UPPSALA
UNIVERSITET

SAMINT-MILI-24011

Master's Thesis 30 credits
May 2024

# AI in the Swedish Food System

## Exploring Adoption, Challenges, and Opportunities in Primary Production through a Socio-Technical Lens

Amirhadi Zakeri
Yiming Lei

Master's Programme in Industrial Management and Innovation

*Masterprogram i industriell ledning och innovation*

UPPSALA
UNIVERSITET

**Faculty of Technology**

Visiting address:
Ångströmlaboratoriet
Lägerhyddsvägen 1

Postal address:
Box 536
751 21 Uppsala

Telephone:
+46 (0)18 – 471 30 03

Telefax:
+46 (0)18 – 471 30 00

Web page:
http://www.teknik.uu.se/education/

# Abstract

## **AI in the Swedish Food System:** Exploring Adoption, Challenges, and Opportunities in Primary Production through a Socio-Technical Lens

*Amirhadi Zakeri & Yiming Lei*

Artificial intelligence (AI) holds immense potential to revolutionize the global food system, driving sustainability, enhancing efficiency, and addressing food security challenges. However, the successful integration of AI in the food system demands a deep understanding of the complex interplay between technology, social factors, economic considerations, and ethical implications. This study explores the opportunities and challenges in implementing AI technologies within the Swedish food system, focusing on primary production. The research utilizes an expanded Socio-Technical System Theory (STST) framework, incorporating economic and ethical dimensions alongside the traditional social and technical levels. Literature review and semi-structured interviews provide insights into the dynamics of AI adoption in the Swedish context. The findings reveal that AI adoption in the Swedish food system is currently in the early adopter phase, with broad range applications. However, the study also uncovers significant barriers to widespread AI adoption, including the lack of suitable business models, fragmented data sharing infrastructures, and ethical concerns surrounding data privacy and ownership.

The analysis emphasizes the need for developing user-friendly interfaces, leveraging narrow AI applications, and establishing seamless data flow across the food value chain. The study contributes to the theoretical development of the Socio-Technical System Theory framework by demonstrating the importance of incorporating economic and ethical dimensions in understanding the complex dynamics of AI adoption in socio-technical systems. The findings also have practical implications for policymakers, industry actors, and researchers, emphasizing the significance of context-specific AI development, as well as the need for collaborative innovation processes. The research acknowledges its limitations, including the focus on primary production and the reliance on qualitative methods, and identifies potential areas for future research, such as comparative analyses across different food sectors and the use of quantitative approaches.

In conclusion, this study provides a timely and critical contribution to the understanding of AI's role and potential in transforming the Swedish food system. It indicates the need for developing suitable business plans, establishing data sharing platforms, and ensuring a harmonized data flow to harness the benefits of AI while navigating its challenges and risks, paving the way for a more sustainable and resilient food future.

**Keywords**: artificial intelligence, Swedish food system, food value chain, primary production, sustainability, Socio-Technical System Theory.

Supervisor: Thomas Lennerfors
Subject reader: Paul Plummer
Examiner: First Michal Zawadzki
SAMINT-MILI-24011
Printed by: Uppsala Universitet

# Popular Science Summary

Imagine a world where robots tend to cultivate, where computers can predict the perfect time to harvest, and where your food's journey from farm to fork is traced by intelligent systems. This is not a scene from a science fiction movie, but a look into the future of Sweden's food system, thanks to the transformative power of Artificial Intelligence (AI). In our research, we explored how AI technologies are being adopted and integrated into the Swedish food system, with a particular focus on primary production - the sector responsible for growing and harvesting our food. Through a review of existing literature and in-depth interviews with farmer representatives, researchers, policymakers, and industry experts, we tried to understand the opportunities, challenges, and implications of AI in this context.

What we discovered was a complex interplay of technical, economic, social, and ethical factors shaping the adoption of AI in the Swedish food system. On the one hand, AI offers immense potential to optimize resource use, reduce waste, improve product quality, and enhance the overall sustainability and resilience of the food system. From precision agriculture techniques that help farmers make data-driven decisions, to intelligent supply chain management that minimizes food waste, AI is already demonstrating its value across various stages of food production and distribution.

On the other hand, the integration of AI also raises important challenges and concerns. The food system is getting more digitalized and data-driven, which raises concerns about data ownership, privacy, and security. The uneven distribution of benefits and risks associated with AI adoption, particularly for small-scale farmers and vulnerable communities, shows the need for inclusive and equitable innovation processes. Moreover, the ethical implications of delegating decision-making to intelligent machines, demand careful consideration and governance. To navigate these complexities, we propose an integrated strategy for harmonizing AI adoption throughout Sweden's food system. This strategy emphasizes the importance of collaborative innovation networks, public-private partnerships, and collaborative governance frameworks that engage diverse stakeholders in the responsible development and deployment of AI technologies. By aligning AI with broader societal values and priorities, such as sustainability, resilience, and equity, Sweden has the opportunity to become a global leader in the transition towards intelligent and ethical food systems.

In essence, our research shows the transformative potential of AI for Sweden's food system, while also emphasizing the importance of a thoughtful, inclusive, and values-driven approach to its adoption and governance. As we stand on the edge of this technological revolution, it is crucial that we employ the power of AI not merely to optimize efficiency and productivity, but to build a food system that truly nourishes people, communities, and the planet.

# Acknowledgment

This thesis marks the culmination of our two-year journey at Uppsala University, an experience enriched by the brilliance and support of our colleagues, teachers, and researchers. We are deeply grateful to all who have contributed to this work.

First and foremost, we want to express our heartfelt thanks to each other. Our partnership, transcending cultural boundaries, has been a testament to the power of collaboration and friendship in academia. We have supported, challenged, and inspired one another, making this thesis a true reflection of our combined efforts. This project is an iterative course, we scrutinized the work of each other.

We are profoundly grateful to our subject reader, Paul Plummer, whose guidance over these five months has been instrumental. His precise, constructive feedback significantly elevated the quality of our work. Our sincere thanks also go to our supervisor, Thomas Lennerfors, and the FINEST center for their crucial insights and industry perspectives, which helped us pinpoint the core focus of our study.

This research would not have been possible without the generosity of our interview participants. Their rich, firsthand experiences form the backbone of our exploratory investigation, and we are indebted to them for sharing their valuable knowledge.

We also wish to express our gratitude to Sweden and Uppsala University for providing this enriching educational experience. The opportunity to study in this vibrant, inclusive environment has been transformative, both academically and personally.

Finally, we extend our deepest gratitude to our families spread across China, Iran, the UK, the USA. To our parents, and family: your unconditional love, encouragement, and sacrifices have been the bedrock of our academic journey. Without your unwavering support, this achievement would not have been possible. To those watching over us from above: you are forever in our hearts. Though miles apart, we share this with all of you, hoping it brings you as much joy as your love brings us.

## Table of Content

# List of Figures

# List of Tables

# Table of Abbreviations

| Abbreviation | Meaning |
|---|---|
| AI | Artificial Intelligence |
| ML | Machine Learning |
| STST | Socio-Technical Systems Theory |
| IoT | Internet of Things |
| SVM | Support Vector Machine |
| BBO | Biogeography-Based Optimization |
| FNN | Feedforward Neural Network |
| PLSR | Partial Least Squares Regression |
| LS-SVM | Least Squares Support Vector Machine |
| ELM | Extreme Learning Machine |
| NIR | Near-Infrared |
| SOC | Soil Organic Carbon |
| TN | Total Nitrogen |
| RMSE | Root Mean Square Error |
| NWP | Numerical Weather Prediction |
| RBF | Radial Basis Function |
| MAE | Mean Absolute Error |
| SI | Scatter Index |
| SOM | Self-Organizing Map |
| SKN | Supervised Kohonen Network |
| CNN | Convolutional Neural Network |
| LSTM | Long Short-Term Memory |
| MODIS | Moderate Resolution Imaging Spectroradiometer |
| VIS-NIR | Visible-Near Infrared |
| GA | Genetic Algorithm |
| ANN | Artificial Neural Network |
| ABC | Artificial Bee Colony |
| CAGR | Compound Annual Growth Rate |
| FCN | Fully Convolutional Network |
| CRNN | Convolutional-Recurrent Neural Network |
| WSE-mMPN | Whole Sample Enrichment - Miniature Most Probable Number |
| TTI | Time-Temperature Indicator |
| RFID | Radio Frequency Identification |
| R&D | Research and Development |
| EPOK | Centre for Organic Food and Farming (SLU) |
| SIANI | Swedish International Agricultural Network Initiative |
| SIK | Swedish Institute for Food and Biotechnology |
| SLU | Swedish University of Agricultural Sciences |
| RISE | Research Institutes of Sweden |

| Abbreviation | Meaning |
|---|---|
| BTH | Blekinge Tekniska Högskola |
| DMCii | Disaster Monitoring Constellation for International Imaging |
| GPU | Graphics Processing Unit |
| K-NN | K-Nearest Neighbor |
| BPNN | Back-Propagation Neural Network |
| R-CNN | Region-Based Convolutional Neural Network |
| MCRP | Markov-Chain Extended with Rainfall Prediction |
| RBFNN | Radial-Basis Function Neural Network |
| E-H-MM | Ensemble Learning-Centered Daily Mean Air Temperature-Member Mean |
| GloSea5GC2 | Global Seasonal Forecasting System Version 5 |
| RELM | Regularized Extreme Learning Machine |

# 1 Introduction

*This section provides context for the study, outlining the problem it addresses. It then presents the study's aims and research questions, followed by the scope and delimitations, which provides the background of this study.*

Throughout human history, our relationship with food has been transformative, shaping not just what we eat but entire civilizations. The transition from hunter-gatherers to cultivators marked a pivotal juncture, with the ability to grow food catalyzing the rise of great societies. Food, in its rich diversity of flavors and traditions, has long been a catalyst for social, cultural, and technological changes. Beyond mere sustenance, it molds our identities, traditions, and the fabric of communities built around its cultivation and preparation. Today, a new force is emerging that holds the potential to profoundly impact our food systems once again - artificial intelligence. AI presents both boundless opportunities and complex challenges as we grapple with ensuring future food security.

This research investigates the opportunities and obstacles of leveraging AI technologies within Sweden's food system through the lens of socio-technical system theory. With a looming global food crisis driven by population growth, climate change, and constrained resources, AI-powered solutions could help optimize production, minimize waste, and ensure adequate nutrition for all. Yet, the successful integration of AI requires a multi-faceted approach that considers its potential benefits and drawbacks, alongside careful consideration of its broader implications for society.

## 1.1 Background

The worldwide food system, essential for supporting billions of people, is facing many challenges. Climate change disrupts harvests, resources dwindle, and market volatility creates uncertainty (FAO, 2023). Addressing these interconnected threats requires transformative solutions, not just incremental improvements. Artificial intelligence (AI), after decades of evolution, is expected to be that catalyst. Its ability to analyze vast amounts of data, detect hidden patterns, and automate complex tasks can reshape the food system (Sadiku, Fagbohungbe and Musa, 2020). AI offers innovative solutions for a more resilient and sustainable food system (Esmaeily and Razavi, 2024). The food industry is the third largest sector of the Swedish economy, generating 200 billion SEK in yearly revenue and providing employment to more than 300,000 (Jordbruksverket, 2023). Furthermore, Sweden's strong digital infrastructure and excellence in AI research create a fertile environment for transformative technologies to take root (Government Offices of Sweden, 2018). Yet, the Swedish food system, like many around the world, faces a complex landscape. This sector's comparatively lower level of digitization could initially slow AI integration (Sweden Food Arena, 2021). Furthermore, ongoing structural changes within the market highlight the need to ensure that the benefits of AI reach stakeholders of all scales and production models (Sandqvist and Bengtsson, 2022).

It is anticipated that AI will have a significant impact on almost every facet of business, including supply chain management, production, marketing, decision-making, and logistics (Makarius et al., 2020; Murray Alex, Rhymer and Sirmon, 2021; van den Broek, Sergeeva and Huysman, 2021; Holmström, 2022; Mishra, Ewing and Cooper, 2022). Recently businesses generally perceive implementing AI technologies as advantageous and even necessary.

Numerous scholars have argued that one of the biggest drivers of change for businesses currently is the widespread adoption of AI across almost all company operations and sectors(Ransbotham et al., 2017; Acemoglu and Restrepo, 2020; Obschonka and Audretsch, 2020; Murray Alex, Rhymer and Sirmon, 2021). However, AI adoption proves that it is more complicated than anticipated. Several studies indicate the substantial difficulties many firms faced when attempting to adopt AI solutions (Ransbotham et al., 2017; Browder et al., 2022). A central challenge lies in AI's unique capability to make autonomous decisions and continually adapt those decisions, distinguishing it from other advanced technologies (Murray Alex, Rhymer and Sirmon, 2021). By exploring AI's accomplishments, challenges, and transformative potential within the Swedish food system with a focus on primary production, this research seeks insights that extend beyond the farm.

## 1.2 Problematization

As discussed in the background section, global food systems face a variety of challenges. These interconnected issues necessitate innovative solutions, driving the rapid development of technologies like AI. Given its transformative potential, the Sweden stands to benefit from AI integration (Galaz, Wilson and Janson, 2021). However, as a complex socio-technical system, successful implementation isn't merely a technical upgrade. Adopting AI within the Swedish food system demands a broader socio-technical lens to address the interconnected challenges and potential social disruptions. AI integration is likely to redefine tasks, roles, and the skills required across the [food] system (Lezoche et al., 2020). Understanding these shifts, their impact on stakeholders, and adapting strategies is crucial for a just and equitable transition.

Despite its potential benefits, the Swedish food system faces specific challenges that make AI adoption particularly complex. These include the impacts of climate change on Swedish agriculture, threatening traditional practices and creating the need for data-driven adaptation strategies that AI could provide (Sweden Food Arena, 2021; Jordbruksverket, 2023). Additionally, the sector's reliance on global trade networks and sensitivity to market volatility could be potentially mitigated with AI-powered market analysis and supply chain optimization tools. Also, the fact that primary production is spread out and has different levels of digital readiness at different scales could make it harder for AI to be used evenly and make existing inequality worse. An aging workforce within the agricultural sector may necessitate upskilling and new strategies to ensure AI enhances, rather than replaces, existing expertise (Jordbruksverket, 2023). Additionally, Sweden grapples with broader challenges related to AI. AI's reliance on data and its ability for autonomous decision-making raise concerns about privacy, algorithm transparency, and the potential to worsen existing power imbalances within the food system (Johan, Carlberg and Jerhamre, 2021). Sweden's emphasis on ethical practices indicates that navigating these issues is critical. Trends like lab-grown meat further highlight how AI becomes embedded in complex food production systems (Smith et al., 2022). This shows that AI isn't just about farm-level optimization but intersects with consumer behavior and the evolving definition of "food".

Existing research on AI in food systems often focuses on the technical aspects of specific applications, such as precision agriculture or supply chain optimization (Lezoche et al., 2020). While valuable, these studies overlook the factors that will influence AI's adoption and shape its broader implications within the distinct Swedish context. This study seeks to address this gap through a focused investigation of AI integration within the Swedish food system.

In the field of precision agriculture, for instance, studies by Xie et al., (2017), Partel, Charan Kakarla and Ampatzidis, (2019), and Sharma, A. et al., (2021) have shown AI's potential to optimize crop yields and reduce resource usage. However, these studies primarily emphasize technological capabilities without fully addressing the practical challenges of implementation within diverse agricultural systems. Similarly, in the domain of food supply chain management, research by Zhang, G., Li and Peng, (2020) and Sharma, P. et al., (2022) emphasizes AI's role in improving logistics efficiency and reducing food waste. Yet, their work, like many others, does not sufficiently explore the regulatory barriers that may limit widespread adoption of AI technologies. This gap in the literature is particularly notable when considering the unique characteristics of national food systems, such as Sweden's, which are shaped by distinct cultural preferences, policy frameworks, and market structures.

Furthermore, existing research often fails to adequately address the ethical implications and potential societal impacts of AI integration in food systems. While studies like Mark, (2019) touch upon issues of data privacy and inequality in agricultural AI applications, there remains a shortage of broad analyses that consider these issues within specific national contexts. The Swedish food system, with its strong emphasis on sustainability, transparency, and ethical production practices, presents a unique case study for examining these broader implications. Also, much of the current literature on AI in food systems adopts a fragmented approach, focusing on individual segments of the value chain rather than considering the system holistically. For example, research by Rai et al., (2005) and Koc, Heinemann and Ziegler, (2007) examines AI applications in food processing, while the work by Yousef AlShamsi, (2022) explores AI-driven consumer behavior analysis in food retail. However, there is a lack of integrative studies that consider how AI technologies might reshape interactions and power dynamics across the entire food system.

The integration of AI across diverse sectors such as healthcare, finance, automotive, and retail indicates its progression into the early majority phase of adoption (Bughin et al., 2017). This phase is defined by a broader acceptance and implementation of AI technologies, reflecting their transition from novel innovations to essential business tools across industries (Jöhnk, Weißert and Wyrtki, 2021). The integration of AI technologies varies significantly, showing a variety of maturity and readiness across industries (Jöhnk, Weißert and Wyrtki, 2021). From healthcare to finance and technology to manufacturing, each sector experiences unique transformations driven by AI. This variance in AI adoption across sectors indicates the need for research that examines the specific factors influencing AI adoption within particular industries, such as the Swedish food system. This study aims to address this gap by investigating the unique challenges and opportunities associated with AI adoption in the Swedish food system, contributing to a deeper understanding of how different sectors within the food system are adapting to and integrating AI technologies.

Appendix A summarizes the essence of AI's market adoption, providing a sector-wise breakdown of its impact that indicates different levels of AI's adoption and maturity, that not only indicates the diverse applications of AI but also showcases the strategic requirements that different industries are focusing on to leverage AI for competitive advantage. The State of Global AI Adoption in 2023 report by InData Labs offers additional insight, emphasizing the broad application of AI technologies across industries. This includes advancements in natural language processing, predictive analytics, computer vision, and various other AI-powered solutions, which are increasingly being adopted in sectors like healthcare, finance, retail, and logistics (InData Labs, 2023). The widespread adoption of AI tools and services across these sectors further emphasizes the transition of AI, where its applications are not only more diverse but also more deeply integrated into the operational and strategic fabric of businesses.

The increasing adoption of AI across various sectors is a clear indicator of its progression. This trend is supported by the growing number of enterprises and industries implementing AI solutions to drive innovation, enhance efficiency, and create new value streams (Lu, 2019). As AI technologies continue to mature, their transformative potential across different sectors is likely to become even more noticeable, emphasizing the critical role of AI in shaping future industry landscapes (Dwivedi et al., 2021). However, the adoption of AI in the food system lags behind other sectors, indicating the need for research that investigates the specific barriers and opportunities for AI integration in this context. This study aims to contribute to an understanding of how this sector can leverage AI technologies to enhance productivity, sustainability, and resilience.

A wide range of obstacles and challenges are presented by the advancement and integration of AI across multiple industries, demanding careful thought and action (Nishant, Kennedy and Corbett, 2020). These challenges include ethical concerns, data privacy issues, and the imperative need for comprehensive regulatory frameworks (Dwivedi et al., 2021). Overcoming these barriers is crucial for AI adoption, ensuring its ethical and responsible use across industries (Dwivedi et al., 2021). Ethical concerns surrounding AI range from algorithmic bias and discrimination to autonomous decision-making processes. As AI systems operate in critical domains like healthcare, finance, etc., the risk of reinforcing existing biases or creating new ones. Ethical AI development requires methodologies that ensure fairness, accountability, and transparency in AI systems (Whittlestone et al., 2019). The Swedish food system, with its emphasis on transparency and sustainability, faces unique ethical challenges in AI adoption.

The explosion of data generated and processed by AI systems raises concerns (Schrader & Ghosh, 2018). AI's ability to analyze and infer insights from vast datasets can lead to unintended privacy breaches and misuse of personal information. The fast-paced evolution of AI technology outstrips the current regulatory landscape, emphasizes the urgent need for updated and comprehensive regulatory frameworks. Appropriate regulation needs to maintain a balance between fostering innovation and mitigating potential harm to ensure that AI technologies are developed and utilized in ways that align with societal values and standards (Čerka et al., 2015). Appendix B summarized a classification of the challenges related to AI, detailing their descriptions, showing that the rapid evolution of AI technologies in the food system necessitates the development of agile and adaptable regulatory frameworks that can keep pace with these advancements while ensuring ethical and responsible AI use.

## 1.3 Aim and research questions

This research explores AI within primary production, recognizing its connection with the broader Swedish food value chain as presented in Figure 1 (Eriksson, Pano and Ghosh, 2016). From crop cultivation and livestock rearing to downstream sectors like processing, trade, and consumption, this research considers the complex network within which AI exists. The focus on primary production is justified by its foundational role within the Swedish food system. As the starting point, primary production influences subsequent stages of the food system. Additionally, many of the challenges faced throughout the food system originate within primary production. Therefore, transforming primary production is key to transforming the entire food system. Also, primary production offers a huge opportunity to leverage AI. By optimizing resource use, improving yields, and enhancing decision-making, AI can unlock significant gains in efficiency and resilience within primary production.

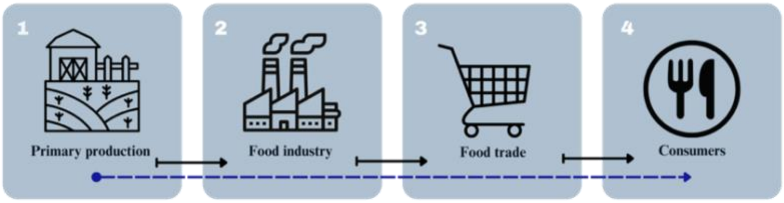



*Figure 1 Swedish Food Chain Sectors (Eriksson et al., 2016).*

Crucially, this research approaches AI not as a merely technological concept but as a multifaceted innovation embedded within a complex system. Its successful implementation depends on understanding multiple factors, which include the technical aspects of data collection and algorithm design as well as the broader socio-technical landscape. Regulatory frameworks, stakeholder attitudes, ethical considerations surrounding data, and algorithm transparency all play crucial roles in determining how AI transforms the food system and society. To achieve harmony within this complex system, this research emphasizes the vital flow of data across the entire food system. AI's potential for optimizing processes and informing decisions relies on seamless data integration along every stage (Bécue, Praça and Gama, 2021). The holistic benefits of AI can be unlocked, and bottlenecks can be identified by understanding the information flows among farmers, processors, distributors, and consumers.

The urgency of this research stems from the dynamic global context within which the Swedish food system operates. AI, within a balanced, multi-dimensional approach, holds the potential to drive the needed innovations. This research strives for more than just theoretical insight; it seeks to bridge the gap between abstract potential and on-the-ground realities, exploring the complexities of data sharing, and highlighting the human element vital to technological acceptance. The findings hold value for academics seeking a deeper understanding of AI in food systems and equally for stakeholders striving to shape a Swedish food system that is both technologically advanced and rooted in sustainability and societal well-being.

This research investigates the role of AI within the Swedish food system, with a specific focus on its potential to address challenges and unlock opportunities within the vital sector of primary production. While the Swedish context is central, the initial phase is exploring relevant AI applications and research insights from food systems around the globe, providing a foundation for exploring the unique dynamics of AI within Sweden. The overarching purpose is to understand how AI can be properly deployed in the Swedish food system, aiming to enhance productivity, profitability sustainability, and resilience in each sector. This includes looking at the current state of AI adoption, focusing on specific use cases in Swedish food system, looking at the factors that affect Swedish AI dynamics (such as policies, stakeholder views, and ethical concerns), looking into the possibility of harmonized AI integration, and finally giving suggestions that can be put into action. The significance of this research lies in its contribution to both practical decision-making within the Swedish food system and a theoretical understanding of AI's transformative potential.

**Research Questions:**

*1. How are AI technologies applied in global food systems and what are the opportunities and challenges for leveraging these technologies within Sweden's food system, with a focus on primary production?*

*2. Through a socio-technical system lens, what key factors need to be considered to develop an integrated strategy for harmonizing AI adoption throughout Sweden's food system?*

To address the research questions, this study employed a qualitative research methodology, combining insights from both the literature review and the interviews. The literature review provided a detailed overview of AI applications in global food systems, including potential opportunities and challenges relevant to the Swedish context. This global perspective served as a foundation for understanding the broader landscape of AI in agriculture and food production. The interviews, conducted with a diverse group of stakeholders in the Swedish food system, offered in-depth, context-specific insights into the practical realities and nuances of AI adoption. These qualitative data deepened the understanding of the challenges and opportunities identified in the literature review, providing a grounded perspective on the Swedish context. To analyze the data and address the research questions, this study utilized the socio-technical systems theory (STST) framework. By applying the STST lens to both the literature review and interview data, the study aimed to answer research questions.

## 1.4 Scope and delimitations

It is crucial to define the boundaries of a research project, especially when studying intricate socio-technical systems with lots of interdependent components. In the context of this study, which explores the role of AI within the Swedish food system, the authors have carefully delineated the scope to concentrate on the primary production sector, specifically agriculture. This decision was justified in the previous part since the actions and decisions of actors involved in this sector have far-reaching implications for the entire food value chain. While the primary production sector serves as the core focus, the authors recognize the interconnected nature of the Swedish food system as shown in Figure 2.

