013, *Research methods: a process of inquiry*. 8th ed. Boston: Pearson.

Griffiths, P., Nendel, C., Pickert, J., Hostert, P., 2020. Towards national-scale characterization of grassland use intensity from integrated Sentinel-2 and Landsat time series. Remote sensing of Environment. [Journal]. 238/2020. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Grosan, C., Abraham, A. 2011. Intelligent Systems. 17:th ed. Springer-Verlag: Berlin, Heidelberg.

Heidler, K., Fietzke, A., 2019. Remote Sensing for Assessing Drought Insurance Claims in Central Europe. In: *IGARSS 2019 - 2019 IEEE International Geoscience and Remote Sensing Symposium*.

Herhem, T., Rooijakkers, L., Berckmans, D., Pena Fernández, A., Norton, T., Berckmans, D., Vranken, E., 2017. Appropriate data visualisation is key to Precision Livestock Farming acceptance. [Journal]. 138/2017. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

ISPA (International Society for Precision Agriculture). 2019. ISPA Forms Official Definition of 'Precision Agriculture'. [online] Available from <https://www.precisionag.com/market-watch/ispa-forms-official-definition-of-precision-agriculture/>. [Accessed 2021-02-15].

Janghorban, R., Latifnejad Roudsari, R., Taghipour, A. 2014. Skype interviewing: The new generation of online synchronous interview in qualitative research. *International Journal of Qualitative Studies on Health and Well-being, 9:1, 24152, DOI: 10.3402/qhw.v9.24152*

Jordbruksverket. n.d. *Processen för EU:s gemensamma jordbrukspolitik*. [online] Available at: <https://jordbruksverket.se/stod/jordbrukspolitiken-cap/processen-for-eus-gemensamma-jordbrukspolitik> [Accessed 2021-02-16]

Kamienski, C., Soininen, J., Taumberger, M., Dantas, R., Toscano, A., Cinotti, T., Maia, R., Neto, A., 2019. Smart Water Management Platform: IoT-Based Precision Irrigation for Agriculture. *Sensors*. [PDF]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Karlsson, A-M, 2020. Mindre än 1 procent av jordbruksföretagen inom EU skapar 38 % av produktionsvärdet. *Jordbruket i siffror*. [blog] 2020-01-03. Available at: <https://jordbruketisiffror.wordpress.com/2020/01/03/mindre-an-1-procent-av-jordbruksforetagen-inom-eu-skapar-38-av-produktionsvardet/> [Accessed 2021-02-18].

Kerkow, A., Wieland, R., Koban, M., Hölker, F., Jeschke, J., Werner, D., Kampen, H., 2019. What makes the Asian bush mosquito Aedes japonicus feel comfortable in Germany? A fuzzy modelling approach. Parasites & Vectors. [Journal]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Kernecker, M, Knierim, A., Wurbs, A., Kraus, T., Borges, F., 2020. Experience versus expectation: farmers' perceptions of smart farming technologies for cropping systems across Europe. *For Corporate & Health*. [PDF]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Khanal, S., Kushal, K., Fulton, J., Shearer, S., Ozkan, E., 2020. Remote sensing in agriculture - Accomplishments, limitations, and opportunities. Remote Sensing. [Journal]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Kleinschmidt, J., Kamienski, C., Prati, R. Kolehmainen, K., Aguzzi, C., 2019: End-to-end Security in the IoT Computing Continuum: Perspectives in the SWAMP Project, *IEEE*, [PDF]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-11].

Kopper, A., Karkare, R., Paffenroth, R C., Apelian, D. 2020. Model Selection and Evaluation for Machine Learning: Deep Learning in Materials Processing. *Integrating Materials and Manufacturing Innovation.* 9:2020, (287–300), [Journal]. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-04-26].

Kvale, S., Brinkmann, S. 2009. InterViews: Learning the Craft of Qualitative Research Interviewing. 2nd ed. Thousand Oaks, California: SAGE Publication, Inc.