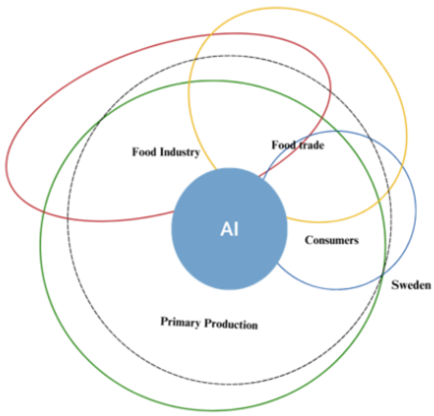



*Figure 2 Scope and Focus of the research (Own elaboration).*

However, these linked sectors are considered in relation to their connections and dynamics with the primary production sector, rather than being the primary focus of the study. This approach allows for a manageable and well-defined scope while maintaining a broader perspective on the potential impacts and interdependencies across the food system landscape. Simultaneously, the acknowledgment of interconnections with other sectors ensures a broad understanding of the potential ramifications and synergies across the Swedish food system.

# 2 Literature review

*The section presents the results of the literature review. The literature review provides an overview of AI and its applications in global food systems, as well as insights into the specific context of the Swedish food system.*

## 2.1 Artificial Intelligence

Artificial Intelligence (AI) is a branch of computer science that aims to provide machines with intelligent behavior (Sarker, 2022). AI covers a range of technologies that try to mimic human abilities, such as learning, reasoning, problem-solving, seeing, and talking (Deng, 2018; Dellermann et al., 2019). The types of AI are broadly categorized into machine learning (ML), neural networks, and robotics (Górriz et al., 2020). Machine learning, a subset of AI, enables systems to learn from data, identify patterns, and make decisions with minimal human intervention (Helm et al., 2020) . Neural networks, inspired by the human brain's architecture, facilitate deep learning, a technique that allows machines to process inputs and perform tasks such as speech and image recognition with increasing accuracy (Lecun, Bengio and Hinton, 2015). Robotics integrates AI to create machines capable of performing tasks autonomously, ranging from industrial manufacturing to complex surgery (Javaid et al., 2021). An artificial intelligence system consists of the following components at its basic level as shown in Figure 3: gathering and organizing data for training and validation, supplying the technical infrastructure required to conduct the training and monitor the AI systems that are deployed, and hosting and managing a collection of AI models that are utilized by the systems (Wang, Y. et al., 2024).

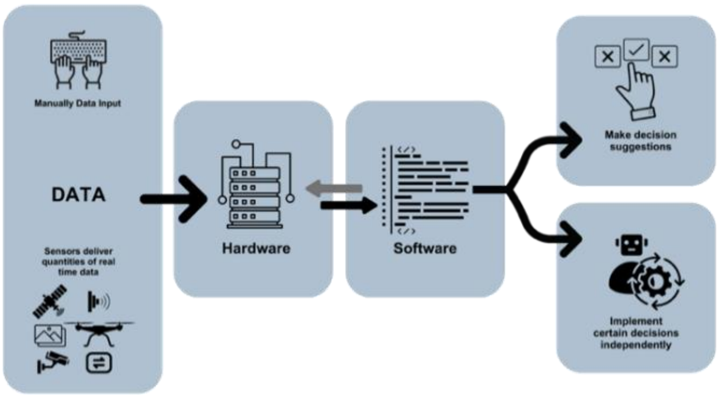



*Figure 3. Basic Components of AI system (Own elaboration).*

### 2.1.1 AI development stage and timeline

The evolution of AI technology has been characterized by rapid advancements and transformative impacts across various industries (Duan, Edwards and Dwivedi, 2019). Initially conceptualized in the mid-20th century, AI has transitioned from simple rule-based algorithms to sophisticated systems capable of learning and adapting to new information without explicit programming as illustrated in Figure 4 (Varan Nath et al., 2020).

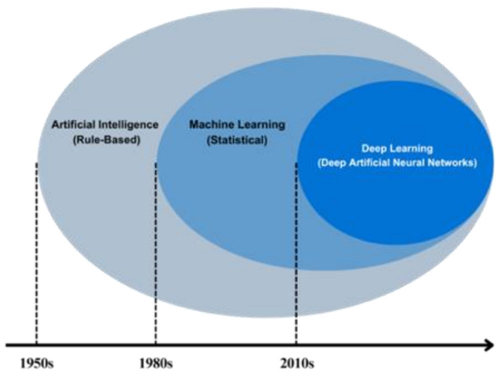



*Figure 4. Various AI-related fields and the chronological order they became popular (Varan Nath et al., 2020).*

The evolution of AI is driven by concepts such as computational intelligence, cognitive modeling, and algorithmic efficiency, which have expanded the capabilities of AI systems (Lu, 2019). As shown in Appendix C, Initially, AI research was heavily focused on developing basic algorithms that could mimic aspects of human cognition, such as problem-solving and decision-making (Pomerol, 1997). An early goal of artificial intelligence, for example, was to figure out how machines could carry out tasks that required intelligence if done by humans. This period was characterized by the development of algorithms for search problems, logical reasoning, and simple forms of pattern recognition. As computational power increased and data became more abundant, AI research advanced into more complex areas, including Natural Language Processing (NLP), Computer Vision, and Autonomous Systems (Sarker, 2022). These advancements represent a significant shift in AI's capabilities, moving from theoretical explorations to practical applications with tangible benefits.

### 2.1.2 Key AI technologies

Key AI technologies like real-time decision support, computer vision, natural language processing, big data analytics, robotics, and wireless sensor networks are depicted as integrated components. This convergence of advanced technologies enables the AI system to possess a diverse set of skills and functionalities that closely resemble the inherent abilities of humans as illustrated in Figure 5.

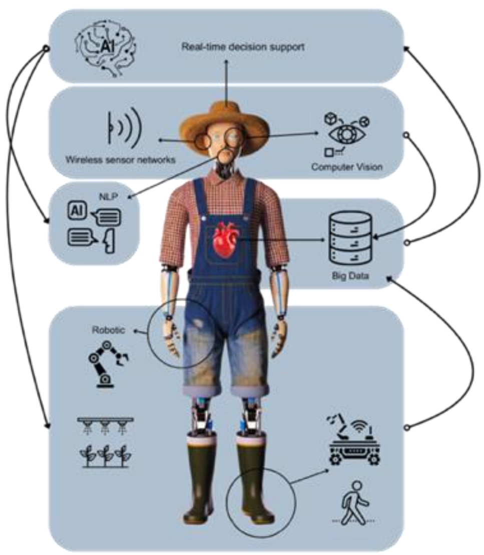



*Figure 5. AI capabilities (Own elaboration).*

**Natural Language Processing (NLP)**: Advancements in NLP have enabled these technologies to comprehend, interpret, and produce human language with coherent meaning (Cambria & White, 2014) (Cambria and White, 2014). Applications of NLP range from chatbots and digital assistants to sophisticated tools for sentiment analysis, language translation, and content creation (Adamopoulou and Moussiades, 2020). This development of NLP indicates a deepening of AI's integration into systems where human-like interaction and understanding are crucial (Chandra, Shirish and Srivastava, 2022).

**Computer Vision:** Thanks to advances in AI, machines are now able to recognize, understand, and react to visual data from their environment (Leo et al., 2017). This technology allows for applications such as facial recognition systems, automated quality control in manufacturing, and autonomous vehicle navigation. The ability of AI to process and analyze visual data at or beyond human levels of accuracy represents a major milestone in AI's development.

**Autonomous Systems**: The development of autonomous systems, from drones to self-driving cars, showcases the application of AI in navigating complex, unstructured environments. These systems leverage AI to make decisions in real-time, responding to dynamic conditions with high levels of precision and autonomy (Tien, 2017). The progression towards fully autonomous systems highlights AI's growing capability in handling tasks that require comprehensive understanding and interaction with the physical world.

### 2.1.3 Complexity level of AI

Understanding the spectrum of AI types is crucial for appreciating both the potential and limitations of this transformative technology. AI systems can be classified into different types based on their complexity and potential. As shown in Figure 6, these include Weak AI (Narrow AI), Strong AI (Artificial General Intelligence) (Goertzel, 2014), and Artificial Superintelligence (ASI) (Goertzel, 2014; Brundage, 2015).

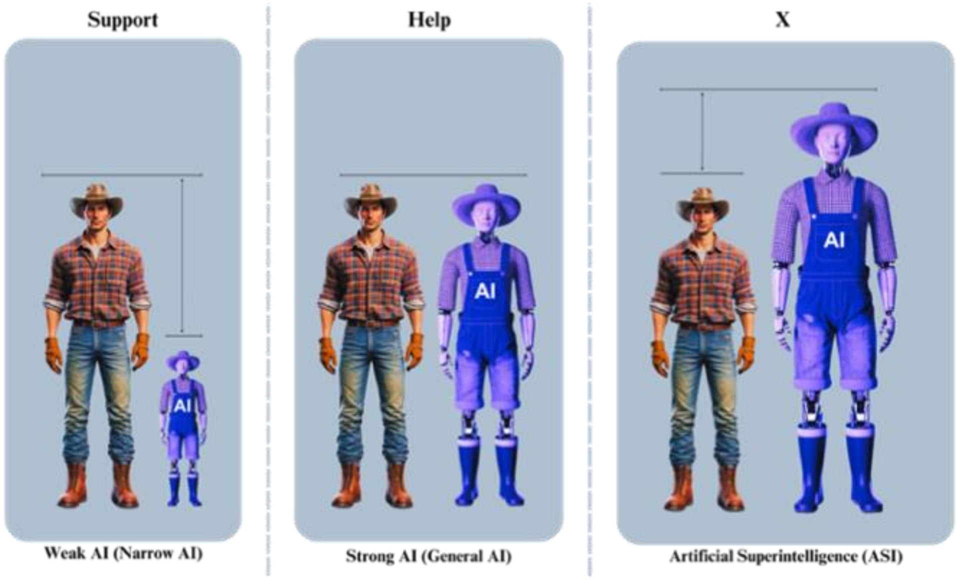



*Figure 6. Three Types of Increasing Complexity and Potential of AI (Own elaboration).*

Weak AI excels at specific tasks, while Strong AI remains theoretical, aiming to possess human-level cognitive abilities (Brundage, 2015; Mehryar Mohri, Afshin Rostamizadeh, 2018). Artificial Superintelligence (ASI) extends this concept further, hypothesizing an AI that would significantly surpass human intelligence in all areas (Brundage, 2015). Beyond these broad categories, other AI types exist. Reactive machines operate solely based on current inputs, while Limited Memory AI leverages historical data to improve decision-making (Hassani et al., 2020). Theory of Mind AI is a future aspiration, aiming to create systems that can understand the mental states and intentions of others (Wester et al., 2024). These varied classifications show the ongoing evolution of AI and the diverse problems it seeks to address.

### 2.1.4 AI's Role in Transforming Industries

The theory of disruptive innovation, which explains how simpler, less expensive products initially targeting overlooked segments can ultimately redefine industry standards, offers a valuable framework for understanding AI's development(Christensen et al., 2018). AI's evolution from a developing technological curiosity to a pivotal business tool across sectors like healthcare, finance, automotive, and retail shows its profound impact on market dynamics and competitive landscapes (Varan Nath et al., 2020). AI technologies, by automating complex tasks, enhancing data analytics, and enabling personalized interactions, are not merely improving existing processes but are laying the groundwork for entirely new business models and services (Sjödin et al., 2021). For instance, in healthcare, AI's capability to diagnose diseases with higher accuracy than human practitioners are not just improving diagnostic processes but is reshaping patient care paradigms (Jiang et al., 2017). Similarly, in the financial sector, AI-driven innovations are catalyzing a shift away from traditional bankimodels to more agile, customer-centric fintech solutions. Moreover, in retail, AI's application in personalizing customer experiences and streamlining supply chains indicates a shift from conventional retailing towards more integrated and responsive business operations (Grewal et al., 2020). The core of AI's disruptive influence is in its initial appeal to neglected or niche markets, a key component of Christensen's disruptive innovation. AI's development from serving specific, often overlooked needs to broader adoption shows its growing feasibility and declining cost, challenging traditional players across various industries (Dwivedi et al., 2021). This pattern is shown by the rise of AI applications that, while initially limited in scope, have gradually expanded their reach, compelling traditional enterprises to innovate or face obsolescence. The strategic response of established companies to AI's rise further reflects Christensen's insights into how organizations navigate disruptive innovations. Firms that recognize AI's potential and adapt their strategies accordingly are more likely to leverage this technology to redefine their competitive edge and market position (Borges et al., 2021). This requires not only investing in AI technology but also rethinking business models, operational processes, and customer engagement strategies to utilize AI's full potential (Varan Nath et al., 2020).

## 2.2 AI in the Agriculture and Food Industry

### 2.2.1 AI applications in agriculture

AI has become a transformative force in agriculture, providing innovative solutions to improve efficiency, sustainability, and productivity. This section of the literature review explores the implementation of AI and related technologies in agriculture. Table 1 offers an overview of the various AI applications in this field. Detailed discussions of these applications, methodologies, and results are provided following the table.

| Application | AI In problem-solving | References |
|---|---|---|
| Soil management and prediction | With the help of sensors, AI can help predict the soil's future, elements, and moisture and classify soil. | (Rahman et al., 2018) (Yang et al., 2019) (Reda et al., 2019) (ACAR et al., 2019) |
| Weather Prediction | A precise weather prediction powered by AI, like air temperature and rainfall prediction, can help achieve better crop cultivation and water resource management. | (Sharma, A. et al., 2021) (Shin, J. Y., Kim and Ha, 2020) (Cramer et al., 2017) |
| Yield Prediction | AI models and algorithms can use physical and chemical metrics with crop growth and health data to predict the yield production of different crops. | (Liakos et al., 2018) (Pantazi et al., 2016) (Sun et al., 2019) |
| Precise and smart irrigation | AI can develop precise and on-demand irrigation systems, which can ensure enough water supply for the growth of crops while saving water resources. | (Ayoub Shaikh, Rasool and Rasheed Lone, 2022)(Xie et al., 2017) (Seyedzadeh et al., 2020) |
| Pest and disease detection | AI can conduct early detection and intervention on pest and disease problems of crops in non-destructive methods. | (Unal, 2020) (Chung et al., 2016) (Shen et al., 2018) |
| Weed detection | AI can detect weeds in complex environments where plants, weeds, soil, and other matters coexist, and can make the herbicide spraying more precise. | (Unal, 2020) (Partel, Charan Kakarla and Ampatzidis, 2019) (Abouzahir, Sadik and Sabir, 2018) |
| Crop recognition and classification | AI can use images of different crops to find different patterns and distinguish crop species automatically. | (Hu et al., 2017) (Grinblat et al., 2016) |
| Crop quality | AI can use data from crops as input variables to classify the geographic origin and quality level of crops, which can reduce the involvement of experts. | (Papageorgiou et al., 2018) (Maione et al., 2016) |
| Livestock management | AI can improve animal welfare and livestock production in precision livestock farming, such as the health situation of animals and exception monitoring in production. | (Benos et al., 2021) (Gorczyca et al., 2018) (Morales et al., 2016) |

*Table 1. Overview of AI Applications Across Agriculture Sectors (Own elaboration).*

##### 2.2.1.1 Soli Management and Prediction

Machine learning can be applied to the management and prediction of soil (Benos et al., 2021). Because of the degradation, desensitization, and imbalance of nutrition of soil, soil management becomes an important issue (Chasek et al., 2015). Predicting the properties of soil is the first step of crop selection and the future selection of seeds and fertilizer (Sharma, A. et al., 2021). Some sensors can gauge the soil texture, organic content, moisture ratio, sodium content, nitrogen content, and other indicators (Adamchuk et al., 2004) Based on the features and evaluation of soil as well as different elements in the soil, farmers can decide which crop is suitable for a certain area, which can decrease the cost of fertilizers and the reliance on soil experts while improving the soil health and profit (Sharma, A. et al., 2021; Ayoub Shaikh, Rasool and Rasheed Lone, 2022).

Rahman, Chandra Mitra and Mohidul Islam, (2018) made a system structure including two phases (training and testing) and two datasets (soil and crop), where three kinds of machine learning algorithms were applied. The result showed that bagged tree and weighted K-NN[1] have good performance in accuracy, but in soil categorization, Gaussian SVM[2] have an accuracy of 94.95% which is the highest (Rahman, Chandra Mitra and Mohidul Islam, 2018). Yang et al., (2019) evaluated the prediction accuracy of soil organic matter (SOM) and pH levels by the application of visible-near infrared (vis-NIR) spectroscopy with machine learning models. The Extreme Learning Machines (ELM) combined with reduced bands processed by

[1] K-NN: k-Nearest Neighbor, a machine learning algorithm.

[2] Support Vector Machines (SVMs) are a type of supervised learning algorithm that can be used for classification or regression tasks.

a genetic algorithm is the best method, which suggests that vis-NIR spectroscopy together with useful machine learning models can provide a fast, non-destructive, and precise method to predict soil features (Yang et al., 2019).

Reda et al., (2019) estimated the content of soil organic carbon (SOC) and total nitrogen (TN) in agricultural fields by applying near-infrared (NIR) spectroscopy combined with machine learning model. The performance of a new ensemble learning modeling approach is the best compared with all other models, with the $R^2$ values of 0.94 and 0.96 for TN and SOC as well as the RMSE[3] values of 0.57 kg/g and 1.92 kg/g (Reda et al., 2019). Even the moisture prediction of vegetated fields can also be accurate by using polarimetric features from Synthetic Aperture Radar (Radarsat-2) and machine learning technologies [Extreme Learning Machine based Regression (ELM-R)] together, RMSE can be 2.19% (ACAR, OZERDEM and USTUNDAG, 2019).

#### *2.2.1.2 Weather Prediction*

Many farmers cultivate crops relying on monsoon, the weather prediction from different sectors could be important in this case (Ayoub Shaikh, Rasool and Rasheed Lone, 2022). For example, rainfall prediction could be vital in managing water resources and predicting flood disaster risk (Sharma, A. et al., 2021). Shin, J. Y., Kim and Ha, (2020) aimed to develop a hybrid model able to forecast daily mean air temperatures to improve agricultural decision-making. A global climate model (GloSea5GC2) and a machine learning approach (RELM: regularized extreme learning machine) were combined to develop 20 hybrid model structures, and the result shows that the hybrid models can provide seasonal forecasts with higher performance compared to the climatology model, E-H-MM[4] framework having the best performance in the prediction of seasonal or long-range mean air temperatures (Shin, J. Y., Kim and Ha, 2020).

The prediction of rainfall is quite difficult, radial-basis function neural network (RBFNN) could be considered as a solution in the future as it has a better statistical performance compared to Markov-chain extended with rainfall prediction (MCRP) based on the data from 42 cities in America and Europe (Cramer et al., 2017).

#### *2.2.1.3 Yield Prediction*

Yield prediction is one of the most important topics in precision farming because yield estimation, coordination between demand and supply, and crop management all rely on a precise prediction (Liakos et al., 2018). Pantazi et al., (2016) gauged the soil's physical and chemical parameters (like total nitrogen, organic carbon, moisture content, and so on) by soil sensors (vis-NIR). Then they combined them with calculated crop growth and health parameters (normalized difference vegetation index) derived from satellite (UK-DMC-2)[5] imagery. The data was processed by three self-organizing map (SOM) models, the result shows that Supervised Kohonen Networks (SKN) has the best performance at predicting the low category of wheat yield with a categorization accuracy of more than 90%, which means high-

---

[3] RMSE: root mean square error.

[4] E-H-MM: Ensemble Learning-Centered daily mean air temperature-Member Mean.

[5] UK-DMC-2 Satellite: This satellite is part of the Disaster Monitoring Constellation for International Imagining (DMCii).

resolution soil data with satellite images can improve the accuracy of predicting crop yield (Pantazi et al., 2016).

Sun et al., (2019) predicted the yield of soybeans by using a combination of deep learning models. The result shows that compared with individual Convolutional Neural Network (CNN) or Long Short-Term Memory (LSTM) models, a combined, GEE-based CNN-LSTM model which was trained by different data (weather data, MODIS[6] Land Surface Temperature data, and MODIS Surface Reflectance data) has the best performance in prediction accuracy, with the $R^2$ values of 0.78&0.74 for end-of-season prediction and early prediction, this model also shows a huge potential in improving the prediction accuracy for other crops in the future (Sun et al., 2019).

#### 2.2.1.4 Precise and Smart Irrigation

Because of the shortage of water resources all over the world, efficient irrigation and water management have become a special area in the agriculture industry, especially for those low-rainfall areas (Unal, 2020; Ayoub Shaikh, Rasool and Rasheed Lone, 2022). The productivity of fields requires enough irrigation while 70% of the global freshwater is used for irrigation, smart irrigation based on machine learning can keep a balance between cultivation and water use by helping farmers achieve optimal irrigation (Ayoub Shaikh, Rasool and Rasheed Lone, 2022).

Xie et al., (2017) proposed an on-demand irrigation scheduling system, considering both numerical weather prediction (NWP) and the fluctuation of electricity price, which means the system can minimize water use (like avoiding useless irrigation just before a rain) also can cache energy at low-peak price if irrigation needs more than solar energy. The simulation result shows that compared with soil moisture-based irrigation models, the hybrid system can save 7.97% of water and energy use while reducing the amortized cost of irrigation by 25.34% (Xie et al., 2017). Seyedzadeh et al., (2020) made a drip-irrigation physical model to estimate the emitter discharge and improve the drip irrigation system. The emitter outflow discharge was simulated by using five different AI and machine learning models, and the least square support vector machine (LS-SVM) has the lowest error, that LS-SVM model with the Radial Basis Function （RBF） kernel can improve the performance regarding the parameters of mean absolute error (MAE) and scatter index (SI) by 54% and 58% respectively compared to linear kernel (Seyedzadeh et al., 2020).

#### 2.2.1.5 Pest and Disease Detection

One of the most important issues in agriculture is pest and disease control for crops, but the most common solution regarding this issue is using chemicals in the whole agricultural area indiscriminately, which is effective but will cause huge financial costs and environmental problems (Liakos et al., 2018). Monitoring the situation of crops as well as early detection and intervention can prevent the spread of disease and further costs (Unal, 2020). Using AI-based smart systems during the cultivation period can not only decrease the spread of pests and diseases in fields and economic impacts but also minimize the negative impact on the environment caused by traditional agriculture (Sharma, A. et al., 2021).

Chung et al., (2016) used machine learning and computer vision to detect Bakanae disease in rice seedlings non-destructively. The researchers inoculated the pathogen “Fusarium fujikuroi”

[6] Moderate Resolution Imaging Spectroradiometer.

into the seeds and then cultivated them for three weeks. Two flatbed scanners were used to get seedling images. Support vector machine (SVM) classifiers were built to detect whether seedlings were infected or not, with the help of a genetic algorithm to choose significant traits and optimal parameters for the model. The result shows that the detection accuracy is 87.9%.

Machine learning and deep learning can also be used in detecting stored-grain insects mixed with fines and other foreign materials (Shen et al., 2018). A database of insect images was set, and then, an object detection algorithm based on Faster R-CNN[7] and a deep neural network was developed to detect small insects with improved accuracy. The result shows that the mean average precision of this method can be 88 (Shen et al., 2018).

#### *2.2.1.6 Weed Detection*

Weeds have a relatively long survival time and high seed productivity, they can grow very fast, invade the crop field, and then occupy the nutrition and resources of crops (Sharma, A. et al., 2021) Another problem is that it is difficult to detect and distinguish weeds from crops, which makes weeds a huge threat to agricultural production (Liakos et al., 2018). Herbicides are the most common solution, but they also have some defects, including cost, effectiveness, drug resistance, and pollution (Ayoub Shaikh, Rasool and Rasheed Lone, 2022). The application of smartweed detection can make the use of herbicides more precise (Unal, 2020).

Partel, Charan Kakarla and Ampatzidis, (2019) introduced and assessed a low-cost intelligent system (overall cost less than 1500 USD) aimed at precise weed management, which utilizes deep learning to recognize target and non-target plants and spray herbicides on only target plants. A smart sprayer prototype was built, and convolutional neural networks (CNN) were trained to detect objects, a software can analyze images and command hardware, and the hardware will scan the field by cameras and implement spray work. The result shows that the prototype with NVIDIA GTX 1070 Ti (GPU)[8] can reach an overall accuracy of 71% and recall of 78% in a complex circumstance and 91% in an artificial environment (Partel, Charan Kakarla and Ampatzidis, 2019).

Abouzahir, Sadik and Sabir, (2018) used a new feature vector (histograms of grayscale images) to detect weeds, the image database consisted of photos taken by drones. For classifying weed, soil, and soybean, the accuracy of the back-propagation neural network (BPNN) and support vector machine (SVM) are 96.601% and 95.078% respectively.

#### *2.2.1.7 Crop Recognition and Classification*

Because the future development direction of harvesting is automated harvesting robotics and robotics systems can't be applied to all kinds of crops, crop-specific systems need to be developed (Unal, 2020). Automatic recognition and classification of different crops and plants is drawing the attention of different scholars from several areas (Benos et al., 2021), as it can reduce the categorization time and the participation of human experts (Liakos et al., 2018).

Grinblat et al. (2016) used a deep convolutional neural network (CNN) to distinguish legume species by identifying the leaf vein patterns, CNN was used to replace the steps of vein measures and classification. The result shows that the model of CNN 5 layers reached overall

[7] R-CNN: Region-based Convolutional Neural Network.

[8] The NVIDIA GTX 1070 Ti is a graphics card (GPU) released in 2017 that was once a high-performance option for smooth gameplay and even virtual reality (VR) experiences.

accuracies of 93±0.3% and 96.9±0.2% respectively in the setup of "combined veins only" and "combined veins with 3 scales", which is higher than the previous model.

Hu et al., (2017) proposed a non-destructive method to distinguish deciduous-calyx pear and persistent-calyx pear. The features of peers were derived from a hyperspectral imaging system, then the optimal wavelengths, morphological characteristics, and spectral characteristics were extracted. Support vector machine (SVM) combined with successive projections algorithm (SPA) was the classification model in this experiment. The result shows that the model combining the degrees of circularity and the spectra of optimal wavelengths can achieve an accuracy of more than 95% in classification.

#### *2.2.1.8 Crop Quality*

The quality of crops is related to environmental conditions, crop species, and planting methods, also, high quality can bring more profits to the agriculture incumbents (Benos et al., 2021). A good assessment of crop quality can increase the price of products and reduce waste (Liakos et al., 2018).

According to the parameters of fruit mass, skin color, soluble solids content, and flesh firmness, a model of fuzzy inference system using knowledge from experts was developed to categorize the quality of apples into five levels (Papageorgiou et al., 2018). The result shows that the model has consistency rates of 83.54%, 92.73%, and 96.36% with the evaluation from experts based on three-year data (Papageorgiou et al., 2018).

Maione et al., (2016) found that Cd, Rb, Mg, and K are four essential elements in the prediction of classifying the geographic origin of rice. Three categorization models, including support vector machines, random forests, and neural networks, were tested, and all showed an accuracy of more than 90% in classification.

#### *2.2.1.9 Livestock Management*

The livestock sector is related to the production of cattle, pigs, sheep, chickens, and other animals that provide consumed meat, livestock management can optimize the production and maximize the livestock's economic efficiency by referring to different parameters of cattle (Sharma, A. et al., 2021). In traditional livestock farming, the experience of incumbents is vital for production, but in precision livestock farming, quantitative data is decisive (García et al., 2020). To utilize a mass of data, machine learning becomes an indispensable part of precision livestock farming as machine learning can develop different models to generate predictions and advice (Benos et al., 2021). There are two parts in livestock management: animal welfare and livestock production (Benos et al., 2021).

Without the help of biophysical data or linear empirical functions, Gorczyca et al., (2018) used four trained machine learning models to forecast the temperature of the rectum, skin surface, and hair-coat surface of pigs with the environmental variables being predictors. The result showed deep neural networks have the best performance in predicting rectal temperature with an error of 0.36%, gradient boosted machines are the best in predicting skin surface temperature with an error of 0.62%, while random forests can achieve an error of 1.35% in the hair-coat surface temperature prediction.

Support vector machines can be successfully used to warn of problems in egg production curves early (Morales et al., 2016). Based on the historical data of egg production, a one-day earlier alter could be achieved with an accuracy of 0.9854, which is significant at the farm level (Morales et al., 2016).

### 2.2.2 IoT and sensors in agriculture

Based on the above part regarding the AI application in agriculture, it is obvious that IoT and different sensors are also playing an important role here as they can provide some primitive data in the field. There are seven commonly used sensors in smart farming generalized in previous studies (Boursianis et al., 2022; Elbasi et al., 2023). The types of sensors and their functions are listed in Table 2.

| **Sensors applied in smart farming** | **Explanation & References** |
|---|---|
| Soil Water Content Sensor | Gauged value=amount of water in the soil/total amount of the soil<br>Meaning: the capability to hold an electrical charge; it ranges from 0 to the value of porosity at saturation of the soil (Lakhankar et al., 2009). |
| Volumetric Water Content Sensor | It can gauge the water content of the soil (Gaikwad et al., 2015). It also indicates the water tension and suction in the soil, the volume of water stored in the soil, and the suitable irrigation volume. |
| Soil Electrical Conductivity Sensor | It can gauge soil salinity which causes salinity stress to plants if the value is too high (Flores et al., 2016). |
| PH Sensor | It can measure the value of the soil, namely acidity and alkalinity. The desirable soil PH value is between 6.0 and 7.0. The PH value should be adjusted by applying alkaline or acidic fertilizers, which will increase the yield production (Goulding, 2016). |
| Weed Seeker Sensor | It can only detect weeds and spray herbicides precisely by its highly developed optical, electronic, and processing powers (an active light source with a chlorophyll-identifying selective spray sensor). Fewer chemicals and herbicides are used, and the cost is also decreased (Peruzzi et al., 2012). |
| Temperature Sensor | If the temperature is abnormal there will be an alarm. Temperature is important as different crops have different optimal temperatures for the activity of enzymes. Sensors can be made by p-n junction diode transistors (Futagawa et al., 2009). |
| Wind Speed Sensors | It can gauge the surface wind speed level as wind speed and direction are important in fields. |

*Table 2. Types of sensors and their functions in smart farming (Own elaboration).*

### 2.2.3 AI in the Food Industry

Nowadays, almost 30% of food is wasted every year, which is equal to 750 USD and means 28% of the agricultural land is wasted (Misra et al., 2022). The increase in global crop demand was predicted to be 100%-110% from 2005-2050 (Tilman et al., 2011). To overcome so many difficulties in the food industry, automation based on AI is a good solution (Kumar et al., 2021). AI can be helpful in food production, delivery, operational competence, quality, safety, waste reduction, and many other aspects (Kumar et al., 2021; Liu et al., 2023). AI in the food industry could achieve a CAGR[9] of 28.64% from 2018-2023 based on the prediction of Mordor Intelligence (Sahni, Srivastava and Khan, 2021). AI shows a huge potential in different aspects and applications in the food industry (Mavani et al., 2022).

[9] Compound Annual Growth Rate. It's a financial term used to represent the average annual growth rate of an investment over a period.

Table 3 summarizes the diverse applications of artificial intelligence (AI) within the food industry, indicating the key challenges addressed and the specific AI techniques employed. A more detailed discussion of these applications can be found in the text after the table.

| Application | Problem-solving | How AI is Used | References |
|---|---|---|---|
| Product Sorting | Labor-intensive, error-prone manual sorting; misclassification of similar-looking products | Image-based fruit classification using biogeography-based optimization (BBO) and feedforward neural networks (FNN) | (Zhang, Y. et al., 2016) |
| Production Packing | Maintaining food quality and traceability from production to consumption | Intelligent packing with sensors and indicators; AI-based date recognition using fully convolutional networks (FCN) and Convolutional–Recurrent Neural Networks (CRNN) | (Kollia, Stevenson and Kollias, 2021; Soltani Firouz, Mohi-Alden and Omid, 2021) |
| Food Processing & Manufacturing | Higher quality, higher accuracy, less uncertainty, waste reduction | Neural networks and genetic algorithm for task automation, optimization of processing parameters, prediction of product properties (e.g., viscosity) | (Rai et al., 2005; Koc, Heinemann and Ziegler, 2007; Mohammadi and Minaei, 2019) |
| Food Safety | Contamination by biological, chemical, and physical agents | Neural network-based prediction of pathogen elimination during cooking, detection of foreign objects, prediction of contaminant levels | (Oscar, 2017; Chen, Y. et al., 2018; Rong, Xie and Ying, 2019; Wang, X. et al., 2022) |
| Food Quality | Destructive and time-consuming quality assessment methods | Non-destructive assessment of sensory attributes and freshness using NIR spectroscopy, electronic noses, and machine learning models | (Mohareb et al., 2016; Curto et al., 2020; Hassoun et al., 2023) |
| Logistics & Distribution | Best logistic route of delivering fresh food, risks of the cold chain transportation | AI-based route optimization, risk prediction using support vector machine, integration with IoT and big data | (Zhang, G., Li and Peng, 2020; Katiyar, Khan and Kumar, 2021) |
| Food Waste | Global food waste problem | AI and IoT-based monitoring and optimization of food production and supply chains, redistribution of surplus food, recycling systems | (Onyeaka et al., 2023; P. Sharma et al., 2022) |
| Personalized Food Nutrition | Finding benefit ingredients, prediction of food effects on health, personalized dietary recommendations | Machine learning for identification of bioactive peptides, prediction of beneficial food combinations, personalized nutrition plans | (Zeevi et al., 2015; Lei et al., 2018; Sundaravadivel et al., 2018; Rein et al., 2019; Miyazawa et al., 2022) |

*Table 3. Applications of AI in the Food Industry (Own elaboration).*

### 2.2.3.1 Product Sorting

Production sorting in the food industry can consume lots of human resources as the volume of a production line is always immense. The sorting needs more attention to the details because it will influence how factories will process the products, which will eventually affect the purchase rate of customers (Sahni, Srivastava and Khan, 2021). For example, due to the similarities of images of fruit varieties, precise fruit classification can be a little difficult (Woo Chaw Seng and Mirisaee, 2009). Zhang, Y. et al., (2016) developed a new kind of fruit classification model, which is based on biogeography-based optimization (BBO) and feedforward neural network

(FNN). They only used digital cameras without any advanced sensors and then extracted the features of textures, colors, and shapes, then the result showed this model could achieve an overall accuracy of 89.11% in classifying 1653 fruit pictures into 18 categories (Zhang, Y. et al., 2016).

#### 2.2.3.2 Production Packing

The role of packing is important in any food product, intelligent packing is an innovation in this area, which can offer customers fresher and higher quality food (Sohail, Sun and Zhu, 2018). Intelligent packing can control the storage conditions from production to consumption by using different sensors and indicators, which can increase food product traceability, safety, and quality (Soltani Firouz, Mohi-Alden and Omid, 2021). There are already different indicators/sensors or techniques in intelligent packing, like time-temperature indicators (TTI), gas indicators, biological sensors, humidity sensors, barcoding techniques, and radio frequency identification systems (RFID) (Soltani Firouz, Mohi-Alden and Omid, 2021). AI can be used here to distinguish the date information on the packages of food products just by taking pictures of packages, once there is an error in the date of products or raw materials the production line would be shut down (Kollia, Stevenson and Kollias, 2021). An FCN (Fully Convolutional Networks) - CRNN (Convolutional–Recurrent Neural Networks) model applied here can achieve an accuracy of 95.44% in date recognition (Kollia, Stevenson and Kollias, 2021).

#### 2.2.3.3 Food Processing and Manufacturing

Food processing and manufacturing is a labor-intensive sector, AI can increase productivity and reduce waste with replacing some employees (Sahni, Srivastava and Khan, 2021). AI can make the current machines, environments, and intelligent robots smarter to replace the work of skilled workers with higher quality, higher accuracy, less uncertainty, less waste, more security, and faster speed (Mohammadi and Minaei, 2019). Based on the techniques from AI, many tasks in food factories can be implemented automatically, like surveillance, quality estimation, automatic adjustment, reasoning, and decision-making (Mohammadi and Minaei, 2019).

In the production of chocolate, the processing of milk powder can be modeled by neural networks and the processing parameters can be optimized by genetic algorithms (Koc, Heinemann and Ziegler, 2007). The result shows that to make milk powder have some desirable functional features, like maximum free fat content and maximum crystallinity, there are nearest operating parameters to the optimums optimized by AI models, and the differences between the predicted and real values are only 5.9% and 0.61% for free fat content and lactose crystallinity (Koc, Heinemann and Ziegler, 2007). Some features like the variance of viscosity caused by the change of physical conditions are important as the viscosity of raw materials, semi-products, and products influences some operations like pumping and filtration (Rai et al., 2005). A model based on neural networks can indicate the viscosity of juice by the values of temperatures and concentration, and the result showed the model is accurate and the values of $R^2$ and mean absolute error (MAE) are 0.96 and 3.78 mPa s respectively in five kinds of fruit juice (Rai et al., 2005).

#### 2.2.3.4 Food Safety

In food supply systems, food can be contaminated with different factors, like biological, chemical, and physical contaminants (van der Fels ‐ Klerx et al., 2017). The concept of food safety is to prevent foodborne diseases by maintaining the health and usability of food (Chen, T. C. and Yu, 2022). AI can be used to control specific food safety hazards in biological, chemical, and physical aspects (Wang, X. et al., 2022).

Oscar, (2017) developed a feedforward neural network model with the enumeration method of WSE-mMPN[10] to predict the elimination of the salmonella bacteria when cooking chicken at a temperature higher than 71°C.

Physical contaminants, like foreign objects, including natural and man-made ones in walnuts, can be detected by computer vision based on deep learning, and two models of convolutional neural networks were applied (Rong, Xie and Ying, 2019). The result of the experiment showed that the proposed models can achieve an accuracy of 95% in classifying foreign objects.

Chen, Y. et al., (2018) made an ANN model based on the back-propagation algorithm to predict the Benzo[a]pyrene (BaP) content in smoked meat products, the three input variables of the model are smoking time, temperature, and the ratio of fat and lean in meat. The result showed that the correlation coefficients of the proposed model are between 0.94 and 0.96 with a validation performance of 0.013, which indicates the model can precisely predict the BaP content.

#### *2.2.3.5 Food Quality*

Food quality mainly refers to sensory traits, shelf life, and freshness of food, which used to be assessed by some destructive and time-consuming methods (Hassoun et al., 2023). With the help of AI, some non-destructive technologies can be applied to test and ensure food quality (Liu et al., 2023). Curto et al., (2020) built a model using near-infrared spectroscopy (NIR) and Artificial Neural Network (ANN) to assess the sensory attributes of cheese. The ANN model was trained by spectral information as input and the sensory score provided by panelists as output. After being trained, it can predict the sensory attributes including taste, texture, aspect, smell, and other sensations. Mohareb et al., (2016) used data from electronic noses and then trained support vector machines to assess the freshness of beef fillets. Compared to the single SVM models, the ensemble-based SVM systems can increase the prediction accuracy of the freshness score from 72.7% to 84.1%, and the overall prediction performance of bacterial species count can also be increased from 76.5% to 85.0%.

#### *2.2.3.6 Logistics and Distribution*

One of the main challenges of the sustainable development goal of "responsible consumption and production" is reducing the food lost in supply chains (Hassoun et al., 2023). The food industry can use AI to closely monitor the supply chain, which will maximize profit and minimize delay (Sahni, Srivastava and Khan, 2021). AI can support IoT-based logistic systems and provide services for incumbents to build a fast way between farms to tables (Ramirez-Asis et al., 2022).

Katiyar, Khan and Kumar, (2021) used an artificial bee colony (ABC) algorithm to optimize the logistic routes of the delivery of fresh food with a fixed number of cars and a fixed cost, which can find the most efficient routes to ensure the food quality and freshness to customers as well as decrease delivery cost and environmental impact. Zhang, G., Li and Peng, (2020) developed a risk assessment and monitoring model by using a support vector machine based on previous data. The model could predict some risks during the cold chain transportation of fresh food with an average accuracy of 90.4% after being trained, including risks in technology,

[10] whole sample enrichment, miniature most-probable-number

biology, sustainability, environment, and emergency. The data used to feed to model can be derived from the use of IoT and big data.

#### *2.2.3.7 Food Waste*

Food waste is a global issue that needs to be solved by a complicated method, AI could be one desirable tool (Onyeaka et al., 2023). AI and IoT can be combined, building the "Internet of Food" which is applied in different sectors in the whole food supply chain (Sharma, P. et al., 2022). AI can reduce food waste by facilitating: (1) monitoring and optimizing food production and supply chains partly according to the prediction of weather, yield, stock level, expiration date, and customer demand; (2) redistributing surplus food to those who need it by connecting food banks, donators, and people in need; and (3) supporting recycling systems by changing food systems from the linear one to a circular one (Onyeaka et al., 2023).

#### *2.2.3.8 Personalized Food Nutrition*

AI can be applied in food nutrition, diet can cause some chronic diseases which may lead to heart attack (Liu et al., 2023). AI is expected to predict the functions of food or ingredients of food on health (Miyazawa et al., 2022). Rein et al., (2019) used machine learning to find dietary bioactive peptides in rice and test their biological effects clinically. AI was used to develop a model based on rough sets, the model can precisely identify two or three ingredients that can benefit the rehabilitation of some diseases respectively, like diabetes, hypertension, and heart attack (Lei et al., 2018).

AI also can be used for personalized nutrition. People have different glycemic responses towards the same diets (Zeevi et al., 2015). An ML algorithm trained by the data of microbiome, blood test, anthropometrics, food diary, lifestyles, medical, and glycemic responses from 800 subjects was developed as a personalized nutrition predictor to predict personal glycemic responses and design personalized diet interventions for lower glycemic responses (Zeevi et al., 2015). An IoT-based system named Smart-Log has sensors to gauge the food weight and phones to input food types, it also integrates a neural network and a Bayesian network-based algorithm to achieve automated nutrition balance monitoring and advising for infants, the prototype experiments had a prediction accuracy of 98.6% (Sundaravadivel et al., 2018).

## 2.3 Swedish Context

This section aims to provide an overview of AI's integration into the Swedish food system, contributing valuable insights to the discourse on AI's impact on this sector. Through a broad investigation, the research examines the complex background of AI's application within Sweden's food system, providing an understanding of its implementation at various operational levels. The review aims to identify actors, their relationships, and the subtle dynamics of the Swedish food system. This involves examining relevant companies, organizations, and government entities, and their roles in shaping the development and adoption of AI technologies in Sweden's food sector. The analysis progresses in three key areas:

1. **Swedish organizations working on AI**: Appendix D presents a classification of Swedish organizations actively involved in AI research, development, and application, emphasizing their contributions and roles in advancing AI technologies within Sweden. This overview aims to showcase the collaborative ecosystem and the innovation-driving forces behind Sweden's AI advancements.

2. **Swedish companies in the food system utilizing AI**: Central to the investigation is the review of how Swedish companies within the food system are integrating AI, from production to distribution. Appendix E categorizes these companies, describing the diverse ways AI is being used.

3. **Perspectives of Swedish organizations on AI in the food system:** The final part focuses on organizations that govern, influence, or directly engage in the Swedish food system. By reviewing reports and publications (Appendix F) from these organizations, the researchers gather insights into their perspectives on AI's role and potential within the sector. This includes discussions on regulatory frameworks, ethical considerations, and the planned future of AI in enhancing the resilience and sustainability of Sweden's food industry.

Figure 7 is derived from mentioned reports, summarizes the key focus areas of the food strategy (Jordbruksverket, 2023). It points out the overarching goal of a sustainable food chain, which includes environmental, social, and economic dimensions. Additionally, the strategy emphasizes the need to strengthen the food supply in times of crisis, addressing factors like input availability, food prices, and inflation to reduce vulnerability. Examining this Swedish context through the lens of the reports and the STST framework, the literature review provides a broad understanding of the current state, challenges, and opportunities for AI in Sweden's food system, particularly in primary production. According to several reviewed reports and the Swedish food strategy, led by the Swedish Board of Agriculture, the Swedish government aims to promote a competitive, productive, and sustainable food chain. The strategy focuses on increasing Swedish market share, driving innovation, boosting labor productivity, and promoting profitability.

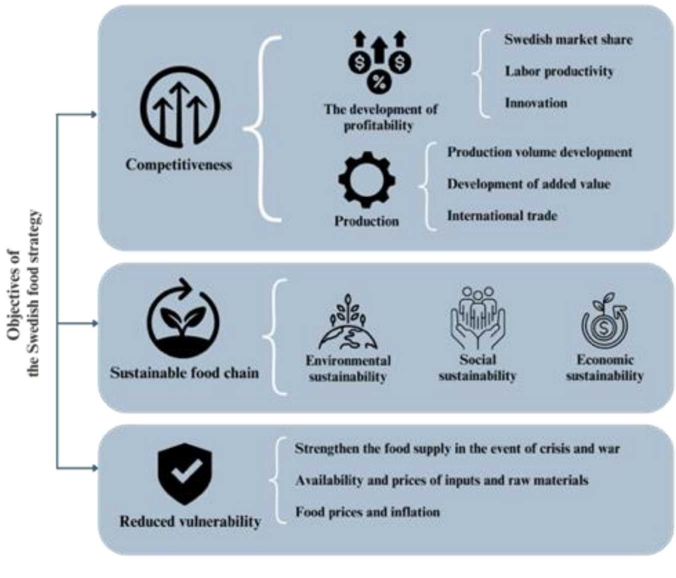



*Figure 7. Focus of food strategy according to Sweden ministry of agriculture (Own elaboration).*

Figure 8 illustrates the identified actors and their relationships at both the social and technical levels within the Swedish food system. Drawing upon information from reports, news articles, and database searches, as well as insights from the previous sections of the literature review. The map represents technical entities related to AI in the field, social entities such as key actors, and the relationships between them. Additionally, the authors clarified the borders between different sections of the Swedish food system to provide a clearer understanding of the complex dynamics at play. The technical entities shown in the map showcase the various AI technologies and applications being utilized within the Swedish food system. These include machine learning, computer vision, robotics, and other AI-driven solutions that are transforming various aspects of the food chain. On the social side, the map identifies key actors such as government agencies, research institutions, private companies, and other organizations that are actively involved in shaping the adoption and development of AI in the Swedish food sector. By visualizing the relationships between these social and technical entities, Figure 8 offers a view of the intricate web of interactions that characterize the integration of AI in the Swedish food system. This map serves as a valuable tool for understanding the current landscape and identifying potential areas for further research and collaboration.

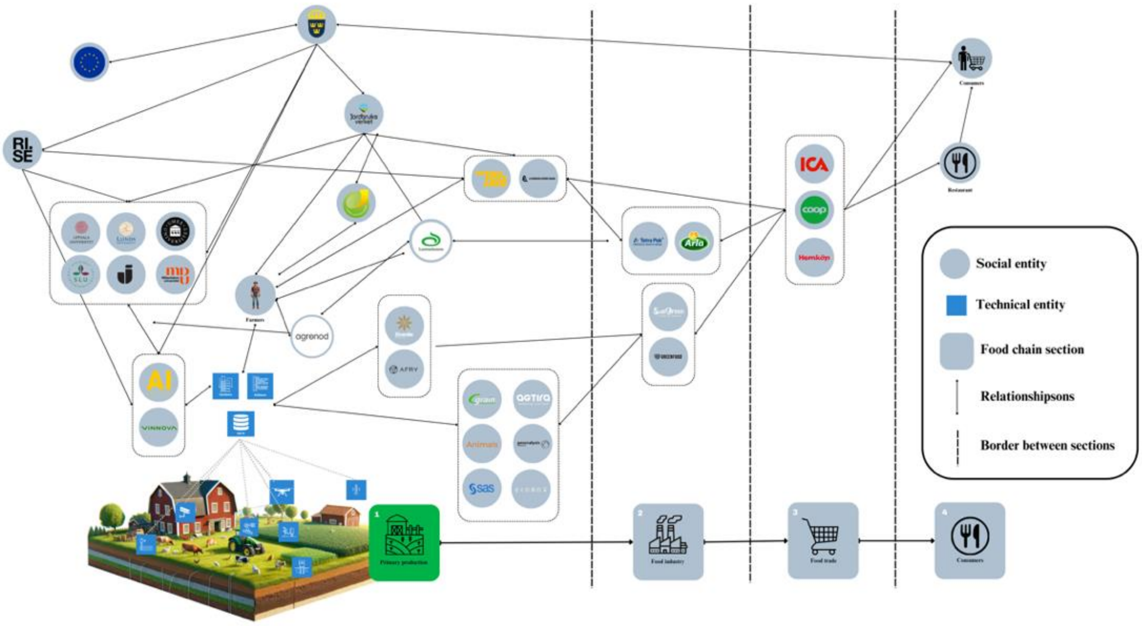



*Figure 8. Identified actors and their relation in Social and technical level in Swedish food system (Own elaboration).*

Figure 8 illustrates the interplay between social and technical entities in the Swedish food system using the STST framework. However, the traditional STST framework has limitations in representing the complex economic and ethical aspects and their relationships within the food system. In Figure 8, these factors are primarily explained as relationships of social actors, making it challenging to track and visualize all entities (economic and ethical entities) within the traditional framework. To address this limitation and provide a more detailed analysis, the researchers introduced an updated version of the STST framework, which incorporates economic and ethical levels. This updated framework is explained in detail in the "output of the extended STST" section. By including these additional levels, the authors aim to better capture the complex nature of the Swedish food system and the role of AI within it.

# 3 Theoretical framework

*This section introduces the Theoretical framework of this paper, explaining the origin of the framework, some previous studies using this framework to analyze AI adoption, and the necessity to expand the framework*

## 3.1 Socio-technical systems theory (STST)

The inception of socio-technical systems theory (STST) can be traced back to the efforts of Tavistock Institute researchers, who discerned that technical system optimization in isolation frequently does not result in the anticipated improvements in performance (Tranfield, 2000). According to STST, effective optimization necessitates a holistic perspective in which social and technical elements are seen as interconnected and coevolving as illustrated on Figure 9 (Cherns, 1976; Manny et al., 2022).