Long, T., Blok, V., Poldner, K., 2016. Business models for maximising the diffusion of technological innovations for climate-smart agriculture. International Food and Agribusiness Review. [Journal]. 20/2016. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Long, T., Thomas, B., Blok, V., Coninx, I., 2019. The diffusion of climate-smart agricultural innovations: Systems level factors that inhibit sustainable entrepreneurial action. Journal of Cleaner Production. [Journal] 09/2019. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Matos-Moreira, M., Lemercier, B., Dupas, R., Michot, D., Viaud, V., Akkal-Corfini, N., Louis, B., Gascuel-Odoux, C., 2017. High-resolution mapping of soil phosphorus concentration in agricultural landscapes with readily available or detailed survey data. European Journal of Soil Science. 05/2017. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Medvedev, B., Molodyakov, S., 2019. Internet of Things for Farmers: Educational Issues. In: *18th International Scientific Conference Engineering for Rural Development*.

Meier, J., Mauser, W., Hank, T., Bach, H., 2020. Assessment on the impact of high-resolution-sensor pixel sizes for common agricultural policy and smart farming services in European regions. Computers and Electronics in Agriculture. [Journal]. 02/2020. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Rotondi, D., Straniero, L., Saltarella, M., Balducci, F., Impedovo, D., 2019. Semantics for Wastewater Reuse in Agriculture. In: *2019 IEEE International Conference on Systems, Man and Cybernetics (SMC)*

SCB, 2016. *Farm labour force in 2016*. [PDF] Available at: <https://www.scb.se/contentassets/106cdea136d34e61a545a022a3aa98cb/jo0401_2016a01_sm_jo30sm1701.pdf> [Accessed 2021-02-16]

SCB, 2020. *Use of agricultural land in 2020: Preliminary statistics*. [PDF] Available at: <scb.se/contentassets/2e011f0876324b1a918c1e70b5ef088a/jo0104_2020a01_sm_jo10sm2001.pdf> [Accessed 2021-02-16]

Svensson, U., Ulf.Svensson@jordbruksverket.se, 2021. *Makrofrågor om svenskt jordbruk.* [email] Message to Carl Johan Casten Carlberg (cj@castencarlberg.se). Sent 2021-02-16 14:32:49. [Accessed 2021-04-26].

Taylor, S.J., Bogdan, R., DeVault, M. 2016. *Introduction To Qualitative Research Methods: A Guidebook Resource*. 4th ed. Hoboken, New Jersey: John Wiley & Sons. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-15].

Torai, S., Chiyoda, S, Ohara, K., 2020. Application of AI technology to smart agriculture: Detection of plant diseases. In: *2020 59th Annual Conference of the Society of Instrument and Control Engineers of Japan (SICE)*

USGS. n.d. *What is remote sensing and what is it used for?* [online] Available at: https://www.usgs.gov/faqs/what-remote-sensing-and-what-it-used?qt-news_science_products=0#qt-news_science_products [Accessed 2021-02-12]

Viljanen, N., Honkavaara, E., Näsi, R., Hakala, T., Niemeläinen, O., Kaivosoja, J., 2018. A Novel Machine Learning Method for Estimating Biomass of Grass Swards Using a Photogrammetric Canopy Height Model, Images and Vegetation Indices Captured by a Drone. Agriculture. [Journal]. 05/2018. Available through: Uppsala University Library <ub.uu.se>. [Accessed 2021-02-14].

Wathes, C.M. 2007. Precision Livestock Farming for Animal Health, Welfare and Production. In Proceedings of the XIII International Congress in Animal Hygiene-ISAH, Tartu, Estonia, 17–21 June 2007; pp. 397–404.

Yin, R. 2011. *Kvalitativ forskning från start till mål*. Studentlitteratur AB: Lund.