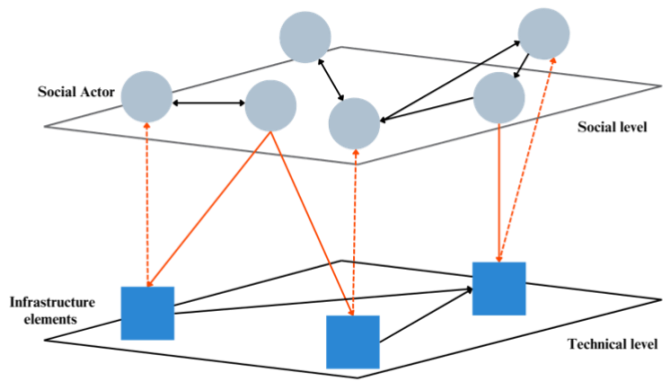



*Figure 9. A Socio-Technical Network is a system where social actors and technical infrastructure interact in various ways (Manny et al., 2022).*

STST was initially derived from the socio-technical model which consists of four core interactive aspects, including technologies, tasks, people, and structures (Leavitt, 2013). In the context of Industry 4.0, an STST model including 6 dimensions (Goals, people, infrastructure, technology, culture, and processes) can be used to test vertical, horizontal, and end-to-end integration (Sony and Naik, 2020). Furthermore, a more sophisticated STST structure with eight interdependent and interrelated dimensions was developed in the medical study, containing (1) hardware and software computing infrastructure, (2) workflow and communication, (3) people, (4) system measurement and monitoring, (5) clinical content, (6) internal organizational policies, procedures, and culture, (7) human-computer interface, (8) and external rules regulations and forces (Sittig and Singh, 2010). In addition, from the external perspective, the general economic circumstance, the stakeholders, and regulatory frameworks are also investigated as elements of STST (Münch et al., 2022).

## 3.2 Socio-Technical System Theory and AI Adoption

STST is a desirable framework for analyzing AI adoption through different industries. There is already some previous research investigating this topic. Haefner et al., (2023) investigated the approaches of AI adoption and scaling in different companies as well as implicated socio-technical elements. Then they developed a socio-technical model, showing that if a company wants to successfully implement AI there are three factors in the technical dimension to focus on: data pipeline, technical infrastructure, and AI model. Meanwhile, there are also three factors in the social dimension: AI growth vision, AI capabilities, and organizational structure.

In the different phases of AI implementation and scaling, these socio-technical factors are not statical, rather, the job entailed by a certain factor is also changing (Haefner et al., 2023)

Based on the 8-dimension model developed in the previous study, then as illustrated in Figure 10, an STST model was developed with technological dimensions and social factors (Weger & Yeazitzis, 2023). The model takes into account 8 socio-technical factors influencing AI-driven technology adoption through design, development, implementation, use, and assessment. In order to improve the successful rate of AI adoption in complex circumstances, these 8 factors should be considered as interdependent and their interactions should be emphasized.


*Figure 10. The Eight Dimensions of the Socio-Technical Model of AI-powered Technology (Weger & Yeazitzis, 2023).*

Xing et al., (2021) also explored socio-technical obstacles to the large-scale deployment of AI-enabled wearable medical devices in China. Their model shows the socio-technical barriers to AI adoption in that field are very complex beyond the only technology. To facilitate AI adoption, socio-technical factors like managerial, legal, personal, financial, technological, and clinic barriers are all needed to be considered, and these factor have complex interactions mutually. It's impossible to only think about one factor.

Salwei and Carayon, (2022) analyzed AI integration in the current workflow and regarded AI as only one small element in the socio-technical system. Their study shows that successful AI adoption must consider several socio-technical elements, including person, technology, task, organization, and physical environment.

STST is valuable as it not only identifies elements but provides a framework for understanding how they might interact dynamically. It allows for an exploration of how AI tools could potentially reshape tasks, decision-making processes, and power relationships throughout the Swedish food system. The theory also provides a lens through which to examine how stakeholders across various sectors may need to adapt to the integration of AI technologies. Additionally, STST will be used to investigate how existing regulations or new policies could shape the successful and ethical implementation of AI across the Swedish food system.

## 3.3 Expanding the STST: Introducing Economic and Ethical Levels

Previous research has shown that extending socio-technical system theory to include additional levels of analysis can provide valuable insights in various domains. For example, Baxter and Sommerville, (2010) note that many disciplines have evolved from the original socio-technical concepts, with each one adapting the theory to a specific environment, culture, or organization by emphasizing certain aspects. This shows there are examples of modifying STST to fit the needs of a particular research context. Savaget et al., (2019) conducted a systematic literature review on the theoretical foundations of sociotechnical systems change for sustainability. They found that researchers investigated sociotechnical systems in specific sectors like energy, transportation, water, sanitation and food, this demonstrates the applicability of sociotechnical approaches to food systems. Another notable extension of socio-technical system theory is the inclusion of the ecological dimension, resulting in the social-ecological-technological systems (SETS) framework. This framework emphasizes the interconnections and interdependencies between social, ecological, and technological systems, recognizing that the ecological context is crucial for understanding and addressing sustainability challenges (McPhearson et al., 2022).

Based on this tradition of extending STST to suit specific research contexts, the current study incorporates economic and ethical levels to investigate AI in the Swedish food system. This approach aligns with the tradition set by previous researchers and allows for a more broad analysis of the complex socio-technical factors. During this research, which included a literature review and in-depth interviews, it became evident that the traditional STST framework, consisting of only social and technical levels, did not fully capture the complexity of AI adoption in the Swedish food system. Two additional levels emerged as crucial factors shaping the adoption and implementation of AI technologies: the **Economic level** and the **Ethical level,** as illustrated in Figure 11.

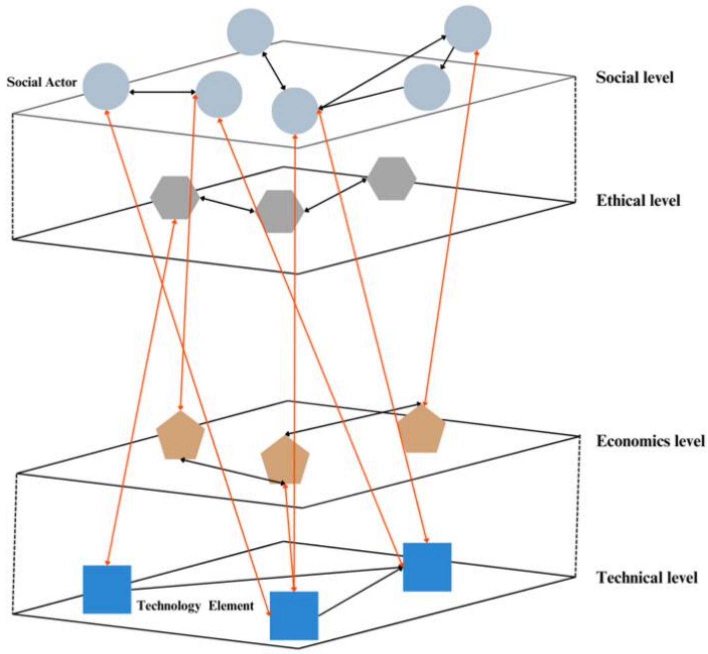



*Figure 11. Expanded STST by adding Economic and Ethical levels (Own elaboration).*

The inclusion of the Economic level acknowledges the significant influence of financial considerations, cost of AI, business models, and market dynamics on the socio-technical dynamics of AI adoption in the Swedish food system. This fits with previous research that has recognized the importance of economic factors in shaping the adoption and scalability of AI solutions in various sectors (Horani et al., 2023; Shang, Low and Lim, 2023).

The Economic level was found to be deeply intertwined with the technical level, making it difficult to consider economic factors as merely actors or relationships within the system.

Economic considerations, such as profitability, return on investment, and costs, play a significant role in driving or hindering AI development and adoption in the food system (Issa, Jabbouri and Palmer, 2022; Georgopoulos, Gkikas and Theodorou, 2023). By introducing the Economic level as a distinct level of the expanded STST framework, it can be better to understand and analyze the impact of economic factors on AI adoption in this specific context. This level is positioned close to the technical level, reflecting their close interconnection. By considering the economic drivers, barriers, and opportunities associated with AI technologies, researchers and practitioners can develop more contextually relevant strategies for their successful implementation. Similarly, the Ethical level recognizes the critical role of moral considerations, values, and principles in guiding the responsible development and deployment of AI technologies in the Swedish food system, closely linked to the social level, reflecting their close interconnection. The importance of addressing ethical concerns related to data ownership, privacy, transparency, and the inequality associated with AI adoption in different sectors has been increasing (Daneshjou et al., 2021; Kim, 2021; Larsson & Heintz, 2020; Miller, 2020; Safdar et al., 2020). By explicitly addressing the ethical dimensions of AI technologies, researchers can develop more responsible, transparent, and inclusive approaches to their implementation (Etzioni and Etzioni, 2017), ensuring that the benefits are equitably distributed while mitigating potential risks and unintended consequences. The expansion of the STST framework to include Economic and Ethical levels is not unprecedented. Other researchers have also recognized the need to adapt and extend the STST framework to better capture the complexity of socio-technical systems in the context of AI adoption. For example, Weger and Yeazitzis, (2023) developed an eight-dimensional model for successful AI adoption in organizations. Similarly, there is a framework that considers the interplay between technical, social, and economic factors in the scaling of AI firms (Haefner et al., 2023).

This expansion provides a balanced and contextually relevant approach to understanding the complex dynamics of AI adoption in the Swedish food system. By recognizing the critical influence of economic and ethical factors on the socio-technical landscape, this framework enables researchers to develop more integrated and responsible strategies for the successful implementation of AI technologies. The expanded STST framework can be used to investigate how existing regulations, new policies, and ethical guidelines could shape the successful and responsible implementation of AI across the Swedish food system. This includes considering data privacy laws and the development of data governance frameworks, in an economically viable and ethically sound manner.

# 4 Methodology

*The following section details the data collection and methods employed to address the research questions, outlines the research process and approach, and discusses the study's credibility, transferability, dependability, confirmability, reflexivity, and ethical considerations.*

## 4.1 Ontology, Epistemology, and Research strategy of this study

The ontology of this study is constructionism, recognizing that the social reality around AI integration and adoption in the Swedish food system is not something universal like a fact existing independently from the people who work with it or researchers who study it (Bell, Bryman and Harley, 2022). Instead, under that social context, this phenomenon and its meaning should be understood as social-constructed existences that are dynamically made and influenced by the interactions of different actors, technologies, regulations, and cultural background (Bell, Bryman and Harley, 2022). Based on the ontology of constructionism, interpretive epistemology is adopted to guide the research process because the given ontology will indicate the choice of how to gain the correct knowledge (Bell, Bryman and Harley, 2022). Interpretivism indicates that the knowledge about AI integration is not an objective fact that needs to be observed or gauged by scientific experiments or some devices (Bell, Bryman and Harley, 2022). Instead, because the attributes of social science are totally different from natural science, interpretivism emphasizes that the way to get knowledge is by understanding the meaning of social interactions, human behaviors, and the experience or opinions of different stakeholders involved in the AI adoption process in the Swedish food system (Bell, Bryman and Harley, 2022).

Given the preceding ontological and epistemological stance, a qualitative research strategy is conducted to get a deep understanding of the socio-technical dynamics of AI adoption in the Swedish food system. This strategy emphasizes that people interpret the social world, which means it entails in-depth exploration and understanding of the views of stakeholders and the social context that influences AI integration (Bell, Bryman and Harley, 2022).

## 4.2 Research design and data collection

### 4.2.1 Research design

To guide the research to answer the two research questions, the research design of this study is the case study. It is suitable for not only exploring complex and in-depth relationships and interactions of different actors but also organically investigating the intricate context of the Swedish food system (Yin, 2014). Although there is a focus on primary production, having a big picture of the whole Swedish food system is also important and the case study has a strong point in viewing the whole process with different aspects (Gummesson, 1988). The case study can also allow different data collection methods (Eisenhardt, 1989), which can gather enough data from different perspectives to answer the two research questions. Finally, the flexibility of the case study can make it able to test hypotheses or theoretical propositions or to build "middle-level" theories (Priya, 2021), which aids the authors in making some theoretical contributions.

### 4.2.2 Data collection

#### *4.2.2.1 Literature review*

The literature review could provide the credibility of the study and help the readers understand the current situation on AI adoption, like the knowledge already known in this area, the relevant concepts or theories, and what other researchers have done in their studies (Bell et al., 2022; Denney & Tewksbury, 2013). This literature review served as the foundation for this study, including two phases (as shown in the Figure 12) and several purposes. Firstly, this review established a comprehensive understanding of the fundamental AI concepts and explored their diverse applications within the global food system. Secondly, it explored the Swedish food system background and gained an initial insight into AI adoption-related issues within this system.

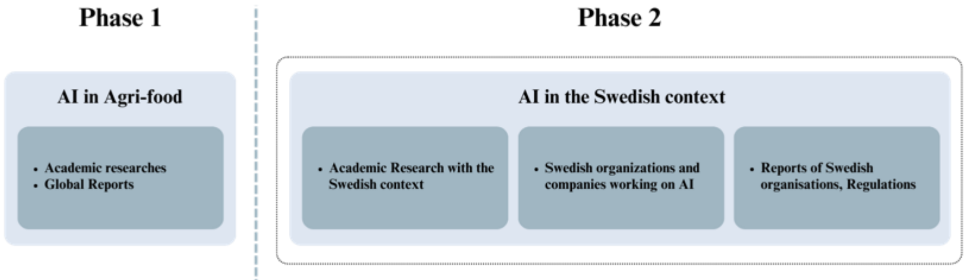



*Figure 12. Literature Review Phase (own elaboration).*

The literature review was conducted through the search of academic resources. The tools used for searching relevant materials in this phase were the Uppsala University Library and Google Scholar with the use of Boolean Search. The keywords used in the search engine were "(agriculture* OR farm* OR "primary production" OR cultivate* OR crop OR agronomy OR husbandry OR food) AND (AI OR "artificial intelligence" OR "machine learning" OR "neural network" OR robotic* OR "deep learning" OR "natural language processing" OR "computer vision" OR "autonomous system" OR smart OR "machine intelligence" OR "computational intelligence" OR "intelligent system" OR "cognitive computing")". The search results were filtered by "peer-reviewed" and ranked by relevance. Additionally, some information on the Swedish context was examined by reviewing reports or research from government agencies (e.g., the Ministry of Agriculture), research institutions, and other relevant organizations. This provided insights into the specific actors, activities, and initiatives shaping AI development and adoption in Sweden.

#### *4.2.2.2 Qualitative interview*

**Semi-structured interviews**

Semi-structured interviews were chosen as the primary data collection method to gain a deeper understanding of the Swedish case beyond the only information from the literature review. This approach aligned with the research design of the case study and is suitable for this study because it emphasizes the importance of capturing different perspectives of stakeholders in the Swedish food system, it can help the authors to get abundant and detailed knowledge, and it has more flexibility for both authors and interviewees to approach unexpected knowledge (Bell, Bryman and Harley, 2022). With these attributes of semi-structured interviews, the author could implement a comprehensive exploration of different considerations and issues related to AI adoption in the Swedish food system. The semi-structured pattern ensured that key topics were covered while also enabling interviewees to share something unique (Bell, Bryman and Harley, 2022).

Before commencing each interview, an introduction of the authors was given to the interviewee, which provided a brief overview of the research project, and the participants had the right of anonymity and confidentiality. Interviews, averaging approximately 45 minutes (almost 900 minutes in total), were conducted both online and in-person to accommodate participants' preferences and geographic distribution. While the authors aimed to interview participants from across Sweden, most of the interviewees were based in the central and southern regions. This hybrid method ensured the researchers captured a wider range of perspectives than would have been possible through a solely in-person approach. All interviews were audio-recorded with informed consent to facilitate accurate transcription. The authors supplemented these recordings with detailed notes, capturing key insights that were not solely evident from the audio.

**Sampling**

This research employed a purposive sampling strategy, this non-probability sampling method is appropriate to the qualitative case study because it helped the authors select participants based on their relevance to the research questions and their potential to provide information-rich knowledge (Patton, 2002). In more detail, they all worked in Swedish society and had experience or insights into AI-related issues and the Swedish food system, especially in primary production. Also, they were willing to share their knowledge unreservedly with the authors in this study. LinkedIn and some websites of different organizations, like “EU CAP Network”, “Landsbygdsnätverket”, “RISE”, “Swedish Food Arena”, and Swedish universities, were used to find their information and contact them. Some of them were contacted by email, others by LinkedIn message. Below is more detailed information about the interviewees in the study.

Researchers: Researchers from institutions like SLU (Swedish University of Agricultural Sciences) and RISE (Research Institutes of Sweden) were actively involved in AI and food systems research. These participants shared valuable insights into the current developments, the academic discourse on AI-related challenges and opportunities, and potential avenues for future inquiry.

Farmer-related experts: Initially, the authors sought to interview farmers directly to gather diverse perspectives on AI adoption. However, after preliminary conversations, it became clear that many farmers had limited familiarity with AI concepts and terminology. To ensure a more fruitful exchange, the authors shifted their focus to engaging with experts who had conducted on-the-ground studies with farmers and possessed a nuanced understanding of their needs and concerns. The authors were fortunate to connect with several experts who also had personal ties to farming families, providing invaluable insights into the practical realities of AI integration in the agricultural context.

Company Managers: Managers from companies across different sections in the food system – such as agricultural technology startups, food processing companies (e.g., Arla), and retail innovators (e.g., ICA) – provided an in-depth understanding of industry trends in AI and their practical applications within the Swedish context.

Representatives from Relevant Organizations: Representatives from some relevant organizations, such as The Rural Network, the Swedish Agency for Economic and Regional Growth, and the National Committee on Food Research, offered broader perspectives on societal concerns, potential regulatory needs, and policy considerations related to the integration of AI in food systems. This sampling approach ensured a diversity of perspectives essential for understanding the multi-faceted nature of AI integration. Table 4 provides details of the interviewees.

| # | Name of interviewee | Role | Organization | Details | Duration |
|---|---|---|---|---|---|
| 1 | Interviewee 1 | Researcher | SLU | Associate Professor at SLU researching food waste quantification and life cycle assessment. | 71 min |
| 2 | Interviewee 2 | Data scientist | Elvenite | Data scientist exploring opportunities for small companies to leverage high-performance computing. | 41 min |
| 3 | Interviewee 3 | Manager | Arla Foods | Ex-Director of Customer Operations & Demand at Arla Foods. | 62 min |
| 4 | Interviewee 4 | Researcher | RISE | Researcher at RISE working on food technology, processing, and automation. | 45 min |
| 5 | Interviewee 5 | Founder | AgriOpt | Democratizing AI in agriculture \| PhD \| Agtech founder | 53 min |
| 6 | Interviewee 6 | Researcher | AFRY | Experienced AI expert at engineering consultancy AFRY | 54 min |
| 7 | Interviewee 7 | Researcher | RISE | Director Agriculture and Horticulture på RISE Research Institutes of Sweden | 56 min |
| 8 | Interviewee 8 | Researcher | RISE | Research in machine learning and deep neural networks. | 36 min |
| 9 | Interviewee 9 | Researcher | Dálvvadis ekonomisk förening, Jokkmokk | Research in reindeer herding, meat production, and animal welfare | 40 min |
| 10 | Interviewee 10 | Researcher | Hushållningssällskapet Skåne | Research in plant pathology, plant disease management, and Agrochemicals | 30 min |
| 11 | Interviewee 11 | Researcher | RISE | Research in computer vision and machine learning | 30 min |
| 12 | Interviewee 12 | Vice President | Lantmännen BioAgri AB | R&D and Product development | 35 min |
| 13 | Interviewee 13 | Senior Advisor | RISE | Led the business and innovation related to Digitization | 38 min |
| 14 | Interviewee 14 | Project Manager | Tillväxtverket | Policy Innovation for Sustainable Food systems | 30 min |
| 15 | Interviewee 15 | CEO and cultivation advisor | Lovang Lantbrukskonsult AB | Providing solutions for crop production, economic issues, environment, energy&technology, EU support, and projects | 37 min |
| 16 | Interviewee 16 | Director Automation&AI | ICA | Drives transformation in the Automation and AI space | 45 min |
| 17 | Interviewee 17 | Owner CEO and researcher | CFB Creative Future Business AB | Food chemistry, food processing, food engineering, digitalization food, and food radar systems | 60 min |
| 18 | Interviewee 18 | Researcher & Manager | Advisors | Business Analyzer | 65 min |
| 19 | Interviewee 19 | Analyst & Business Development Manager | HUI Research AB | Digitization of trade, e-commercial, impact of technology development on trade | 30 min |
| 20 | Interviewee 20 | Project Manager | Blekinge Tekniska Högskola | Use AI and camera technology to detect weeds | 35min |

*Table 4. Interviewees (Own elaboration).*

**Interview Guide Development and Customization**

The authors developed a semi-structured interview guide to guide the conversations (Appendix G) while maintaining flexibility to pursue emergent themes and tailor the questions to each participant's unique position in the food system. Key areas covered in the interview guide included perceptions of AI, potential technical and social impacts, ethical considerations, regulatory needs, and so on. Recognizing the diverse roles and expertise of the participants, the authors customized the approach in each interview, ensuring discussions were relevant to the specific experiences and areas of knowledge of interviewees within the Swedish food system.

## 4.3 Data analysis

The qualitative data from the literature review were first gathered together to draw a primitive picture of the socio-technical relationships in the Swedish food system.

The interview transcripts were analyzed by using inductive thematic analysis. This iterative approach involves thoroughly reading transcripts, extracting quotes, assigning codes to salient concepts and patterns from the qualitative data from semi-structured interviews, and then collecting codes into broader themes related to the research question and socio-technical system theory (STST) (Kiger and Varpio, 2020). The extended STST framework helped to explain the complex interactions of different factors on AI adoption in the food system (Fox, 1995).

This research employs STST as its primary analytical framework. Historically, STST has been applied successfully in the study of diverse technological advancements ((Rami) Shani et al., 1992; Ansari and Garud, 2009; Shin, D. H., Choo and Beom, 2011; Li, Trutnevyte and Strachan, 2015; Yun and Lee, 2015). This shows its effectiveness in understanding the complex interplay between novel technologies and the social systems in which they are embedded. The core concept of STST fits seamlessly with the challenges of AI integration. STST emphasizes that technology cannot be understood in isolation from the social, organizational, regulatory, and economic structures within which it operates (Haefner et al., 2023). AI systems include both technical components (algorithms, data infrastructure, etc.) and social dimensions (user perceptions, potential for bias, impacts on labor, etc.). As Weger and Yeazitzis, (2023) noted, STST is valuable for "conceptualizing a socio-technical model for evaluating AI-driven technology". Moreover, recent studies highlight the need for frameworks that support the successful implementation and scaling of AI within organizations (Haefner et al., 2023). Applying an STST lens to the analysis of AI integration within the Swedish food system allows for the identification of both the factors that could promote smooth adoption and those that might pose barriers. During the process of the study, it showed that the traditional STST model is not sufficient to provide insights from different dimensions, so an extended STST was developed, as shown in the section of “Theoretical framework”.

## 4.4 Connection between research questions and methodology

Triangulation was implemented here, both the literature review and qualitative data from the interviews underwent the lens of STST. The literature review offered foundational knowledge of AI application in the food system and a broader perspective related to AI adoption in the Swedish context, which gave some guides to the interviews. The interviews offered rich, context-specific, and more detailed narratives, concerns, and aspirations of those directly involved in the Swedish food system. Figure 13 illustrates the connection between research questions and methodology.

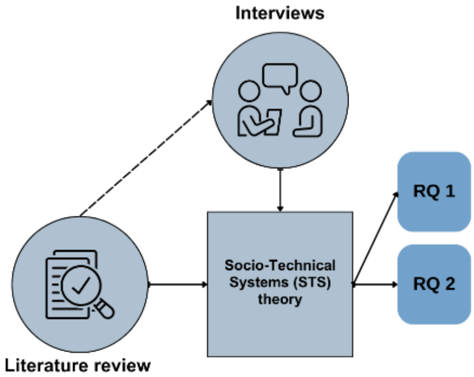



*Figure 13. Connection Between Research Questions and Methodology (Own elaboration).*

## 4.5 Research process and approach

Figure 14 shows the research process of research, including four main phases. Phase 1 involved the literature review, Phase 2 consisted of semi-structured interviews with purposively sampled participants. Phase 3 involved an inductive thematic analysis of the interviews, guided by the extended STST. Phase 4 showed the result of the thematic analysis and discussion of the study.

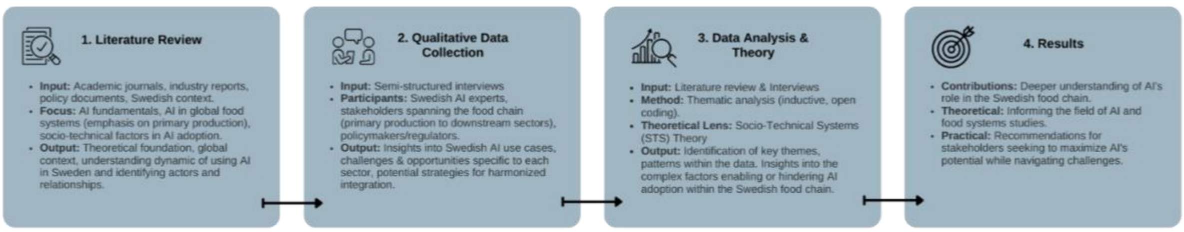



*Figure 14. The Research Process Diagram (Own elaboration).*

## 4.6 Research quality

### Credibility

Credibility has the same meaning as internal validity, which means if there is a good match between researchers' observations and the theories they build or whether researchers can ensure a high accordance between the findings and results, credibility can be ensured by triangulation (Bell, Bryman and Harley, 2022). This study implemented both the literature review and the interviews to gather data with different interviewees to ensure triangulation, so the credibility of this study can be considered high.

### Transferability

Transferability means whether the findings and results can stand in other social contexts, but a qualitative study focuses on the thorough investigation of a small group and the findings are always related to the unique context of the study (Bell, Bryman and Harley, 2022). Considering this issue, this study provided a detailed description of the Swedish context and background to ensure others can decide whether the findings can be transferred to other circumstances.

**Dependability**

Dependability has the same meaning as reliability in quantitative research, which means whether the qualitative research is reliable (Bell, Bryman and Harley, 2022). To ensure the dependability of the qualitative study, the audit trail was implemented in this study in order to let other researchers investigate the whole research process and assess the dependability of the study (Bell, Bryman and Harley, 2022). All the processes of the study were recorded, including the questions in the interviews, the transcripts of the interviews and the thematic analysis procedures.

**Confirmability**

Confirmability means objectivity in a qualitative study, the research and findings should not be influenced by the personal values or tendencies of the researchers (Bell, Bryman and Harley, 2022). To ensure confirmability, the researcher chose every research method based on the nature of the research question and the context, there is minimal subjectivity in the interview guide.

**Reflexivity**

Reflexivity is an important aspect of qualitative research that acknowledges the researcher's role in shaping the study and its findings (Berger, 2015). In this study, the authors recognize that their own experiences, knowledge, and perspectives on AI and the Swedish food system may have influenced the research design, data collection, and analysis. To mitigate potential biases, the authors engaged in ongoing reflexive practices throughout the research process. This included:

1. Engaging in regular discussions with the research team to challenge assumptions and consider alternative interpretations of the data (Berger, 2015).

2. Seeking feedback from participants and external reviewers to ensure that the findings accurately represented the experiences and perspectives of the stakeholders in the Swedish food system (Tracy, 2010).

By engaging in reflexivity, the authors aim to enhance the transparency and trustworthiness of the research, acknowledging that the findings are a product of the interactive process between the researchers and the participants in the specific context of the study.

**Ethical considerations**

The authors prioritized ethical considerations throughout the interview process. All participants received detailed information, including a link to the research website, outlining the research aims, data collection and usage procedures, and their rights. Informed consent was obtained before each interview, the interviewees had the right to anonymity, recording, and other privacy issues. The authors rigorously upheld the commitment to confidentiality throughout the data collection and analysis process. While the questions focused on AI within the food system, care was taken to avoid inquiries that could put participants' employment or the reputation of their organizations at risk.

# 5 Results of the Interview Study

*The thematic analysis of the interviews, guided by the expanded Socio-Technical System Theory (STST) framework, reveals the emergent themes and patterns related to AI in the Swedish food system.*

The semi-structured interviews provided rich insights into the current state, challenges, and opportunities. The authors employed an inductive thematic analysis approach, allowing themes to emerge organically from the data (Braun and Clarke, 2006). This aligns with the exploratory research design, which aims to uncover the complex dynamics of AI integration without imposing preconceived categories (Patton, 2002). The emergent themes were categorized according to the four levels of the expanded Socio-Technical System Theory (STST) framework: technical, economic, social, and ethical. In the following subsections, the codes and themes that emerged from the analysis are presented and organized by the respective STST levels. The structure of the whole codes, themes, and levels can be found in Appendix H.

## 5.1 Technical – level

Table 5 presents the codes and themes classified under the technical level of the STST framework, showing the key aspects of AI capabilities, applications, and data challenges in the Swedish food system.

| Codes | Themes | Layers |
|---|---|---|
| AI Application | **1- AI Capabilities and Applications** | **Technical - level** |
| Automation | | |
| Data Management | **2- Data Challenges** | |
| Data Sharing and Connectivity | | |
| Data Collection | | |
| Data and Knowledge Management | | |
| Data connectivity | | |
| Data processing | | |
| Data limitation | | |
| Data quality | | |
| Data Platform | | |
| Lack of comprehensive data | | |

*Table 5. Extracted codes and themes classified in technical-level (Own elaboration).*

### Theme 1: AI Capabilities and Applications

The theme "AI Capabilities and Applications" emerged from two main codes: "AI Application" and "Automation." These codes indicate the diverse ways in which AI technologies are being utilized and their potential applications in the Swedish food system, with a particular focus on primary production. The code "AI Application" forms the core of this theme, as it covers the wide range of AI technologies and their potential uses in the Swedish food system. Founder of AgriOpt, Interviewee 5 's quote:

*"Today there are [many] products based on AI. we can have data analysis and we can have automation, AI has so many different applications. And to be honest, AI is a lot of different technologies as well".*

This quote points out the versatility and widespread use of AI and its ability to be applied in various contexts within the Swedish food system. Based on this foundation, the code "Automation" emphasizes the specific use of AI in automating processes and tasks within the Swedish food system. Interviewee 5, founder of AgriOpt, statement:

*"But in automation, we have come a bit further actually. for example, in dairy industry, we have these milking robots. They are like packed with AI. When you crop tomatoes, for example in house, in this day you have robots working there. And there are autonomous tractors available to buy today".*

This indicates the progress made in AI-driven automation across different agricultural sectors, from dairy farming to crop harvesting and autonomous vehicles. The combination of these two codes indicates the diverse capabilities and applications of AI in the Swedish food system. AI technologies are being leveraged to automate various processes, improve efficiency, and unlock new possibilities in primary production and beyond (other sections). Researcher at RISE, Interviewee 7's quote:

*"There's a tremendous use for AI or ML in agriculture. When you add fertilizers to your fields, a combination of location GPS and analyzing when you move the machine, do the plants in this area need spraying for insects or fertilizer. The use [of AI] is endless".*

This emphasizes the vast potential of AI in agriculture, particularly in precision farming and optimizing resource management. The participants' insights also clarify the current state of AI adoption in the Swedish food system. While AI technologies are being developed and applied, their widespread adoption among farmers is still limited. As founder of AgriOpt, Interviewee 5 points out:

*"So in those kinds of systems, there is AI today actually helping farmers but it's not that widespread, to be honest".*

This suggests that there is still room for growth and further implementation of AI technologies in the Swedish food system. Despite the challenges in widespread adoption, the participants expressed optimism about the future of AI in the Swedish food system. Interviewee 14, manager at Tillväxtverket, quote:

*"I think here we can talk about a kind of rejuvenation of the whole agricultural sector, making it also very attractive for young people to get involved in the sector".*

This illustrates the potential of AI to breathe new life into the agricultural sector and attract a new generation of farmers and professionals. The theme "AI Capabilities and Applications" provides a focused overview of the diverse ways AI is being utilized and its potential applications in the Swedish food system. These codes indicate the versatility of AI technologies and their role in automating processes and improving efficiency in primary production and other areas of the food system. While challenges remain in terms of widespread adoption, the participants' insights suggest a promising future for AI in transforming the Swedish food system.

**Theme 2: Data Challenges**

The theme "Data Challenges" emerged from a combination of codes that emphasizes the various issues and obstacles related to data in the whole food system. These codes include "Data Management", "Data Sharing and Connectivity", "Data Collection", "Data and Knowledge Management", "Data connectivity", "Data processing", "Data limitation", "Data quality", "Data platform", and "Lack of comprehensive data." At the core of this theme lies the code "Data Management" which covers the overall challenges associated with handling, organizing, and utilizing data effectively within the food system. Researcher at RISE, Interviewee 7 emphasizes the importance of data management, stating:

*"Our main focus is that the database should contain qualified information, its quality insurance is important, it should be updated".*

This quote points to the critical need for robust data management practices to ensure the quality, reliability, and timeliness of data in the food system. Building upon this foundation, the codes "Data Sharing and Connectivity" and "Data connectivity" indicate the challenges associated with the flow and exchange of data among different stakeholders in the food system. Founder of AgriOpt, Interviewee 5's experience illustrates this challenge:

*"We wanted to do analysis. but then we realized okay, first of all, data is scattered over 10 different platforms".*

This fragmentation of data across multiple platforms hinders the ability to perform comprehensive analyses and derive valuable insights. The code "Data Collection" emphasizes the importance of gathering data from various sources within the food system. As Interviewee 5 points out:

*"We have helped them to collect data like from soil from yields from satellites, from terrain information, and so on."*

However, the process of data collection itself can be challenging, as Interviewee 1, researcher at SLU, notes:

*"I mean, farmers don't collect data, because it's difficult to collect it."*

This suggests that there are barriers to data collection, such as technical limitations or a lack of resources and incentives for farmers to engage in data-gathering activities. The code "Data and Knowledge Management" shows the need for effective strategies to organize, store, and leverage data and knowledge within the food system. Researcher at RISE, Interviewee 7 mentioned the importance of creating a useful tool for farmers and advisors, stating:

*"We have a very strong focus on creating a knowledge database, where we put the knowledge that we generate and we want others to put that knowledge into that database. not anything but the things that are directly targeting the advisors and the farmers and it should be a useful tool, it shouldn't be [just] theoretical."*

This quote emphasizes the need for practical, actionable data and knowledge management solutions that cater to the specific needs of farmers and advisors. The codes "Data processing" and "Data limitation" demonstrate the challenges and opportunities associated with analyzing and deriving insights from data, as well as the limitations of available data. Agtech founder, Interviewee 5 quotes:

*"let's say that you have 20 satellite images in 10 yield maps from 10 different years. You can't do anything with that as a human, but we [AI experties]could sort of find interesting patterns in that data and help them actually do something with that".*

This emphasizes the power of AI in processing complex data sets that would be difficult for humans to analyze and its practicality in real scenarios. However, Interviewee 12, researcher at BioAgri, points out the limitations of the available data, stating:

*"... we thought that this data was the most relevant data. But when we started to train the model and use the model, we saw that we needed other types of data. We have started to use new variables as well, because we didn't know that from the beginning".*

This suggests that the lack of comprehensive data can hinder the development and effectiveness of AI models in the food system. The code "Data quality" emphasizes the importance of ensuring the accuracy, reliability, and consistency of data used in the food system. Researcher at RISE, Interviewee 7 stresses:

*"So we are creating this database now and we have a lot of considerations. Our main focus is that the database should contain qualified information, its quality insurance is important, it should be updated."*

This quote emphasizes the critical role of data quality in creating a trustworthy and useful database for the food system. The codes "Data platform" and "Lack of comprehensive data" indicate the need for centralized, integrated platforms to manage and share data across the food system, as well as the current absence of such comprehensive data solutions. This fragmentation of data across multiple platforms hinders the ability to perform precise analyses and derive valuable insights. Data scientist at Elvenite, Interviewee 2, further emphasizes the lack of comprehensive data, stating:

*"Perhaps that (unified platform for sharing data) will never happen since you will need an organization that could own and handle the data from production to the table where people eat the food."*

This suggests that the absence of a centralized data platform and comprehensive data sets is a significant obstacle to leveraging AI effectively in the food system. The theme "Data Challenges" represents a wide range of issues and obstacles related to data in the Swedish food system and highlights the importance of effective data management, the need for practical data and knowledge management solutions. These challenges emphasize the need for a holistic approach to data management and governance in the food system, as well as the development of integrated data solutions that can support the effective implementation of AI technologies.

## 5.2 Economic – Level

Table 6 presents the codes and themes classified under the economic level, emphasizing the economic drivers and factors influencing the commercialization of AI technologies in the Swedish food system.

| Codes | Themes | Layers |
|---|---|---|
| AI based Business plan | 3- Economic Drivers | Economic - level |
| Data as a Commodity | | |
| Costs of AI | | |
| Profitability and Resource Management | | |
| economies of scale | | |
| Economic Rationality as a Driver | | |
| Technology cost | 4- Commercializing AI Technology | |
| Marketing AI products | | |
| Entrepreneur Mindset | | |
| Funding | | |

*Table 6. Extracted codes and themes classified in Economic – level (Own elaboration).*

**Theme 3: Economic Drivers**

The theme "Economic Drivers" emerged from a set of codes that include "AI based Business plan", "Data as a Commodity", "Costs of AI", "Profitability and Resource Management", "economies of scale" and "Economic Rationality as a Driver". The code "AI based Business plan" emphasizes the importance of developing business strategies that involve AI technologies to drive innovation and competitiveness in the food system. Founder of AgriOpt, Interviewee 5 shares his experience with building an AI-based business model, stating:

*"So that's where I spent my last six years. We founded AgriOpt. And in the beginning, we ran it as a startup company. We built a precision farming platform".*

However, he also notes the challenges in finding a suitable business model, adding:

*"We ran that for four years; it was however quite difficult to find a good business model in that area because everyone is doing that."*

This suggests that while AI-based business plans hold promise, there are still obstacles to overcome in terms of differentiation and long-term viability. Building upon this, the code "Data as a Commodity" emphasizes the growing recognition of data as an asset. Interviewee 1states: *"at the moment data is gold"* emphasizing the increasing importance placed on data in driving business decisions and innovation. Interviewee 6, manager and researcher at AFRY, further reinforces this notion, saying:

*"It's a bit of a cliche to say data is the new electricity but it is a commodity, it is valuable. We must gather it and then when we have too much of it, then let's take the insight out of this."*

These quotes indicates the need for businesses to strategically collect, manage, and leverage data as a key resource in the AI-driven [food] system. The code "Costs of AI" indicates the financial considerations associated with implementing AI technologies in the food system. Vice President at BioAgri, Interviewee 12 acknowledges the investment required, stating:

*"Of course, the development [of AI] costs money. We know Vinnova financed a three-year project, they contributed 50% of the investment. AI consultants are today not very cheap."*

This quote suggests that the high costs associated with AI development and expertise can be a barrier to adoption, particularly for smaller businesses or those with limited resources. The code "Profitability and Resource Management" emphasizes the potential of AI to optimize resource utilization and improve profitability in the food system. Data scientist, Interviewee 2 discusses the value of connecting data across different stages of the food supply chain, stating:

*"The stores [trade section] know how much waste there is in stores, but farmers have no idea about that. If we could connect two databases, to make farmers learn what to produce and when to produce it. I think there is a lot of value in making this kind of connections."*

This quote illustrates how AI-driven data integration can help optimize production, reduce waste, and ultimately improve profitability for businesses across the food system. The code "Economies of Scale" proves the potential advantages of larger-scale AI adoption in the food system. BioAgri Vice President, Interviewee 12 notes:

*"In our case, AI is strongly connected to the business plan and to restructure the plan. To be able to reach the global market, to reach more customers on different corners of the globe, we need a faster test and the solution to this is AI. I'm 100% Sure."*

This quote suggests that AI can enable businesses to scale their operations and reach new markets more efficiently, leading to increased competitiveness and growth opportunities. Finally, the code "Economic Rationality as a Driver" highlights the deeper economic motivations and decision-making processes that drive AI adoption in the food system. Researcher at RISE, Interviewee 13, emphasizes the importance of economic benefits, stating:

*"The important driver of using AI is economic benefit. For a specific company, it needs to know that they benefit from it."*

This quote points out the central role of economic considerations in shaping the adoption and implementation of AI technologies in the food system. The theme "Economic Drivers" represents a range of economic factors that influence the adoption and implementation of AI. The codes that contribute to this theme indicate the importance of developing AI-based business plans, recognizing data as a valuable commodity, navigating the costs associated with AI adoption, leveraging AI for profitability and resource management, exploring economies of scale, and understanding the underlying economic rationality that drives decision-making. These Economic drivers emphasize on the balance between innovation and pragmatic considerations of costs, benefits, and long-term sustainability.

**Theme 4: Commercializing AI Technology**

The theme "Commercializing AI Technology" emerged from a set of codes that indicates the various aspects and challenges associated with bringing AI technologies to market in the Swedish food system. These codes include "Marketing AI products", "Technology cost", "Entrepreneur Mindset" and "funding". The code "Marketing AI products" emphasizes the importance of effectively communicating the value and benefits of AI technologies to potential customers [farmers in this case] in the food system. Interviewee 5, founder of AgriOpt, indicates the challenges in marketing AI to farmers, stating:

*"It's hard to market technologies to farmers but I can feel they're interested in that. There is much more interest today than six years ago. Still, there is a knowledge gap between farmers who should use the technology and people who are developing technology."*

This quote suggests that while there is growing interest in AI among farmers, there are still barriers to adoption due to a lack of understanding and effective communication between technology providers and end-users. To address this challenge, Interviewee 7, researcher at RISE emphasizes the need for specific and tangible examples when marketing AI products, by stating:

*"You have to be more specific because if you say that this AI can identify between the 1000 pigs, the ones who are sick, two days before they become sick, then we can isolate them and prevent the rest from becoming sick. Okay, [farmers will say] I see your point there."*

This quote highlights the importance of providing clear, practical examples of how AI technologies can solve specific problems and deliver value to farmers and other stakeholders in the food system. The code "Technology cost" demonstrates the financial considerations associated with commercializing AI technologies in the food system. Interviewee 7, Researcher notes:

*"If we look at everything else in the digital world, it will be exponential growth, and the cost fall down [in the long term]. So, I'm not worried, it's the first movers will pay by mistake and win by being first mover and then the rest will follow when they feel the prices wise."*

This quote suggests that while early adopters may face higher costs, the long-term trend of decreasing technology costs will make AI more accessible and affordable for a wider range of businesses and stakeholders in the food system. Then the code "Entrepreneur Mindset" points out the importance of an entrepreneurial approach to commercializing AI technologies in the food system. Researcher and business owner, Interviewee 5 shares his experience as an entrepreneur, stating:

*"... I sort of took an entrepreneurship course, but I realized that there are many working in that area [AI for automation], so I switched a bit and worked more with data analysis. For crop farming."*

This quote illustrates the entrepreneurial drive and willingness to take risks that are often necessary to bring new AI technologies to market and navigate the challenges of building a successful business by leveraging AI in the food system. Finally, the code "funding" emphasizes the critical role of financial support in commercializing AI technologies in the food system. Researcher at RISE, Interviewee 7 reveals the importance of funding for research and development, stating:

*"We have some funding that so we can hire both Scientists and agricultural advisors experts."*

Similarly, Vice President of BioAgri, Interviewee 12 notes the significance of government funding, saying:

*" ... We know Vinnova financed a three-year project, they contributed 50% of the investment."*

These quotes emphasize the need for both private and public funding to support the development and commercialization of AI technologies in the food system, particularly given the high costs associated with AI expertise and infrastructure. The codes that contribute to this theme emphasize the importance of effectively marketing AI products to end-users, navigating the costs associated with technology adoption, having an entrepreneurial mindset, and securing adequate funding for research and development.

## 5.3 Social – Level

Table 7 presents the codes and themes classified under the social level, indicates the importance of human-centered AI design, AI development dynamics, the unique characteristics of the Swedish context, and the need for harmonized AI integration across the food system.

| Codes | Themes | Layers |
|---|---|---|
| AI Perception - understanding | **5- Human-Centered AI Design** | **Social - level** |
| UI/UX | | |
| Technology maturity | **6- AI Development** | |
| AI for efficiency | | |
| Skepticism | | |
| AI optimization | | |
| User adoption | | |
| Food security | **7- Swedish context** | |
| Swedish Food System Dynamics | | |
| Sweden's Unique factors | | |
| Food system complexity | | |
| Unequal negotiation | | |
| Supply chain disconnection | | |
| Natural factors | | |
| Power dynamics | | |
| Different Nature of sections | | |
| Swedish Innovation | | |
| Human-AI Collaboration | **8- Harmonized Integration** | |
| Need for Standardization | | |
| Disconnected systems | | |
| Focus on Practicality | | |
| Accessibility of AI | | |
| Collaboration and Partnerships | | |
| Uneven Adoption | | |

*Table 7. Extracted codes and themes classified in Social – level (Own elaboration).*

### Theme 5: Human-Centered AI Design

The theme "Human-Centered AI Design" emerged as a critical consideration in the development and deployment of AI technologies in the Swedish food system. The code "AI Perception—Understanding" reflects the varying levels of awareness, knowledge, and attitudes towards AI among different stakeholders in the food system, particularly farmers. The analysis reveals that while there is a growing interest in AI and its potential applications in agriculture, many stakeholders, especially farmers, do not have a clear understanding of what AI means and how it can be effectively utilized in their specific contexts. Cultivation advisor, Interviewee 15 notes the limited adoption of AI in normal production, stating,

"My impression is that we just read about AI, but we haven't started to really use it. In some small experimental projects, it has started to be used. But I think we are almost not using it at all in production for the moment"

This quote suggests that despite the hype and discussion around AI, its practical implementation in everyday farming operations is still in the early stages. AI scientist at RISE, Interviewee 11 mentioned the challenge of managing expectations around AI, stating:

"It's always a problem with very hyped technologies. People can get the impression that it somehow just solves the problems."

This quote points out the need for clear communication and education about the capabilities and limitations of AI, to ensure that stakeholders have realistic expectations about what these technologies can and cannot achieve. At the same time, the analysis also reveals a growing interest and curiosity about AI among farmers and other stakeholders in the food system. Researcher and farmers representative, Interviewee 10 notes the generational differences in attitudes towards technology adoption, stating:

"I think the young farmers are very interested in technical things. They are driving the tractors with GPS. But older farmers are not so interested, but I think there is a turning point now."

This quote suggests that while there may be some initial hesitation or skepticism among older generations of farmers, there is a growing recognition of the potential benefits of AI and a willingness to explore its applications in agriculture. The code "UI/UX" emphasizes the importance of designing user-friendly interfaces and experiences when implementing AI technologies in the food system. The analysis highlights that the success of AI adoption in agriculture depends not only on the technical capabilities of the solutions but also on their ease of use and integration into existing workflows and decision-making processes. Interviewee 5 stresses the importance of user-centered design in the development of AI solutions for farmers, reflects the value of involving end-users in the design process, to ensure that AI solutions are tailored to their specific needs and contexts. The adoption of AI in agriculture will depend on the development of solutions that are not only technically advanced but also user-friendly and aligned with the practical needs and priorities of farmers. The analysis also reveals the potential for AI to transform the way farmers interact with technology and make decisions. Interviewee 6 envisions a future where farmers have access to AI-powered control panels and decision support tools.

**Theme 6: AI Development**

The theme "AI Development" emerged from a set of codes that reflect the various aspects and challenges associated with the adoption, maturity, and optimization of AI technologies in the Swedish food system. The code "AI Adoption" shows the current state and progress of AI implementation in the Swedish food system. Interviewee 6, emphasizes the reluctance among some stakeholders to fully embrace AI, stating:

*"One of the big problems I would say is that people are taking too small steps now. So, it's like I'll start with AI, but I will only progress the data with linear regression. I tell them, why don't you go the full gamut and do everything that can be done because it costs equally much. No, no, I want to do linear regression first. So, why wait? because everything is here, it's today's technology already."*

This quote suggests that there may be a tendency to approach AI adoption incrementally rather than fully leveraging the potential of available technologies. However, Interviewee 3, ex-manager at Arla notes the progress being made in AI adoption, particularly in the dairy industry, stating:

*"We are already utilizing it today in cows, some have electronic devices. So, when the machine comes in for milking, it reads the temperature and other parameters of the cows, like blood pressure, how much it has been feeding, how much milk it has begun giving, how long it has been sleeping, etc."*

This quote illustrates the practical applications of AI in monitoring and optimizing animal health and productivity in the food system. The code "Technology maturity" indicates the varying levels of AI technology readiness and the challenges associated with bringing research innovations to market. AI scientist at RISE, Mogren notes:

*"Even though computer vision has been a thing for 10 or 20 years, it hasn't really gone to the stage where we have polished products that work well for farmers. And it takes time from what we do in our lab, we do this with experiments, and we write scientific papers showing that we can do stuff. And then someone else needs to take over and make a polished product that works well in all situations."*

This quote suggests that there is often a gap between the development of AI technologies in research settings and their successful commercialization and adoption by end-users in the food system. The code "AI for efficiency" emphasizes the potential of AI to optimize processes and improve efficiency in the food system. Researcher at RISE, Interviewee 13 stresses the importance of embracing AI for efficiency gains, stating:

*"I must say that it's a question of using AI as much as possible at this point, in almost any industry you need to embrace it [AI] and find a way to use it because that creates efficiency."*
This quote shows the growing recognition of AI as a key driver of efficiency and competitiveness in the food system and beyond. The code "Skepticism" illustrates the challenges associated with overcoming doubts and resistance to AI adoption among various stakeholders in the food system. Researcher at SLU, Interviewee 1 expresses skepticism about the current state of AI adoption, stating:

*"At the moment, I think it's just kind of like greenwashing. I mean, this is, you know, everyone is talking about AI and big data. And it's supposed to solve all problems. But the question is, I mean, what problems do we actually have to solve?"*

This quote suggests that there may be a gap between the perceived potential of AI and its actual application in solving real-world problems in the food system. To address these challenges, Manager at Tillväxtverket, Interviewee 14 emphasizes the need for a shift in mindset, stating:

*"When we're looking at the agricultural sector, I think that they think of AI as a tool to help them in their current way of producing. And that's very unfortunate because it has a very radical potential..."*

This quote suggests that a more transformative approach to AI adoption, one that goes beyond incremental improvements, is necessary to fully realize the potential of AI in the food system. The code "AI optimization" reflects the potential of AI to optimize various processes and decision-making in the food system. AI researcher, Interviewee 5 provides an example of AI optimization in autonomous vehicles, stating:

*"If you have an autonomous tractor or an autonomous car, how can you compute an optimal way between two points without hitting an object! [just AI can help]"*

This quote illustrates how AI can be used to optimize complex tasks and improve efficiency in the food system. Finally, the code "User adoption" emphasizes the importance of considering end-user needs and preferences when developing and implementing AI technologies in the food system. Founder of AgriOpt, Interviewee 5 stresses the need for user-friendly AI solutions, noting:

*"Farmers cannot efficiently use that kind of tools because the tools are designed by engineers for engineers, more or less not for farmers, which is a problem."*

This quote explains the challenge of developing AI technologies that are accessible and intuitive for end-users, rather than simply catering to the technical expertise of developers. In conclusion, this theme emphasizes the importance of bridging the gap between research and commercialization, the potential of AI for efficiency gains, the challenges of overcoming skepticism and resistance, the opportunities for AI optimization, and the critical importance of user-centered design and adoption.