Author Contribution

This thesis has two authors, Elsa Jerhamre and Carl Johan Casten Carlberg. Both have contributed equally to the project. The conceptualization and the execution of the project has been a group effort in which we both were greatly involved. Although division of tasks have been conducted to make the project efficient, both authors have contributed to the methodology, investigation, analysis, validation, and visualization of the project. We have held every other interview while the other one was taking notes, and the literature review was conducted by reading and summarising half of the number of included articles each. Additionally, the writing of the report has been conducted by both, where we have written approximately half of it each. However, both of us have contributed to all parts of the report.

Appendix A

QUESTIONS FOR ORGANISATIONS

1. Do you consent to this interview being recorded as well as documented by written notes?
    1. If no: Do you consent to this interview being documented by written notes?
2. Would you please describe your role at the company?
3. Are you familiar with the concept of smart farming and precision agriculture?
    1. How would you define them?
    2. How do you work with technology in agriculture?
    3. What role do AI or smart farming play in the strategic agenda of your organisation for the coming years?
4. What would you like to gain from adding technology to agriculture?
    1. How have you identified that need?
        1. How does the need for smart farming differ between your different types of agricultural businesses?
        2. How do you work to reach an optimal usage of smart farming?

Which use cases for smart farming do you regard are relevant?

1. Which applications have you begun implementing?
2. Do you think implementing the following use cases would add value to farmers? If so, in which way?
    a. Predict the volume of the yield
    b. Predict the quality of the yield
    c. Determine the optimal timing of harvest
    d. Detect the spread of weed
    e. Predict the outbreak of parasites
    f. Predict how much water, fertilizer, etc that is needed at a specific time and place
    g. Identify cattle (e.g. cows) without using sensors
    h. Give indicators for the well-being of cattle
    i. Visualise data in real-time for the farmer

What knowledge and capacity are there to implement smart farming on actual farms today?

1. Where in the organisation is that knowledge located?
2. How does it reach the farms?

How do farmers regard:

1. Gathering the necessary data for smart farming applications?
    a. What data is being gathered today?
    b. Would it be possible to collect other types of data?
        1. In that case: what kind of data?
2. Making the investments that are needed?
    a. Who pays for investments in smart farming?

How long has the work with smart farming developed in Sweden, according to you?

1. What has made the development possible?
2. Which obstacles exist for smart farming to continue developing?
3. How does the work with Smart Farming differ between different types of agricultural businesses?

Within Machine Learning there is an important trade-off between making technology either adapted to the local needs that it is created to help or to make it more generalisable.

How do you approach this trade-off between having the technology adapted after local needs against standardised technology adapted for more farmers?

1. What other trade-offs do you do when you plan for smart farming in the future?

How do you help farmers transform to smart farming?

1. Do you offer help/support?

a. Economically
b. With consultancy
c. Technically
d. With something else?

How do you have contact with farmers?

2. Through which channels?
3. How often?
4. Do you think your views on smart farming and agriculture differ?

How do you expect that smart farming will lead to increased revenue?

1. After how long do you expect to make a positive Return of Investment with Smart Farming?
2. Who pays for the investments in Smart Farming?

Is there anything else that you would like to discuss regarding smart farming?

Thank you!!!

Appendix B

QUESTIONS TO FARMERS

1. Do you consent to this interview being recorded as well as documented by written notes?
    1. If no: Do you consent to this interview being documented by taking written notes?
2. Would you please describe your farm in terms of main practices?
3. Would you please tell us about your background?
    1. How long have you been working in agriculture?
    2. How did you end up working as a farmer?
        1. Have you undergone any education to become a farmer?

Have you encountered the concept of smart farming and precision agriculture before?

IF FAMILIAR WITH SMART FARMING

1. How do you define smart farming and precision farming?
2. In what context did you encounter these concepts?
3. When did you encounter the concepts?

Which use cases for smart farming do you regard as relevant to your farm?