**Theme 7: Swedish context**

The theme "Swedish context" emerged from a set of codes that demonstrate the unique characteristics, challenges, and opportunities associated with the Swedish food system in relation to AI adoption and development. The code "Food security" emphasizes the importance of ensuring a stable and reliable food supply in Sweden, particularly in the face of global challenges and uncertainties. Interviewee 3, ex-manager at Arla, reflects the critical role of the food chain in Sweden's infrastructure, stating:

*“The food chain is a critical part of the Swedish infrastructure [national level]. And the times we are in today, it's becoming more and more hostile, it is important from the Swedish food supply security point of view."*

This quote suggests that safeguarding the food system is not only a matter of economic importance but also a strategic priority for national security and resilience. The code "Sweden's Unique factors" points to the specific advantages and challenges associated with Sweden's context in relation to AI adoption in the food system. Interviewee 12, researcher at BioAgri emphasizes the need for customized AI solutions that account for Sweden's unique environmental and climatic conditions, stating:

*"Sweden needs a kind of customized algorithm or customized system, it doesn't work if we buy it from other countries. It's very important that we invest in the infrastructure in Sweden according to its environment, climate, and features."*

This quote suggests that off-the-shelf AI solutions may not be suitable for the Swedish food system, and that tailored approaches are necessary to leverage the full potential of AI in this context. Also, Researcher at RISE, Interviewee 7 notes the complexity of dealing with living organisms in agriculture [related to Sweden], stating:

*"Compared to other sectors, when you look at agriculture, you are dealing with living organisms, and they do not behave predictably. Seeds in Sweden have different characteristics rather than the same breeds in Italy, for example."*

This quote emphasizes the need for AI solutions that can accommodate the inherent variability and unpredictability of unique biological systems in the Sweden's food system. The code "Food system complexity" reflects the diverse and interconnected nature of the Swedish food system, which poses challenges for AI adoption and development. Researcher at RISE, Interviewee 7 notes the difference between the controlled environment of a food factory and the unpredictable conditions of a field, stating:

*"If you are in in in a in a food factory, then you have control over all the parameters. If you are in a field, you don't have control in weather in sun and then and how fast the plants are growing and so on. Therefore, the level of AI needs to be higher than when you are in a factory."*

This quote indicates the need for AI solutions that can handle the complex and dynamic nature of the food system, particularly in primary production.

The code "Unequal negotiation" emphasizes the power imbalances and asymmetries between different actors in the Swedish food system, which can hinder the equitable adoption and benefits of AI. Researcher at SLU, Interviewee 1 notes the pressure on farmers from large retailers, stating:

*"I mean, farmers are squeezed by the supermarkets, but in general, I will say there is a reasonable profit, but the main part of the profit ends up in the refrigerator (for the trade section)."*

This quote suggests that the concentration of market power among a few large players in the food system can limit the bargaining power and profitability of smaller actors, such as farmers, which may impact their ability to invest in and benefit from AI technologies. The code "Supply chain disconnection" clarifies the lack of integration and coordination between different stages and actors in the Swedish food system, which can hinder the effective adoption and benefits of AI. Researcher at SLU, Interviewee 1 notes the challenges faced by primary producers during the pandemic due to labor shortages, stating:

*"I mean, during the pandemic, the main problem was that the primary production in Sweden was cheap labor. And during the pandemic, they couldn't import people to work on the field. And then they have a problem. Because in Sweden, no one wants to work on the field."*

This quote suggests that disruptions in one part of the food system can have cascading effects on other parts, and that a lack of coordination and resilience can exacerbate the impacts of such disruptions. The code "Natural Factors" emphasizes the role of environmental and climatic conditions in shaping the Swedish food system and the challenges and opportunities for AI adoption. Interviewee 6, Vice President at AFRY, notes the potential impacts of land degradation and extreme weather on food production, stating:

*"The bigger problem is that if land is degraded, we don't have too much land [for farming]. So, the problem is getting enough food. How do we get enough for everybody if land continues to degrade with extreme weather? [Also, he mentioned harsh weather in Sweden in almost 9 months in a year]"*

This quote highlights the need for AI solutions that can help the food system adapt to and mitigate the impacts of changing natural conditions, such as climate change and land degradation. The code "Power dynamics" underscores the unequal distribution of power and influence among different actors in the Swedish food system, which can shape the adoption and benefits of AI. Interviewee 1, researcher at SLU, notes the dominance of large retailers in the food system, stating:

*"But the problem is now that, sort of, these companies have grown organically, and therefore they have grown to this position, but they will not be allowed."*

This quote suggests that the concentration of market power among a few large players can limit the ability of smaller actors to compete and innovate, including through the adoption of AI technologies. The code "Different Nature of Sections" highlights the distinct characteristics and challenges of different stages and actors in the Swedish food system, which can impact the adoption and benefits of AI. Interviewee 2, Data scientist as Elvenite, notes the differences between primary production and downstream stages of the food system, stating:

*"Primary production would be the most interesting. The biggest challenge is changing the mindset of farmers [but in other section challenges are more technical]."*

This quote suggests that the unique needs, constraints, and mindsets of different actors in the food system may require tailored approaches to AI adoption and development. The code "Swedish Innovation" emphasizes the potential for Sweden to leverage its strengths in innovation and technology to drive the adoption and benefits of AI in the food system. Manger at Tillväxtverket, Interviewee 14 notes Sweden's technological curiosity and potential for cross-sectoral knowledge transfer, stating:

*"I think that we are a technologically curious country, we want to be seen as early adopters, we want to be seen as a modern country, and I think we have a lot of people who are interested in and we have a lot of knowledge in other sectors."*

This quote suggests that Sweden's culture of innovation and expertise in other sectors, such as technology and engineering, can be leveraged to accelerate the development and adoption of AI in the food system. The theme "Swedish context" reflects the unique characteristics, challenges, and opportunities associated with the Swedish food system in relation to AI adoption and development. The codes that contribute to this theme emphasize the importance of food security, considering the complexity and dynamics of the Swedish food system, the need for customized AI solutions that account for Sweden's unique factors, the challenges of unequal negotiation and power dynamics, the impacts of supply chain disconnection and natural factors, the distinct needs and mindsets of different actors in the food system, and the potential for Swedish innovation to drive AI adoption and benefits.

**Theme 8: Harmonized Integration**

The theme "Harmonized Integration" emerged as a crucial aspect of the successful adoption and development of AI technologies in the Swedish food system. This theme includes the various factors that contribute to the effective and cohesive integration of AI into the existing processes, systems, and relationships within the food sector. The code "Human-AI Collaboration" shows the importance of designing AI systems that work in harmony with human users and complement their skills and knowledge. Interviewee 5, Agtech founder, emphasizes the potential for AI to augment and enhance human capabilities, stating:

"We should combine data with human experience or farmer experience because that is where you can actually excel, because data and AI are often worse than the human expert, but data and AI plus the human expert would be sort of unbeatable."

To facilitate effective human-AI collaboration in the food system, it is important to adopt human-centered approaches. It requires ongoing training and support for users to help them effectively integrate AI into their workflows and decision-making processes. The code "Need for Standardization" indicates the importance of establishing common standards and protocols for the development and deployment of AI in the food system. Interviewee 3, ex manager at Arla Food emphasizes the role of standardization in facilitating the effective integration of AI, stating:

"…I think it is related to standardizations. And I think it's important as we move on if there are other standards that we need to adopt."

This quote suggests that the adoption of common standards can help to ensure the interoperability and consistency of AI systems across different applications and domains within the food sector. Data scientist at Elvenite, Interviewee 2 points out the need for standardization in the context of AI-driven decision-making, stating:

"… We used to make decisions [by ourself], but in the future, if you could have machines make decisions for you, there is a huge change... which needs standardization (Scale of self-decision making by AI tools)."

This quote illustrates the importance of establishing clear guidelines and protocols for the use of AI in decision-making processes, to ensure that these systems are transparent, accountable, and aligned with human values and priorities. To promote standardization in the development and deployment of AI in the food system. It requires ongoing monitoring and evaluation of AI systems to ensure their compliance with established standards and to identify areas for improvement and refinement. The code "Disconnected systems" emphasizes the challenge of integrating AI into the existing patchwork of systems and processes within the food sector. To address the challenge of disconnected systems, it is important to adopt a systems-level approach to AI integration that considers the interdependencies and relationships between different components of the food system. The code "Focus on Practicality" emphasizes the importance of developing AI solutions that are grounded in the practical needs and challenges facing stakeholders in the food system. Interviewee 7, researcher at RISE, stresses the importance of creating AI tools that are directly useful and relevant to farmers and advisors, stating:

"… not anything but the things that are directly targeting the advisors and the farmers and it should be a useful tool, it shouldn't be [just] theoretical."

This quote suggests that the most effective AI solutions are those that are designed to address the specific pain points and priorities of end-users in the food sector. Interviewee 11, Computer vision researcher at RISE, points out the potential for AI to enable more efficient and targeted approaches to problem-solving in the food system, stating:

"It is true that when I'm working, I feel that I can do so many more things at once. For any given thing that you want to do, there are many angles of it and many specific things that you might be interested in"

This quote indicates the importance of developing AI solutions that are flexible and adaptable to the diverse needs and contexts of different stakeholders in the food system. To ensure a focus on practicality in the development and deployment of AI in the food system, it is important to adopt a problem-driven approach that starts with a clear understanding of the specific challenges and opportunities facing different stakeholders. The code "Accessibility of AI" emphasizes the importance of ensuring that AI technologies are accessible and usable by a wide range of stakeholders in the food system, regardless of their technical expertise or resources. Founder of AgriOpt, Interviewee 5 notes the challenge of making AI tools accessible and user-friendly for farmers, stating:

"Farmers cannot efficiently use that kind of tools because the tools are designed by engineers for engineers, more or less not for farmers, which is a problem."

This quote suggests that the design and implementation of AI solutions need to take into account the diverse needs and capabilities of different user groups, in order to ensure their widespread adoption and impact. Also, this points out the need for AI solutions that are seamlessly integrated into existing workflows and decision-making processes, and that provide clear and actionable insights to users. The code "Collaboration and Partnerships" indicates the importance of fostering collaboration and partnerships among diverse stakeholders in the development and deployment of AI in the food system. To facilitate collaboration and partnerships in the development and deployment of AI in the food system, it is important to establish clear incentives and frameworks for cooperation and data sharing among stakeholders. The code "Uneven Adoption" indicates the challenge of ensuring that the benefits and opportunities of AI are distributed equitably across the food system, given the varying levels of readiness and resources among different stakeholders. Interviewee 14, Manager at Tillväxtverket, explains the challenge of uneven adoption given the traditional nature of the agriculture sector, stating:

"But agriculture is a very traditional sector. I think the adoption of new technologies has not been so strong, I would say, we haven't also had actors focused on this sector."

This quote emphasizes the need for targeted efforts to build awareness, capacity, and readiness for AI adoption among all sections in the food system. To address the challenge of uneven adoption, it is important to develop targeted strategies and support mechanisms that enable all stakeholders to participate in and benefit from the AI-driven transformation of the food system.

## 5.4 Ethical – Level

Table 8 presents the codes and themes classified under the ethical level, emphasizing the critical ethical considerations surrounding data ownership and sharing, the potential of AI for sustainable food systems, the importance of governance frameworks, and the security and privacy implications of AI adoption.

| Codes | Themes | Layers |
|---|---|---|
| Data Ownership | **9- Ethical Considerations of Data** | **Ethical - level** |
| Data sharing resistance | | |
| Sustainability | **10- AI and Sustainable Food Systems** | |
| Green washing | | |
| Food Waste | | |
| Role of government in AI adoption | **11- Governance** | |
| Ethical Concerns | **12- Ethical concerns** | |
| Transforming human roles | | |
| Inequitable Power Dynamics | | |
| Privacy concerns | **13- Security and Privacy** | |
| Security and Traceability | | |

*Table 8 Extracted codes and themes classified in Ethical – level (Own elaboration).*

### Theme 9: Ethical Considerations of Data

The theme "Ethical Considerations of Data" emerged from two main codes: "Data Ownership" and "Data sharing resistance". The code "Data Ownership" reflects the fundamental question of who owns and controls the data generated and used in the food system, and how this impacts the adoption and benefits of AI. Researcher at RISE, Interviewee 7 raises the issue of data ownership as a key challenge, stating:

*"What happens to the data that are collected together? Is that used for increased learning by the AI itself? Who is benefiting who owns this data? That is the biggest challenge."*

This quote points to the need for clear and equitable frameworks for data ownership and control in the food system, to ensure that the benefits of AI are fairly distributed and that the rights and interests of data owners are protected. Interviewee 3, manager in food industry, provides an example of how data ownership is managed in the context of a cooperative, stating:

*"In general, I don't think that there's an issue with farmers sharing data with us. Arla is cooperative, so it's owned by the farmers, so they are the owners of Arla."*

This quote suggests that cooperative models, where farmers have a stake in the ownership and control of their data, can help to address some of the ethical concerns around data ownership in the food system. However, the code "Data sharing resistance" highlights the challenges and barriers to data sharing in the Swedish food system, even when ownership and control are clear. Researcher at SLU, Interviewee 1 notes the reluctance of farmers to share data with retailers, stating:

*" Farmers don't collect data because it's difficult to collect it. Secondly, if they had that data, they wouldn't want to share it with the supermarket. I mean, why would they? The supermarket*

*[trade section] is already squeezing them and squeezing the life out of them with the production."*

This quote suggests that farmers, they may be hesitant to share data with other actors in the food system due to concerns about power imbalances and unfair competition. Data scientist, Interviewee 2 echoes this concern, noting the lack of data sharing between different stages of the food system, stating:

*"If a company owns data, it won't want to share it with other companies, which could be problematic. There is not an open system. It is its own, and it's not shared between."*

This quote highlights the need for incentives and mechanisms to encourage data sharing across the food system, while still respecting the rights and interests of data owners. The ethical considerations around data sharing resistance are further complicated by concerns about privacy and security. Agriculture advisor, Interviewee 15 notes the increasing discussions around data sharing, stating:

*"I think it's very easy to share the data. But recently, there has been an increasing discussion about who I could share data with and if there could be problems with sharing data."*

This quote suggests that even when there is a willingness to share data, there may be concerns about how that data will be used and whether it could be misused or lead to unintended consequences. To address these ethical considerations, some participants highlight the need for clear frameworks and guidelines for data sharing in the food system. Researcher at RISE, Interviewee 13 emphasizes the importance of knowing what data is being shared and with whom, stating:

*"Sharing data is critical, you need to know what you're sharing and whom you're sharing it with."*

This quote suggests that transparency and clarity around data sharing practices are essential for building trust and addressing ethical concerns. AI scientist at RISE, Mogren suggests the concept of "half-open" data as a potential solution, stating:

*"We, as a research institute, want to be open to everything we do so that it can benefit as many as possible. But then it's also a question of who is going to contribute to that. And then perhaps half-open is something that you could do. So that you could share it with certain actors, but perhaps not with your direct competitors."*

This quote indicates the need for balanced approaches to data sharing that balance the benefits of openness with the need to protect competitive advantages and sensitive information. The theme "Ethical Considerations of Data" covers the critical issues and challenges associated with data ownership, control, and sharing in the context of AI adoption and development in the Swedish food system. The codes "Data Ownership" and "Data sharing resistance" indicate the need for clear and equitable frameworks for data governance, the challenges of power imbalances and competitive pressures, and the concerns around privacy and security. These factors demonstrate the importance of developing ethical and responsible approaches to data management and sharing in the food system, ones that respect the rights and interests of data owners while still enabling the benefits of AI to be realized.

**Theme 10: AI and Sustainable Food Systems**

The theme "AI and Sustainable Food Systems" emerged from three main codes: "Sustainability," "Green Washing," and "Food Waste." These codes point out the potential of AI technologies to contribute to the development of more sustainable and resilient food systems, as well as the challenges and risks associated with the misuse or misrepresentation of AI in the context of sustainability. The code "Sustainability" explains the potential of AI to support the transition to more sustainable practices and outcomes in the food system. Interviewee 14, manager at Tillväxtverket, emphasizes the need to use AI in ways that align with broader sustainability goals, stating:

*"I think that we will need to use it for our benefit. I think it always has to go hand in hand with how we think about making a sustainable transition as well."*

According to this quote, a broader view of sustainability that considers the economic, social, and environmental aspects of food production and consumption should serve as the basis for the adoption of AI in the food system. Interviewee 12, researcher and amanger, provides an example of how AI can support sustainable practices in the context of seed treatment, stating:

*"We are working with a technique called thermal seed. We use hot, humid air to kill unwanted microorganisms on the seed, we don't add any chemicals at all. To do that, you need to understand the seed lot you're working with because all the seed lots are individual, and they need different treatments, different intensities, or temperatures [and he mentioned how AI can help them in this regard]."*

This quote explains how AI can enable more targeted and efficient approaches to crop management, reducing the need for chemical inputs and contributing to more sustainable production practices. However, the code "Green washing" highlights the risk of AI being used to misrepresent or exaggerate the sustainability benefits of certain practices or products in the food system. Researchet at SLU, Interviewee 1 expresses skepticism about the current sustainability claims around AI, stating:

*"At the moment, I think it's just kind of like greenwashing."*

This quote suggests that there may be a gap between the rhetoric around AI and sustainability and the actual impacts and benefits of these technologies in practice. To address the risk of greenwashing, it is important to develop clear and transparent frameworks for assessing and communicating the sustainability impacts of AI in the food system. The code "Food Waste" indicates the potential of AI to help reduce waste and improve resource efficiency in the food system. Interviewee 3, food industry manager, provides an example of how AI can be used to analyze data on waste and identify opportunities for improvement, stating:

*"By utilizing the data of products that go to waste, we then look at historical data outcomes of the operation. And what happened to parameters such as forecasting? Was the forecast too high a week ago, or two weeks ago? Was that a contributor to the waste?"*

This quote suggests that AI can help to identify patterns and drivers of waste in the food system, enabling more targeted interventions to reduce waste and improve resource efficiency. Data scientist, Interviewee 2 echoes this potential, noting the value of connecting data across different stages of the food system to reduce waste, stating:

*"The stores know how much waste there is in stores, but farmers have no idea about that. If we could connect two databases, to make farmers learn what to produce and when to produce it. I think there is a lot of value in making this kind of connections."*

This quote emphasizes the importance of data integration and collaboration across the food system to enable more effective waste reduction strategies. To fully realize the potential of AI for waste reduction, it is important to develop integrated and collaborative approaches that span the entire food value chain.

**Theme 11: Governance**

The theme "Governance" emerged as a critical aspect of AI adoption and development in the Swedish food system. This theme refers to the various ways in which government and other regulatory bodies can shape the direction, pace, and impacts of AI technologies in the food sector. The code “Role of government in AI adoption” emphasizes the need for clear and effective frameworks to guide the responsible and equitable development and deployment of AI in the food system. "Governance" reflects the important role of government and other stakeholders in setting the overall direction and priorities for AI adoption in the food system. Researcher at SLU, Interviewee 1 highlights the need for government to establish the right conditions and incentives for AI adoption, stating:

*"I will say, depending on what role you want to see the government play, I don't think the government should interfere in private companies like this, but I think the government should put up, you know, use legislation, and so on, to create the settings of the system."*

This quote suggests that while the government should not directly intervene in the operations of private companies, it has an important role to play in creating an enabling environment for AI adoption through appropriate legislation and policy measures. Interviewee 14, manager at Tillväxtverket echoes the importance of government support for AI adoption, noting the role of innovation agencies in funding and scaling up successful projects, stating:

*"I think it's at the government level and there have been a lot of good initiatives on the Innovation Agency [like] Vinnova...But I think the challenge here is how to scale up and how to really make use of those like good cases where there has been a successful turnout from a project."*

This quote points to the need for government to not only provide initial funding and support for AI projects but also to help ensure that successful initiatives are scaled up and integrated into the broader food system. Interviewee 12, manager at BioAgri, provides an example of how regulations can drive the adoption of more sustainable practices, stating:

*"The reason for the seed-producing companies or customers to share our data is that there are political decisions to reduce the use of chemicals in agriculture."*

This quote suggests that regulations around chemical use in agriculture can create incentives for companies to adopt AI-enabled solutions that reduce the need for chemical inputs. Interviewee 3, active in food industry, emphasizes the potential for AI adoption to be driven by regulatory demands, stating:

*"I think it's going to be very much driven by either consumer or customer demands, or regulatory demands or that accompanies or cooperatives such as Arla seeing benefits in doing that."*

This quote highlights the important role that regulations can play in shaping the demand for AI solutions in the food system, alongside other drivers such as consumer preferences and business benefits. To ensure that regulations around AI in the food system are effective and appropriate, it is important to engage diverse stakeholders in the development and implementation of these rules and standards. By involving a wide range of perspectives and expertise in the regulatory process, it is possible to develop frameworks that are robust, transparent, and aligned with broader social and ethical values. Researcher at RISE, Interviewee 13 emphasizes the role of government in setting policies around data sharing and infrastructure, stating:

*"But infrastructure in the Communication and Data Society is more than roads and electricity, it's also building places where you can share the data."*

This quote suggests that government policies around data sharing and digital infrastructure are critical enablers of AI adoption in the food system. AI researcher at RISE, Mogren highlights the importance of addressing legal and ethical issues in AI policy, stating:

*"I usually talk about data readiness, and that includes legal issues. The legal issue is one thing to sort out to be able to work with the data and come up with a solution that's based on data and useful for someone."*

This quote reflects the need for AI policies to consider not only technical and economic factors but also the legal and ethical implications of data use and AI deployment in the food system. To develop effective and appropriate AI policies for the food system, it is important to take a multidimensional and integrated approach that considers the various dimensions and impacts of these technologies. This includes not only the technical and economic aspects of AI but also the social, ethical, and environmental implications. It also requires ongoing monitoring and evaluation of AI policies to ensure that they remain relevant and effective in the face of rapidly evolving technologies and changing societal needs and values.

**Theme 12: Ethical concerns**

The theme "Ethical concerns" emerged as a crucial consideration in the adoption and development of AI technologies in the Swedish food system. This theme emphasizes the various moral and ethical challenges associated with the responsible and equitable deployment of AI in the food sector, this indicates the need for careful consideration of the potential impacts and unintended consequences of AI on individuals, society, and the environment. The code "Ethical Concerns" stresses the importance of addressing the ethical implications of AI deployment in the food system. Researcher at RISE, Interviewee 7 raises the issue of responsibility and accountability in the use of AI, stating:

*"If we are going to be responsible for the information that we provide via an [AI] chatbot, we can't let it loose on the entire internet, quality insurance and updated information are very important."*

This quote suggests that developers and deployers of AI systems in the food sector have a ethical obligation to ensure the accuracy, reliability, and safety of the information and services provided by these systems. Interviewee 6, AI researcher and Vice President at AFRY, points out the ethical challenges associated with the use of autonomous systems in the food sector, stating:

*"If you go to the automated machines, the trolley problem in philosophy is a legal and ethical problem. So, illegally, if something happens, who is to be blamed? Software? Software writer? Farmers who use it?"*

This quote indicates the need for clear frameworks for responsibility and liability in the use of autonomous AI systems, to ensure that potential harm and damages can be properly addressed and compensated. To address ethical concerns in the deployment of AI in the food system, it is important to develop and implement robust ethical frameworks and guidelines. It also requires ongoing monitoring and assessment of AI systems to identify and mitigate potential ethical risks and harms, as well as mechanisms for stakeholder engagement and public participation in the governance of AI in the food sector. The code "Inequitable Power Dynamics" highlights the uneven distribution of power and influence among different actors in the food system. Addressing these inequitable power dynamics requires a focus on creating a more balanced and inclusive food system, where all actors have a fair opportunity to participate in and benefit from the AI-driven transformation of the sector. The code "Transforming human roles" draws attention to the potential for AI to fundamentally alter the nature and distribution of work in the food system, with significant ethical implications. Interviewee 3, manager in food industry, notes the potential for AI and automation to replace human labor in certain tasks, stating:

*"And for sure, you will probably get less and less physical in the future. I've seen it in China where they produce electric cars, and there is nobody in the factory. Everything is automated."*

This quote suggests that the adoption of AI in the food sector could lead to significant job displacement and economic disruption, raising important questions about the fair distribution of the benefits and costs of automation. Researcher at RISE, Interviewee 7 discusses the potential for AI to transform the role of agricultural advisors, stating:

*"I can feel that the College of Agricultural advisors in five or 10 years will sit and look at each other and don't know what hit them. Because then the farmers will be able to search for solutions by themselves."*

This quote indicates the need for proactive measures to support the transition of workers and communities affected by AI-driven job displacement, such as retraining programs, social safety nets, and inclusive economic development policies.