1. Which have you begun implementing?
2. Do you think implementing the following use cases would add value to your farm?
    1. Predict the volume of the yield
    2. Predict the quality of the yield
    3. Determine the optimal timing of harvest
    4. Detect the spread of weed
    5. Predict the outbreak of parasites
    6. Predict how much water, fertilizer, etc that is needed at a specific time and place
    7. Identify cattle (e.g. cows) without using sensors
    8. Give indicators for the well-being of cattle
    9. Visualise data in real-time for the farmer

Do you expect any added value or increased profitability to your farm by implementing smart farming technologies?

1. Why do you think that?
2. In what way?
3. If positive: In what timeframe do you estimate that you will be able to render a positive return of investment by smart farming?
4. If negative: What would be the main obstacles?
5. Who pays for investments in smart farming?

In what part of your daily activities on the farm is there highest potential for some type of smart farming technology?

1. Which are the main needs on your farm for new technologies such as smart farming?
2. Which of the following smart farming technologies would you like to have:
    1. Totally autonomous processes that act without you having to interfere.
    2. Decision support where you get a smart recommendation of an action based on data from your farm.
    3. Visualisation of data from your farm in real-time so that you may make decisions yourself based on the data.

How would you proceed with implementing smart farming technologies?

1. Do you collect any data on the farm today?

        1. What type of data?
        2. Who has access to it?
        3. Why do you collect it? To what purpose? Is it used today?
    2. Are there any help or support from other actors when implementing smart farming technologies?

How does your IT- and communications infrastructure look at your farm?

    1. How has it come to look that way?

How do you collaborate with industry organisations and cooperatives?

    1. Are you aware of their approach towards smart farming?
    2. How does their approach towards smart farming influence your business?
    3. Why is that?

Where do you stand in relation to:

    1. being one of the first to implement smart farming?
    2. making the necessary investments?
    3. collaborating with other farmers to produce smart farming?

Within Machine Learning there is an important trade-off between making technology either adapted to the local needs that it is created to help or to make it more generalisable.

How do you regard having technology adapted after your local needs against standardised technology that is cheaper and can be used by more farmers but with less accurate precision?

Is there anything else that you would like to discuss regarding smart farming?

Thank you!!!

IF NOT FAMILIAR WITH SMART FARMING

Applying data collection and analysis to agriculture is often referred to as 'smart farming' or 'precision agriculture'. These concepts include a wide scope of activities. Smart farming is considered by many to be able to increase yield volumes, mitigate the amount of work for farmers, contribute to climate change adaptation and future-proof farming for the coming centuries. We will give some examples of smart farming soon, but first we would like to hear about your experiences on the topic.

Do you do something similar at your farm today?

Which use cases for smart farming do you see as relevant?

    1. Which have you begun implementing?
    2. Do you think implementing the following use cases would add value to your farm?
        1. Predict the volume of the yield
        2. Determine the optimal timing of harvest
        3. Detect the spread of weed
        4. Predict the outbreak of parasites
        5. Predict how much water, fertilizer, etc that is needed at a specific time and place
        6. Identify cattle (e.g. cows) without using sensors
        7. Give indicators for the well-being of cattle
        8. Visualise data in real-time for the farmer

Do you see any added value/increased profitability to your farm in regard to implementing smart farming technologies?

    1. Why do you think that?

   2. In what way?
   3. If negative: What would be the main obstacles?
      1. If expensive: What is your perception of how much it costs?
      2. If not enough experience: What is your perception of how much experience is needed?
   4. Who pays for investments in new technologies such as smart farming?

How do you decide which technology to implement on your farm?

   1. Are there any help or support from other actors?

How does your IT- and communications infrastructure look at your farm?

   1. How has it come to look that way?
   2. Which data do you gather today?
      1. How is this done?
   3. Who has access to the data you collect?
      1. What do you do with the data?
      2. What would you like to do with the data?