**Theme 13: Security and Privacy**

The theme "Security and Privacy" emerged as a critical consideration in the adoption and development of AI technologies in the Swedish food system. This theme covers various risks and challenges associated with ensuring the security and privacy of data and systems in the context of AI deployment. The code "Privacy concerns" demonstrates the importance of safeguarding personal and confidential information in the deployment of AI technologies in the food system. Interviewee 7, researcher at RISE, raises the issue of data privacy as a key challenge, stating:

*"The biggest problem is the legal aspects, who has the ownership of the data? Is this AI? Is it connected to the big Internet, what is happening there? That would be my biggest worry."*

This quote shows the need for clear and transparent frameworks around data ownership, access, and use in the context of AI deployment, to ensure that sensitive information is protected, and that individuals' privacy rights are respected. Interviewee 8, AI researcher at RISE, emphasizes the importance of considering privacy implications throughout the AI development and deployment process, not just in the training data, stating:

*"Training data is not the whole thing about integrity. We also have the question, like a camera that's supposed to detect weeds, does it also detect humans, can we be sure that all sorts of human traces are removed from this? That's of course also data."*

This quote suggests that privacy considerations need to be embedded in the design and implementation of AI systems from the outset, to ensure that sensitive information is not inadvertently collected or exposed. To address privacy concerns in the deployment of AI in the food system, it is important to develop and implement strong data governance frameworks and practices. This includes establishing clear policies and procedures around data collection, storage, and use, as well as implementing technical measures such as data encryption and access controls to prevent unauthorized access or disclosure of sensitive information. The code "Security and Traceability" highlights the importance of ensuring the security and integrity of AI systems and data in the food sector. Interviewee 6, AI researcher and Vice President at AFRY emphasizes the need for robust cybersecurity measures to protect against attacks and data breaches, stating:

*"We should cyber secure our agriculture and AI immediately. Don't assume that people don't attack agriculture. And we should be very careful about data security in the food system."*

This quote emphasizes the critical importance of securing AI systems and data in the food sector, given the potential impacts of security breaches on food safety, supply chain integrity, and public trust. To ensure the security and traceability of AI systems in the food sector, it is important to adopt a comprehensive and proactive approach to risk management. This includes conducting regular risk assessments and penetration testing to identify and mitigate potential vulnerabilities, as well as implementing incident response and disaster recovery plans to minimize the impact of security breaches or system failures.

The inclusion of themes such as "AI and Sustainable Food Systems," "Governance," and "Security and Privacy" under the ethical level of the STST framework may seem unconventional at first glance. However, these themes are intrinsically linked to the ethical dimensions of AI adoption in the Swedish food system. The development and deployment of AI technologies in the food system raise important ethical questions related to their impact on sustainability, the distribution of benefits and risks, and the governance frameworks needed to ensure responsible and equitable adoption. Similarly, concerns around data security and privacy are closely tied to ethical considerations of data ownership, control, and the potential for misuse or unintended consequences. To better understand and visualize these relationships, a diagram (Figure 15) was created based on the extended STST framework, with the addition of two new levels: Economic and Ethical.

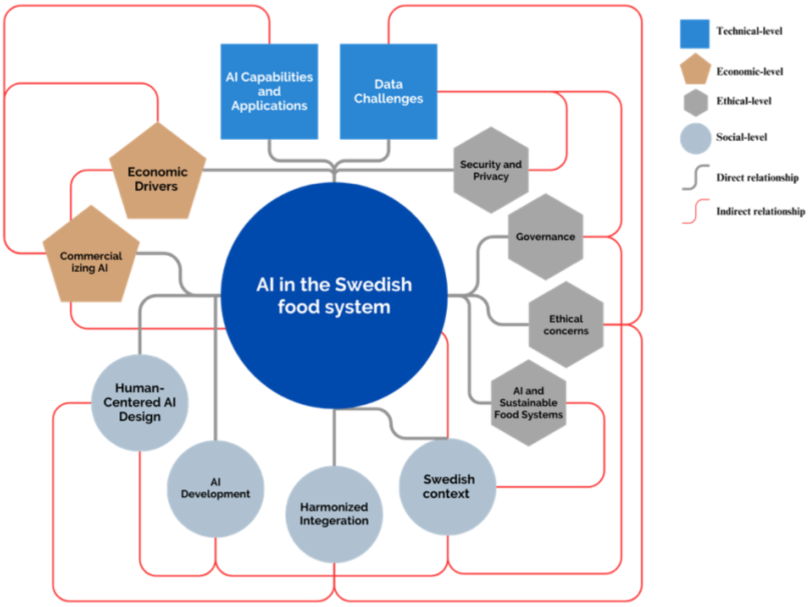



*Figure 15. A conceptual framework illustrating the relationships between extracted factors influencing AI in the Swedish food system, based on the extended STST (Own elaboration).*

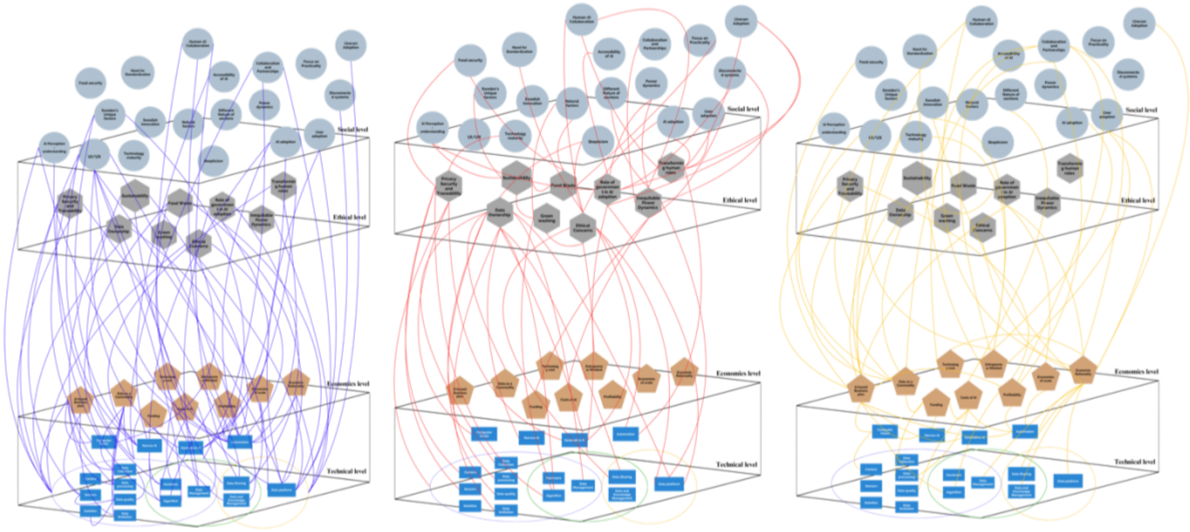
Figure 15 illustrates the interconnectedness of the themes identified in the analysis, demonstrating both direct and indirect relationships. The central node, "AI in the Swedish food system," represents the main focus of the research, while the surrounding nodes show the various themes that emerged from the analysis. The direct relationships, represented by the solid lines, show the immediate connection between each theme and the central node. For example, "AI Capabilities and Applications" and "Data Challenges" are directly linked to the main system, as they represent the technical aspects of AI implementation in the Swedish food system. However, the indirect relationships (red lines) in the diagram also demonstrate the complexity of the relationships between the themes themselves. These indirect relationships demonstrate how factors from different levels of the STST framework interact with and influence each other. For instance, "Ethical Concerns," which is related to the ethical level, indirectly influences "Data Challenges," a technical-level theme. This relationship indicates the importance of considering ethical implications when addressing data-related challenges in AI implementation.

The diagram also emphasizes the importance of "Harmonized Integration," a theme that covers various factors crucial for the successful adoption and development of AI in the Swedish food system. This theme is connected to multiple levels of the STST framework, including the "Need for Standardization," "Disconnected systems", social level ("Human-AI Collaboration," "Focus on Practicality"), and economic level. The centrality of "Harmonized Integration" in the diagram indicates the need for a unified and coordinated approach to AI implementation that takes into account the diverse needs, challenges, and opportunities facing different stakeholders in the food sector.

In conclusion, the thematic analysis and the accompanying diagram provide a broad overview of the factors influencing AI adoption and development in the Swedish food system. By visualizing both direct and indirect relationships between themes, the diagram helps to clarify the complex interplay of technical, economic, ethical, and social factors that shape the implementation of AI in this context.

## 5.5 Output of the extended STST

This study developed a new STST model according to the information gathered in the literature review and semi-structured interviews, which is unique to analyzing the AI dynamics in the Swedish food system. As mentioned in the Theoretical framework section, this new model expands the traditional STST model with two more levels, the economic level and the ethic level. Compared with previous studies, some findings of this study align with the conclusion of others, but this one explored deeper. The outputs from this analysis were then utilized to address the research questions, as depicted in Figure 16.



Connection of the technical factors to other levels

Connection of the ethical factors to other levels

Connection of the economic factors to other levels

*Figure 16. Analysis of the connection of levels according to the extended STST (Own elaboration).*

Our study provides a deeper understanding of AI adoption in the Swedish food system compared to the 8-dimension model proposed by Weger & Yeazitzis (2023). While both studies acknowledge the importance of UI/UX and human-centered design, our findings emphasize the need for AI products to be intuitively usable without extensive training. This customer-focused approach prioritizes user experience beyond mere technological performance. Additionally, our study highlights the prevalence of "Skepticism" and "AI Perception-understanding" among potential users, indicating a need for education and clear communication about AI's benefits. This aligns with their emphasis on users' insufficient knowledge in the factor of "people", but we suggest finding a balance between education to users and user-friendly tools to minimize the learning burden for end users. Furthermore, our research identifies the significant role of "Governance" in shaping the AI landscape. Government and regulatory bodies can influence innovation, funding, data infrastructure, and scaling up AI adoption. This echoes the "external rule, regulations, and forces" factor in their model, emphasizing the need for government involvement in facilitating AI development within the Swedish food system. Finally, while they consider "content", including some data and knowledge which are mainly related to the use in the technical aspect, our study specifically emphasizes the crucial role of data in the Swedish food context as content in different aspects. Data emerges as a multifaceted issue, encompassing technical challenges like collection, management, sharing, quality, and segmentation, as well as economic considerations like data as an asset and ethical concerns like ownership, sharing, and privacy. In summary, our study both aligns with and extends beyond the 8-dimension model, offering a more nuanced understanding of the factors influencing AI adoption within the unique context of the Swedish food system.

Our study's findings align in some ways with the findings of Haefner et al. (2023) for AI adoption, yet notable differences arise due to the unique context of the Swedish food system and the early stage of AI adoption therein. While they focused on organizational-level adoption and different phases of AI maturity, our study examined the broader food system and its current adoption landscape, where few actors have reached advanced stages like "productionizing" or "platforming." In terms of technical aspects, both studies highlight the importance of data. However, our study delves deeper into the multifaceted nature of data challenges, encompassing not only technical obstacles but also economic use and ethical concerns. Additionally, while they emphasize technical infrastructure in terms of AI system development, our study emphasizes shared data platforms within the food system as crucial infrastructure. Regarding the AI model itself, they recommend simple and open-source models, whereas our findings reveal that AI model development is intertwined with social factors. The unique dynamics and factors of the Swedish food system necessitate developing AI models tailored to the Swedish context, indicating a social dimension to the technical development of AI. In the social aspect, both studies recognize the importance of demonstrating AI's benefits to stakeholders. However, our study highlights the codes "Economic Rationality as a Driver" and "Marketing AI products," emphasizing that companies and farmers need tangible evidence of AI's potential for profit and improvement in the Swedish food system. This reflects the need for context-specific communication and marketing strategies in the early stages of AI adoption.

The ethical considerations surrounding AI adoption in the Swedish food system emerged as a critical theme in the interviews. Concerns were raised about data privacy, ownership, and control, as well as the security and transparency of AI decision-making processes. The need for responsible and inclusive AI development, which takes into account the potential biases and power asymmetries in data collection and algorithm design, was highlighted as a key challenge. The research also stressed the importance of establishing clear ethical guidelines and governance frameworks for AI in the food system, to ensure that its benefits are distributed equitably, and its risks are mitigated. Finally, the expanded STST framework provided a holistic lens to analyze the interdependencies and interactions between the technical, economic, social, and ethical dimensions of AI adoption in the Swedish food system.

# 6 Analysis and discussions

*This section addresses the research questions by examining and interpreting the results of the Literature Review, the thematic analysis of the Interviews and the output analysis of the extended STST.*

The application of AI technologies in the Swedish food system, particularly in primary production, presents a complex interplay of actors, relationships, and dynamics that span across the technical, economic, social, and ethical levels of the extended socio-technical system framework. This section provides insights into the current state and future potential of AI in this context. By employing an extended version of the socio-technical system theory as a framework, we aim to address the research questions.

## 6.1 Positioning AI in the Swedish Food System: Early Adoption Phase

Through analysis of the findings, the researchers gained insights into how AI is disrupting the traditional food system. The theory of disruptive innovation, supported by the findings, provides a lens for understanding the current position and future potential of AI in the Swedish food system. Based on the analysis, it is evident that AI in the Swedish food system is currently positioned in the "Early Adopters" stage Figure 17.


*Figure 17. The current position of AI in the Swedish food system (Own elaboration).*

The analysis revealed that while there is growing interest and experimentation with AI technologies among researchers, innovative farmers and food companies, but widespread adoption is still limited. Early adopters are pioneering the use of AI in various applications, such as precision farming, crop disease detection, and supply chain management. However, the majority of the food system actors, particularly small-scale farmers and traditional food processors, are yet to fully embrace AI. The position of AI in the Early Adopters phase can be attributed to several factors identified in the analysis. Firstly, the level of AI maturity in the Swedish food system is still relatively low. While there are several cases of advanced AI development and implementation, particularly in research institutions like RISE and large agri-food companies like Arla, the overall level of AI knowledge and skills among food system actors is limited. This is partly due to the lack of understanding of AI capabilities and partly due to the perceived complexity and cost of implementing AI solutions.

Economic dynamics also impact the adoption of AI in the Swedish food system. The high cost of AI technologies, particularly for small-scale farmers and food businesses, is a significant barrier to widespread adoption. The analysis revealed that many actors are hesitant to invest in AI due to uncertain returns on investment and the lack of clear business models. Additionally, the fragmented nature of the food system, with many small players operating in isolation, makes it challenging to develop scalable and profitable AI solutions. Social factors play a crucial role in shaping the adoption of AI in the Swedish food system. The analysis revealed a lack of public awareness and understanding of AI, which can lead to mistrust and resistance to adoption. Addressing these social barriers requires a multi-faceted approach, including education and outreach programs to raise awareness about the potential benefits of AI, as well as the development of user-friendly and transparent AI solutions that are tailored to the specific needs and contexts of different actors in the food system.

Ethical considerations are becoming increasingly important as AI advances in the Swedish food system. The findings revealed concerns about data privacy, algorithmic bias, and the transparency of AI decision-making processes. As AI systems become more complex and autonomous, there is a risk that they could reinforce or amplify existing inequalities in the food system. Ensuring that AI is developed and deployed in an ethical and responsible manner, with appropriate governance frameworks and public oversight, is critical for building trust and acceptance.

As AI technologies mature and become more affordable and user-friendly, we can expect to see wider adoption across the food system. This transition will require significant efforts to address the challenges identified in the research, such as improving data availability and quality, developing standardized data-sharing protocols, and creating viable business models that incentivize AI adoption. The transition from Early Adopters to Early Majority is anticipated to be more rapid than previously estimated, potentially occurring within the next five years. This acceleration can be attributed to the increasing awareness of AI's potential benefits, the declining costs of AI technologies, and the growing availability of user-friendly AI solutions tailored to the specific needs of the Swedish food system.

## 6.2 From Narrow AI to Big Data

The technical aspects of AI in the Swedish food system can be categorized into three main circles (categories), as illustrated in Figure 18. The first circle consists of sensors and digital devices that gather, produce, and store data. In this circle, the focus is on field devices, gadgets, and the foundational database, with data serving as input to mostly narrow AI applications. The concept of narrow AI is particularly relevant in the Swedish context, as many interviewees emphasized their focus on using narrow AI in their research or businesses. This finding aligns with the Swedish perspective on innovation, which emphasizes incremental changes with practical benefits. The adoption of narrow AI in the first technical circle is closely linked to the economic level, as it is more affordable, easier to implement, and can be integrated into existing products and processes. For example, an interviewee mentioned the use of AI-enhanced cameras in farms, which enable farmers to analyze crops and livestock health more effectively, potentially leading to increased productivity and profitability.

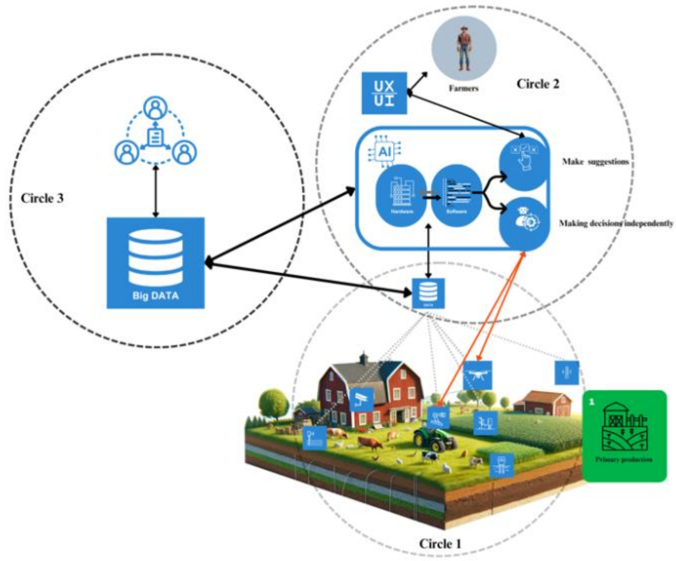



*Figure 18. Three identified circles of technical level (Own elaboration).*

The second circle consists of the core AI components, such as algorithms and hardware for data analysis, and the outputs of this system. User interface (UI) plays a crucial role in this circle, as it determines how easily users can interact with and benefit from AI systems. The relationship between the first and second technical circles highlights the importance of data quality, data collection, and interoperability for the effective functioning of AI systems. The third circle is based on big data, which includes multiple dependent data stores. In this circle, the concept of data sharing is crucial, as the main focus is on strong AI (general AI) and knowledge management. The main challenges regarding data sharing are revealed in this circle, as the development and deployment of strong AI require access to vast amounts of high-quality, diverse, and accurate data.

Our findings suggest that one way to address the challenges of sharing raw data, which can be problematic due to privacy and security concerns, is to share the output of analyzed data instead. This approach can also lead to reduced energy consumption, as analyzing data individually can be computationally intensive and energy-consuming. The third technical circle emphasizes the importance of connectivity, data sharing, big data utilization, and harmonizing data flow for the successful adoption of AI in the Swedish food system. These aspects are closely linked to the social and ethical levels of the STST framework, as they require the development of trust, collaboration, and governance mechanisms among stakeholders. For example, the development of secure and transparent data-sharing platforms, as well as the establishment of data governance frameworks that guarantee privacy, security, and ethical use of data, are crucial for promoting collaboration and innovation in the Swedish food system. The relationships and dynamics between the three technical circles and the other levels of the STST framework indicate the need for a unified and integrated approach to AI adoption in the Swedish food system.

## 6.3 Computer Vision: A Key Driver of Innovation in the Swedish Food System

The research reveals that computer vision is one of the most prevalent AI technologies in Sweden, with numerous applications across various sectors, including the food system. As discussed earlier, computer vision can be easily integrated into existing systems, and its outputs are highly precise and valuable. Many interviewees mentioned the potential of computer vision in enhancing agricultural practices, such as crop monitoring, yield prediction, and livestock management. For instance, computer vision can be used to monitor crop health and identify early signs of disease or pests, enabling farmers to take timely action and prevent yield losses. It can also be used to analyze images of livestock to assess their health and well-being, leading to improved animal welfare and productivity. The widespread adoption of computer vision in the Swedish food system can be attributed to several factors. First, the technology is relatively accessible and easy to implement, making it an attractive option for farmers and other stakeholders in the food system. Second, the outputs of computer vision systems are readily interpretable and actionable, enabling users to make informed decisions quickly. Finally, the potential applications of computer vision extend beyond the food system, such as in surveillance and security, making it a versatile technology with a wide range of use cases.

The adoption of computer vision in the Swedish food system has the potential to create new business opportunities and drive innovation. As more farmers and other stakeholders recognize the benefits of computer vision, there is a growing demand for AI services and solutions tailored to the specific needs of the food system. As Interviewee 20, a farmer, beekeeper, and researcher who's developing a program that uses drones and computer vision to identify unwanted weeds, said:

*"When I saw the results of this computer vision technology – what some people call AI – I was amazed. It was almost 90% accurate! That helped me secure funding, and now we're expanding the project in collaboration with other farmers and researchers. It's truly remarkable!"*

This presents opportunities for technology providers, startups, and other innovators to develop and market new computer vision applications that address the unique challenges and requirements of the sector. For example, some companies are already developing AI-powered drones that can survey crops and collect data on their health and growth, while others are developing computer vision systems that can automatically identify and sort different types of produce.

## 6.4 Automation in Primary Production: Addressing Labor Challenges

Automation is another key area of AI application in the Swedish food system, with significant implications for primary production. The potential benefits of automation in the agricultural sector are particularly relevant in the Swedish context, where the majority of actors in primary production are small family-owned companies. This contrasts with other countries, such as the United States, where large corporations dominate the farming landscape. The socio-economic characteristics of Swedish agriculture have important implications for the adoption of automation technologies.

According to the Swedish Agriculture Ministry (Jordbruksverket, 2023), the workforce in this sector is aging, and younger generations are showing less interest in pursuing farming as a career. This demographic shift presents significant challenges for the long-term sustainability and resilience of the Swedish food system. In this context, automation emerges as a key solution to address the challenges associated with an aging farming population and declining interest among younger generations. By automating various agricultural tasks, such as planting, harvesting, and monitoring, automation technologies can help reduce the physical burden on farmers and make farming more attractive to younger generations. Moreover, automation can help address the labor shortages that many Swedish farms are currently facing. By reducing the need for manual labor, automation technologies can help ensure the continuity of agricultural operations even in the face of declining workforce participation. This is particularly important for small family-owned farms, which may struggle to attract and retain workers in a competitive labor market.

However, the adoption of automation technologies in the food system is not without its challenges. One of the main barriers is the high cost associated with investing in automation equipment, such as self-driving tractors. While these technologies can offer significant long-term benefits, such as increased efficiency and productivity, the upfront investment can be prohibitive for many small-scale farmers. This highlights the importance of considering the economic level of the extended STST framework when analyzing the adoption of automation technologies in Swedish agriculture. The high cost of automation equipment can be a significant barrier for small family-owned farms, which may lack the financial resources to make such investments. This can lead to a widening gap between larger, well-capitalized farms and smaller, resource-constrained operations, potentially worsening existing inequalities in the Swedish food system.

To address these challenges, policymakers and other stakeholders in the Swedish food system should consider a range of measures to support the adoption of automation technologies among small-scale farmers (and other actors). This could include financial incentives, such as subsidies or low-interest loans, to help farmers overcome the initial investment hurdle. Additionally, the development of shared infrastructure, such as cooperative ownership models for automation equipment, could help reduce the financial burden on individual farmers. Several interviewees explained that they do not believe that direct financial support from the government is a proper strategy. Instead, they suggest that the government should focus on creating a supportive environment for innovation and collaboration, such as by investing in research and development, promoting knowledge sharing, and facilitating partnerships between farmers, technology providers, and other stakeholders.

## 6.5 Updating the Swedish Food Value Chain: Novel Food and Food Waste

The application of AI in novel food production methods is rapidly gaining momentum, with numerous research projects and startups exploring innovative ways to leverage AI technologies in the development of novel food products (Barthwal et al., 2024; Kamalapuram & Choudhury, 2024). One of the most promising areas is the use of AI for protein extraction and the production of lab-grown meat (Ghosh & Mitra, 2024; Kamalapuram & Choudhury, 2024). AI algorithms can aid in streamlining the process of extracting proteins from various sources, including plants, insects, and even algae (Bedoya et al., 2022; Helmy et al., 2023; Neo et al., 2023). By analyzing vast amounts of data on protein sources, AI can help identify the most suitable extraction methods and conditions, leading to higher yields and improved protein quality (Dong et al., 2012). In the context of lab-grown meat, AI algorithms and machine learning techniques can be used to optimize the growth conditions for cells, leading to the production of meat products that closely mimic the texture, flavor, and nutritional profile of conventionally produced meat (Kamalapuram & Choudhury, 2024; Ng & Tan, 2024). As Interviewee 6, AI researcher mentioned:

*"We need proteins, and [we] don't get enough of the good proteins and the right ones. We want to create the right and enough kind of proteins from other sources. So, there are a lot of tricky scientific problems. There is a lot of very interesting and complicated science where AI can make it faster."*

This has significant implications for the sustainability and ethical dimensions of meat production, as lab-grown meat has the potential to reduce the environmental impact and animal welfare concerns associated with traditional livestock farming (Bryant and Barnett, 2020). In addition to protein extraction, AI can also be applied in the development of new food products that combine different ingredients and nutrients in novel ways. For example, AI algorithms can help identify optimal combinations of plant-based ingredients to create new food products with desired nutritional profiles and sensory characteristics (Bedoya et al., 2022; Mengucci et al., 2022).