How do you collaborate with industry organisations and cooperatives?

   1. Are you aware of their approach towards smart farming?
   2. How does their approach towards smart farming influence your business?
   3. Why is that?

Where do you stand in relation to:

   1. being one of the first to implement smart farming?
   2. making the necessary investments?
   3. collaborating with other farmers to produce smart farming?

In what part of your farming or day-to-day tasks would you say there are potential uses of some kind of smart farming technology?

   1. What would, in your opinion, be optimally helpful or valuable in your specific farm, in terms of smart farming?

Is there anything else that you would like to discuss regarding smart farming?

Thank you!!!

Appendix C

QUESTIONS ABOUT USE CASES

1. Do you consent to us publicising the results from this interview with your name?
2. Do you consent to us recording this interview?
3. Purpose of this interview: We have identified three possible use cases in crop production, milk production and meat production. This interview aims to analyse technically and give an overview on how these use cases can be practically feasible. We would like to discuss with you what concretely is needed to implement these use cases. We will ask you about what input is needed, what the corresponding output is, which mathematical models might potentially solve the problem and how to evaluate that model, and finally what practical considerations the system would imply. Please exemplify and answer as concretely as possible.

USE CASE 1 - Crop production
Predict the quality of the harvest of some crop

- General thoughts:
- Input:
- Output:
- Model:
- Evaluation of the model:
- Practical considerations:

USE CASE 2 - Milk Production
Indicators for animal health and welfare

- General thoughts:
- Input:
- Output:
- Model:
- Evaluation of the model:
- Practical considerations:

USE CASE 3 - Meat production
Optimise the time for slaughter of beef

- General thoughts:
- Input:
- Output:
- Model:
- Evaluation of the model:
- Practical considerations:

Appendix D

Research information sheet and consent form that was sent beforehand to respondents of the holistic-oriented interviews.

Research information sheet
You are invited to participate as a respondent in an interview study as part of a master thesis about the use of technology in agriculture from Uppsala University.

The aim of the study is to examine the need for new technology in the agricultural sector and which practical difficulties there are to implement these. Actors from both large industry organisations and cooperatives as well as farmers of different sizes and from different sectors will be interviewed.

Your participation in this project will involve taking part in an interview which approximately will last an hour. The interview will be recorded with your permission. If you do not wish for the interview to be recorded, written notes will be taken during the interview instead.

The end product of the study will be a written report which will be published. In the report you will be anonymous, which means that no given information will be linked back to you or your organisation. Before publication of the report, a draft will be sent to you for approval of your answers. Should you wish to revise your given information, as result of misconception, there will be given opportunity for that at this point. To ensure anonymity the following precautions will be taken:

- A code will be used in place of your name
- No individual identifying information will ever appear in written or oral presentations
- Any quotes from the interviews will be anonymised and used only with expressed consent

You may terminate the interview at any stage. If you wish not to answer a question you do not have to. You can also withdraw from the study, including given information, up to a month after the date of the interview.

This project is being carried out by:
Elsa Jerhamre
Uppsala University

Carl Johan Casten Carlberg
Uppsala University

Supervisors:
Susanne Björkman
Peltarion

Vera van Zoest
Uppsala University

Consent form

I have read and understood the description of the project. On this basis I agree to participate in the project, and I consent to publication of the results of the project with the understanding that anonymity will be preserved. I understand also that I may at any time withdraw from the project, including withdrawal of any information I have provided, up to a month after the interview.

Please tick one of the following two boxes:

- ▢ I consent to having an audio recording made of my interview.
- ▢ I do not consent to having an audio recording made of my interview, but agree to notes being taken.

Please tick one of the following two boxes:

- ▢ I consent that any quotes taken from my interview may be published and that these, in that case, will be anonymised.
- ▢ I want to review any quotes you would like to publish and may then give my permission.

THANK YOU FOR YOUR PARTICIPATION!

Appendix E

Research information sheet and consent form that was sent beforehand to respondents of the use case-oriented interviews.

Research information sheet
You are invited to participate as a respondent in an interview study as part of a Master Thesis-project about the use of technology in agriculture from Uppsala University.

The aim of the study is to examine the need for new technology in the agricultural sector and which practical difficulties there are to implement these. Actors from both large industry organisations and cooperatives as well as farmers of different sizes and from different sectors will be interviewed.

Your participation in this project will involve taking part in an interview which approximately will last an hour. The interview will be recorded with your permission. If you do not wish for the interview to be recorded, written notes will be taken during the interview instead.

The end product of the study will be a written report which will be published. Before publication of the report, a draft will be sent to you for approval of your answers. Should you wish to revise your given information, as result of misconception, there will be given opportunity for that at this point.

You may terminate the interview at any stage. If you wish not to answer a question you do not have to. You can also withdraw from the study, including given information, up to a month after the date of the interview.

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Consent form

I have read and understood the description of the project. On this basis I agree to participate in the project, and I consent to publication of the results of the project with the understanding that anonymity will be preserved. I understand also that I may at any time withdraw from the project, including withdrawal of any information I have provided, up to a month after the interview.

Please tick one of the following two boxes:

▢ I consent to having an audio recording made of my interview.

▢ I do not consent to having an audio recording made of my interview, but agree to notes being taken.

Please tick one of the following two boxes:

▢ I consent that any quotes taken from my interview may be published and that these, in that case, will be anonymised.

▢ I want to review any quotes you would like to publish and may then give my permission.

Please tick one of the following two boxes:

▢ I consent to the result of the interview being published with my name.

▢ I consent to the result of the interview being published anonymously.

THANK YOU FOR YOUR PARTICIPATION!

Appendix F

Table A. List of respondents' interview numbers and referenced ID, their occupation, and the date of the interview. In the Occupation-column the respondents are marked as farmers, researchers, commercial enterprises, and governmental agencies. Additionally, each farmer is marked with 'Organic' or 'Conventional', which refers to the method of the farm.

RESPONDENT ID	OCCUPATION	FARMING METHOD	DATE
Interview 1 / C1	Commercial enterprise		2021-02-11
Interview 2 / C2	Commercial enterprise		2021-02-16
Interview 3 / C3	Commercial enterprise		2021-02-17
Interview 4 / C4	Commercial enterprise		2021-02-17
Interview 5 / C5	Commercial enterprise		2021-02-18
Interview 6 / C6	Commercial enterprise		2021-02-22
Interview 7 / R1	Researcher		2021-02-23
Interview 8 / F1	Farmer	Organic	2021-02-23
Interview 9 / F2	Farmer	Conventional	2021-02-23
Interview 10 / R2	Researcher		2021-03-01
Interview 11 / F3	Farmer	Conventional	2021-03-02
Interview 12 / A1	Governmental agency		2021-03-02
Interview 13 / F4	Farmer	Organic	2021-03-03
Interview 14 / F5	Farmer	Conventional	2021-03-03
Interview 15 / C7	Commercial enterprise		2021-03-04
Interview 16 / F6	Farmer	Conventional	2021-03-04
Interview 17 / F7	Farmer	Conventional	2021-03-05
Interview 18 / F8	Farmer	Conventional	2021-03-08
Interview 19 / F9	Farmer	Organic	2021-03-08
Interview 20 / A2	Governmental agency		2021-03-09

Interview 21 / F10	Farmer	Organic	2021-03-09
Interview 22 / R3	Researcher		2021-03-23
Interview 23 / R4	Researcher		2021-03-25
Interview 24 / R5	Researcher		2021-03-29
Interview 25 / R6	Researcher		2021-03-29
Interview 26 / C8	Commercial enterprise		2021-04-07
Interview 27 / R7	Researcher		2021-04-07