The application of AI in managing food waste is another area of growing interest. Food waste is a significant challenge across the entire food chain, almost 1.33 billion tons of food are wasted every year roughly equal to 750 billion USD (Cho, BCIT School of Health Sciences and Heacock, 2020). AI technologies can help address this challenge by enabling more precise monitoring and prediction of food waste at different stages of the food chain (Onyeaka et al., 2023). AI algorithms can analyze data on crop growth, weather patterns, and market demand to help farmers optimize their harvesting and distribution strategies, reducing waste at the primary production stage (Pathan et al., 2020). Similarly, AI can be applied in the retail and consumer sectors to help optimize inventory management, reduce spoilage, and encourage more sustainable consumption patterns, as Interviewee 16, manager at trade section (ICA) mentioned that they are already using these tools.

Recognizing the growing importance of novel food and food waste management in the Swedish food system, the authors have updated the traditional Swedish food value chain to include these emerging sections (Figure 19).

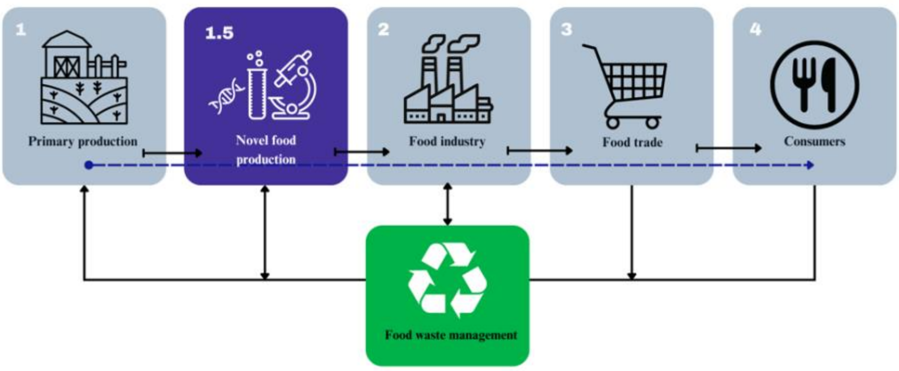



*Figure 19 Updated Swedish Food Chain (Own elaboration).*

By acknowledging the role of experimental food and food waste management in the food chain, we aim to highlight the potential of AI technologies to drive innovation and sustainability across the entire food system. An approach that considers the entire food chain, from farm to fork, is necessary to fully realize the potential benefits of AI, rather than focusing solely on primary production or traditional food processing. The growing application of AI represents a significant opportunity for the Swedish food system to drive innovation, sustainability, and resilience. By updating the traditional Swedish food system to include these emerging areas, we emphasize the potential of AI technologies to transform the entire food system, from primary production to consumption.

## 6.6 Answering RQ1: AI Applications in Global and Swedish Food Systems

The first research question (RQ1) explores how AI technologies are applied in global food systems and the opportunities and challenges for leveraging these technologies within Sweden's food system, with a focus on primary production. The literature review revealed a wide range of AI applications in global food systems, spanning from precision agriculture and yield prediction to supply chain optimization, food waste reduction, and customized nutrition. These applications leverage various AI techniques, such as machine learning, computer vision, and robotics, to enhance efficiency, productivity, and sustainability in different stages of the food value chain. For instance, precision agriculture technologies, such as sensor-based crop monitoring and autonomous tractors, have shown significant potential to optimize resource use, reduce environmental impacts, and improve crop yields(Peruzzi et al., 2012; Pantazi et al., 2016; Partel, Charan Kakarla and Ampatzidis, 2019). Similarly, AI-powered supply chain management systems have demonstrated their ability to streamline logistics, reduce food waste, and improve traceability and food safety (Smith et al., 2022).

The findings provided valuable insights into the specific opportunities and challenges for AI adoption in the Swedish food system. At the technical level, findings indicated the importance of narrow AI applications, such as computer vision for crop monitoring and robotics for automation, which can be easily integrated into existing farming practices. The modular and scalable nature of these technologies was seen as a key enabler for their wider adoption, particularly among small-scale farmers. However, the findings also revealed technical challenges related to data availability and quality, which can hinder the development and deployment of AI solutions in the Swedish food system. The fragmented nature of data sources and the lack of standardized data formats pose significant obstacles to the effective utilization of data for AI applications.

At the economic level, the research identified both opportunities and barriers for AI adoption. On the one hand, AI technologies were seen as potential drivers for increased productivity, profitability, and competitiveness in the Swedish food sector. The ability to optimize resource use, reduce labor costs, and create new value-added services through AI was highlighted as a significant opportunity. On the other hand, the high upfront costs of AI technologies, coupled with the lack of clear business models and return on investment, were identified as major barriers to adoption, particularly for small-scale farmers and food businesses. The economic viability of AI solutions remains a critical concern, especially in a context where many actors in the food system operate with limited resources and face financial constraints.

The social dimension of AI adoption in the Swedish food system was also prominently featured in the discussions. The research recognized the potential of AI to attract younger generations to agriculture by making farming more technology-driven and data-oriented. The importance of engaging farmers and other stakeholders in the design and implementation of AI solutions was also emphasized to ensure their alignment with local needs, knowledge, and practices. However, the interviews also revealed social barriers to AI adoption, such as skepticism and mistrust among some farmers, as well as concerns about the potential impact of AI on employment and traditional farming practices. Building trust and addressing these social concerns through education, outreach, and participatory approaches are crucial for the successful integration of AI in the Swedish food system.

## 6.7 Data and Harmony of the System

The findings of this research emphasize the critical role that data plays in the successful implementation and harmonization of AI in the Swedish food system. The importance of data and its interconnectedness with various actors and challenges across different levels of the STS framework emerged as a significant theme in the interviews. By examining these relationships and considering the relevant academic literature, we address the second research question (RQ2) and provide insights into how data influences the adoption and integration of AI in the Swedish food system.

At the technical level, the availability, quality, and interoperability of data are fundamental prerequisites for developing and deploying AI solutions. The findings revealed that the Swedish food system generates vast amounts of data from various sources, such as sensors, machines, and digital platforms. However, the main issue is the segmentation of databases, as Interviewee 5 stated:

"...but then we realized, okay, data is scattered over 10 different platforms."

However, the lack of standardized data formats, protocols, and infrastructures often hinders the effective utilization of this data for AI applications. As noted by Wolfert et al., (2017), the fragmented nature of data in the agri-food sector poses significant challenges for developing interoperable and scalable AI solutions. Addressing these technical barriers requires collaborative efforts among all stakeholders to establish common data standards, APIs[11], and platforms that enable seamless data sharing and integration across the food value chain.

The social and ethical dimensions of data in the Swedish food system are closely intertwined with the technical aspects. The interviews highlighted concerns among farmers and other food system actors about data ownership, privacy, and security. The fear of losing control over their data and the potential misuse of sensitive information by third parties can hinder the willingness of actors to share their data for AI applications (Fielke, Taylor and Jakku, 2020). Ensuring that AI algorithms do not perpetuate or amplify existing biases and inequalities in the food system requires robust ethical frameworks and governance mechanisms that prioritize the responsible and inclusive use of data (Ryan, 2023).

The economic level of the STS framework also influences the dynamics of data in the Swedish food system. The interviews identified the concept of "data as a commodity" as a potential incentive for farmers and other actors to share their data for AI applications. By recognizing the value of their data as an asset, farmers could benefit from new revenue streams and business models that leverage their data for AI-driven services and solutions. However, this also raises questions about the fair distribution of benefits and the potential for data exploitation, which need to be addressed through appropriate governance mechanisms and ethical guidelines.

The harmonized implementation of AI in the Swedish food system relies heavily on the efficient flow and integration of data across different levels and actors. The interviews emphasized the need for collaborative data-sharing platforms and ecosystems that enable multiple stakeholders, including farmers, technology providers, researchers, and policymakers, to access and utilize data for AI development and deployment. The concept of "data connectivity" or "data sharing" has emerged as a promising approach to facilitate data sharing

[11] API stands for Application Programming Interface. It's a set of rules and specifications that allows different software programs to communicate with each other, enabling them to share data and functionality.

while ensuring data sovereignty, privacy, and security. This approach involves creating secure and transparent platforms where data can be shared and accessed by authorized parties, while still allowing data owners to retain control over their data and benefit from its use.

## 6.8 Answering RQ2: An Integrated Strategy for Harmonizing AI Adoption

To address the second research question (RQ2) and develop an integrated strategy for harmonizing AI adoption throughout Sweden's food system, it is crucial to consider the key factors identified in the updated socio-technical system (STS) framework. Along with the results from the literature review and thematic analysis of interviews, this study gives us useful information about how technical, economic, social, and ethical factors interact to affect the use of AI in the Swedish food system.

At the technical level, the development of a harmonized AI strategy requires a focus on interoperability, scalability, and modularity. The interviews emphasized the importance of narrow AI applications, which can be easily integrated into existing systems and processes. These applications should be designed to be adaptable and scalable, allowing for gradual adoption and integration across different sectors and scales of operation. Additionally, the development of standardized data formats, protocols, and APIs is crucial for ensuring seamless data sharing and interoperability between different AI systems and platforms. This will enable the creation of a unified data ecosystem that can support the development and deployment of AI solutions across the entire food system.

The economic dimension plays a crucial role in shaping the adoption of AI in the Swedish food system. The high cost of AI technologies and the lack of clear business models were identified as significant barriers to adoption. The recognition of data as a valuable asset and the creation of fair and transparent data markets can provide incentives for farmers to share their data and participate in AI-driven value chains. However, it is important to acknowledge that economic incentives alone may not be sufficient to drive widespread AI adoption. The interviews revealed that many farmers are hesitant to share their data due to concerns about privacy, security, and potential misuse. Therefore, a balanced approach that combines economic incentives with robust data governance frameworks and ethical guidelines is necessary to ensure the responsible and equitable use of data in the Swedish food system.

The social dimension of AI adoption in the Swedish food system was also prominently featured in the discussions. The research recognized the potential of AI to attract younger generations to agriculture by making farming more technology-driven and data-oriented. The importance of engaging farmers and other stakeholders in the design and implementation of AI solutions was also emphasized to ensure their alignment with local needs, knowledge, and practices. However, the interviews also revealed social barriers to AI adoption, such as skepticism and mistrust among some farmers, as well as concerns about the potential impact of AI on employment and traditional farming practices. Building trust and addressing these social concerns through education, outreach, and participatory approaches are crucial for the successful integration of AI in the Swedish food system. This requires a shift in mindset from viewing AI as a threat to employment to recognizing it as a tool that can enhance human capabilities and improve working conditions. Ethical considerations surrounding AI adoption in the Swedish food system emerged as a critical theme in the interviews. Concerns were raised about data privacy, ownership, and control, as well as the security and transparency of AI decision-making processes. The need for responsible and inclusive AI development, which takes into account the potential biases and power asymmetries in data collection and algorithm design, was highlighted as a key challenge. The research also stressed the importance of establishing clear ethical guidelines and governance frameworks for AI in the food system, to ensure that its benefits are distributed equitably, and its risks are mitigated. This includes addressing issues such as algorithmic bias, ensuring transparency and explainability of AI systems, and establishing mechanisms for accountability and redress in case of unintended consequences.

The expanded STS framework provided a lens to analyze the interdependencies and interactions between the technical, economic, social, and ethical dimensions of AI adoption in the Swedish food system. The framework emphasizes the importance of considering not only the technological aspects of AI but also the broader institutional, regulatory, and cultural contexts that shape its development and deployment. The harmonized adoption of AI in the Swedish food system requires a unified and systemic approach that takes into account the interdependencies and synergies between different levels and actors. The interviews emphasized the importance of collaborative innovation networks and platforms that bring together farmers, technology providers, researchers, policymakers, and civil society organizations to co-create and co-implement AI solutions. The development of living labs, innovation hubs, and demonstration projects can provide spaces for experimentation, learning, and scaling of AI technologies, while fostering trust and mutual understanding among stakeholders.

To operationalize these insights into an integrated strategy, policymakers and practitioners should consider the following key actions:

1. Develop a national AI strategy for the food system that sets clear goals, priorities, and principles for the responsible and inclusive adoption of AI, aligned with the Sustainable Development Goals (SDGs) and the European Green Deal (Anon. n.d.).

2. Invest in research and innovation programs that focus on the development of interoperable, modular, and user-friendly AI solutions, as well as the assessment and mitigation of their social, ethical, and environmental impacts.

3. Facilitate the development of collaborative data infrastructures and platforms that enable the secure and transparent sharing of both raw and analyzed data across the food chain, while ensuring the protection of personal and sensitive information. Sharing analyzed data, in addition to raw data, reduces privacy risks, decreases energy consumption from redundant computations, fosters harmonized AI development, and accelerates the refinement of efficient algorithms.

4. Provide training programs that enhance the digital and AI literacy of farmers, food businesses, and consumers, and support the development of new skills and competencies required for the adoption of AI technologies.

5. Develop innovative financing and business models that incentivize the adoption of AI solutions, particularly among small-scale and resource-poor farmers, and promote the equitable distribution of benefits and risks.

The development of an integrated strategy for harmonizing AI adoption throughout Sweden's food system requires a broad and participatory approach that considers the complex interplay of technical, economic, social, and ethical factors. The proposed actions provide a roadmap for operationalizing these insights and building a more sustainable, resilient, and equitable food system in Sweden and beyond.

# 7 Conclusion

*This concluding section begins with a concise overview of the study, followed by a focused summary of the findings from the analysis and discussions. Practical and theoretical implications arising from the study are then detailed and explored. Finally, limitations are acknowledged and potential avenues for future research are outlined.*

This study offers an analysis of the role and potential of artificial intelligence (AI) in transforming the Swedish food system, with a particular focus on primary production. Through an exploration of the technical, economic, social, and ethical dimensions, this research provides valuable insights and a nuanced understanding of the opportunities and challenges associated with AI adoption in this vital sector. The findings reveal that while AI technologies are increasingly being recognized as a transformative force in the Swedish food system, their widespread adoption remains limited, positioning AI in the early adopter phase. Technical challenges, such as data availability, quality, and interoperability, hinder the effective development and deployment of AI solutions. Economic constraints, including high implementation costs and the lack of clear business models, present significant barriers, particularly for small-scale actors. Furthermore, social factors, such as skepticism, lack of awareness, and concerns about the impact on traditional practices, contribute to the resistance and slow adoption of AI. However, this study also highlights the immense potential of AI to drive innovation, sustainability, and resilience within the Swedish food system. From precision agriculture and autonomous farming to novel food production and waste reduction, AI offers a wide range of applications that can optimize resource use, enhance productivity, and address pressing challenges such as food security and environmental impact.

A key contribution of this research is the expansion of the Socio-Technical System Theory (STST) framework to include economic and ethical levels. This expanded framework provides a broad lens for analyzing the complex interplay between technical, social, economic, and ethical factors shaping AI adoption in the food system. The study emphasizes the critical role of data governance, ethical frameworks, and inclusive innovation processes in ensuring the responsible and equitable development and deployment of AI technologies.

## 7.1 Practical implications

The findings of this study have practical implications for stakeholders in the Swedish food system. For policymakers, the research emphasizes the need for coherent and adaptive governance frameworks that can guide the responsible development and deployment of AI technologies in the agri-food sector. This includes the development of data sharing protocols, ethical guidelines, and support mechanisms that enable the equitable distribution of the benefits and risks associated with AI adoption. For industry actors, the study provides insights into the opportunities and challenges of implementing AI solutions in the Swedish context. It emphasizes the importance of designing user-centric and context-specific AI applications that are mindful of the needs and constraints of farmers and other actors in the food system. The research also underscores the potential for collaborative innovation models, such as public-private partnerships and living labs, to facilitate the co-creation and scaling of AI technologies.

For researchers and practitioners, the study offers a novel conceptual framework that can guide further investigations into the complex interplay between technology, society, economy, and ethics in the context of AI and food systems. The expanded STS framework provides a tool for analyzing the multi-dimensional impacts and implications of AI adoption, and for informing the design of responsible and inclusive innovation processes.

## 7.2 Theoretical implications

This study makes several theoretical contributions. Firstly, it extends the traditional STS framework by incorporating economic and ethical dimensions, thereby providing a more detailed understanding of the factors shaping the adoption and impact of AI in complex socio-technical systems like the food system. This expanded framework can serve as a conceptual tool for future research on the societal implications of AI and other emerging technologies.

Secondly, the study contributes to the growing body of literature on responsible innovation and the governance of AI. By recognizing the importance of inclusive, participatory, and value-sensitive innovation processes, the research provides empirical support for the need to align AI development with broader societal goals and values. It also clarifies the critical role of multi-stakeholder collaboration and dialogue in navigating the ethical and social challenges posed by AI.

Finally, the study advances understanding of the specific opportunities and challenges associated with AI adoption in the context of the Swedish food system. By providing a detailed analysis of the technical, economic, social, and ethical factors shaping AI integration in this sector, the research contributes to the development of context-specific theories and strategies for the responsible and effective deployment of AI in agri-food systems.

## 7.3 Limitations and future research

The research focuses mainly on the context of primary production, and while it considers the broader food system, it does not provide a detailed analysis of AI applications in other sectors such as food industry, food trade, and consumption. Future research could extend the scope of analysis to provide a more detailed understanding of AI integration across the entire food value chain.

The study relies on a qualitative methodology, drawing on insights from a literature review and interviews. While this approach allows for a deep understanding of the complex factors shaping AI adoption, it also limits the generalizability of the findings. Future research could employ quantitative methods, such as surveys or economic modeling, to provide a more representative and scalable analysis of AI impacts and implications. Also, the study is situated within the specific context of the Swedish food system, and while it offers lessons for other countries and regions, it is important to recognize the unique social, economic, and political factors that shape AI adoption in different contexts. Future research could undertake comparative analyses across different national or regional food systems to identify common patterns and context-specific challenges and opportunities for AI integration.

In conclusion, this study provides a timely contribution to our understanding of the role and potential of AI in transforming the Swedish food system. By adopting the expanded STS framework and gaining insights from a diverse range of stakeholders, the research offers a deep analysis of the technical, economic, social, and ethical factors shaping AI adoption in this context. The findings of the study have practical and theoretical implications, and indicate the need for collaborative, inclusive, and responsible innovation processes that can leverage the benefits of AI while navigating its challenges. AI is about to revolutionize the food system globally, and Sweden, with its innovative spirit and strong focus on sustainability, has the potential to be the pioneer of this transformation.

## References


Abouzahir, Saad, Sadik, Mohamed and Sabir, Essaid (2018). Enhanced Approach for Weeds Species Detection Using Machine Vision. In: *2018 International Conference on Electronics, Control, Optimization and Computer Science (ICECOCS)*. IEEE, p. 1–6.

ACAR, Emrullah, OZERDEM, Mehmet Sirac and USTUNDAG, Burak Berk (2019). Machine Learning based Regression Model for Prediction of Soil Surface Humidity over Moderately Vegetated Fields. In: *2019 8th International Conference on Agro-Geoinformatics (Agro-Geoinformatics)*. IEEE, p. 1–4.

Acemoglu, Daron and Restrepo, Pascual (2020). The wrong kind of AI? Artificial intelligence and the future of labour demand. *Cambridge Journal of Regions, Economy and Society*, 13(1), p. 25–35, doi:10.1093/cjres/rsz022.

Adamchuk, V. I., Hummel, J. W., Morgan, M. T. and Upadhyaya, S. K. (2004). On-the-go soil sensors for precision agriculture. *Computers and Electronics in Agriculture*, 44(1), p. 71–91, doi:10.1016/j.compag.2004.03.002.

Adamopoulou, Eleni and Moussiades, Lefteris (2020). Chatbots: History, technology, and applications. *Machine Learning with Applications*, 2, p. 100006, doi:10.1016/j.mlwa.2020.100006.

Anon. (n.d.). *Sustainable Development Goals - European Commission*. https://international-partnerships.ec.europa.eu/policies/sustainable-development-goals_en [Accessed: 2024a-05-15].

Anon. (n.d.). *The general data protection regulation - Consilium*. https://www.consilium.europa.eu/en/policies/data-protection/data-protection-regulation/#:~:text=The%20GDPR%20establishes%20the%20general,data%20processing%20operations%20they%20perform. [Accessed: 2024b-02-12].

Ansari, Shahzad and Garud, Raghu (2009). Inter-generational transitions in socio-technical systems: The case of mobile communications. *Research Policy*, 38(2), p. 382–392, doi:10.1016/J.RESPOL.2008.11.009.

Ayoub Shaikh, Tawseef, Rasool, Tabasum and Rasheed Lone, Faisal (2022). Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Computers and Electronics in Agriculture*.

Barthwal, Riya, Kathuria, Deepika, Joshi, Saloni, Kaler, R. S. S. and Singh, Narpinder (2024). New trends in the development and application of artificial intelligence in food processing. *Innovative Food Science and Emerging Technologies*.

Baxter, Gordon and Sommerville, Ian (2010). Socio-technical systems: From design methods to systems engineering, doi:10.1016/j.intcom.2010.07.003.

Bécue, Adrien, Praça, Isabel and Gama, João (2021). Artificial intelligence, cyber-threats and Industry 4.0: challenges and opportunities. *Artificial Intelligence Review*, 54(5), p. 3849–3886, doi:10.1007/s10462-020-09942-2.

Bedoya, Manuela Gallón, Montoya, Daniel Restrepo, Tabilo-Munizaga, Gipsy, Pérez-Won, Mario and Lemus-Mondaca, Roberto (2022). Promising perspectives on novel protein food sources combining artificial intelligence and 3D food printing for food industry. *Trends in Food Science & Technology*, 128, p. 38–52, doi:10.1016/j.tifs.2022.05.013.

Bell, Emma, Bryman, Alan and Harley, Bill (2022). *Business research methods*. Oxford University Press.

Benos, Lefteris, Tagarakis, Aristotelis C., Dolias, Georgios, Berruto, Remigio, Kateris, Dimitrios and Bochtis, Dionysis (2021). Machine learning in agriculture: A comprehensive updated review. *Sensors*.

Berger, Roni (2015). Now I see it, now I don't: researcher's position and reflexivity in qualitative research. Qualitative Research, 15(2), p. 219–234, doi:10.1177/1468794112468475.

Borges, Aline F. S., Laurindo, Fernando J. B., Spínola, Mauro M., Gonçalves, Rodrigo F. and Mattos, Claudia A. (2021). The strategic use of artificial intelligence in the digital era: Systematic literature review and future research directions. *International Journal of Information Management*.

Boursianis, Achilles D., Papadopoulou, Maria S., Diamantoulakis, Panagiotis, Liopa-Tsakalidi, Aglaia, Barouchas, Pantelis, Salahas, George, Karagiannidis, George, Wan, Shaohua and Goudos, Sotirios K. (2022). Internet of Things (IoT) and Agricultural Unmanned Aerial Vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things (Netherlands)*.

Braun, Virginia and Clarke, Victoria (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, 3(2), p. 77–101, doi:10.1191/1478088706QP063OA.

van den Broek, Elmira, Sergeeva, Anastasia and Huysman, Marleen (2021). When the machine meets the expert: An ethnography of developing ai for hiring. *MIS Quarterly: Management Information Systems*, 45(3), p. 1557–1580, doi:10.25300/MISQ/2021/16559.

Browder, Russell E., Koch, Hope, Long, Anna and Hernandez, James M. (2022). LEARNING TO INNOVATE WITH BIG DATA ANALYTICS IN INTERORGANIZATIONAL RELATIONSHIPS. *Academy of Management Discoveries*, 8(1), p. 139–166, doi:10.5465/amd.2019.0048.

Brundage, Miles (2015). Taking superintelligence seriously: Superintelligence: Paths, dangers, strategies by Nick Bostrom (Oxford University Press, 2014), doi:10.1016/j.futures.2015.07.009.

Bryant, Christopher and Barnett, Julie (2020). Consumer Acceptance of Cultured Meat: An Updated Review (2018–2020). *Applied Sciences 2020, Vol. 10, Page 5201*, 10(15), p. 5201, doi:10.3390/APP10155201.

Bughin, Jacques, Brussels, Hazan, Eric, Ramaswamy, Sree, Chui, Michael and Allas, Tera (2017). *ARTIFICIAL INTELLIGENCE THE NEXT DIGITAL FRONTIER?* www.mckinsey.com/mgi.

Cambria, Erik and White, Bebo (2014). Jumping NLP curves: A review of natural language processing research. *IEEE Computational Intelligence Magazine*.

Cave, Stephen, Dihal, Kanta and Dillon, Sarah (2020). *AI narratives. A history of imaginative* *thinking about intelligent machines*.

Čerka, Paulius, Grigiene, Jurgita and Sirbikyte, Gintare (2015). Liability for damages caused by artificial intelligence. *Computer Law and Security Review*, 31(3), p. 376–389, doi:10.1016/j.clsr.2015.03.008.

Chandra, Shalini, Shirish, Anuragini and Srivastava, Shirish C. (2022). To Be or Not to Be …Human? Theorizing the Role of Human-Like Competencies in Conversational Artificial Intelligence Agents. *Journal of Management Information Systems*, 39(4), p. 969–1005, doi:10.1080/07421222.2022.2127441.

Chasek, Pamela, Safriel, Uriel, Shikongo, Sem and Fuhrman, Vivian Futran (2015). Operationalizing Zero Net Land Degradation: The next stage in international efforts to combat desertification? *Journal of Arid Environments*, 112(PA), p. 5–13, doi:10.1016/j.jaridenv.2014.05.020.

Chen, Tzu Chia and Yu, Shu Yan (2022). The review of food safety inspection system based on artificial intelligence, image processing, and robotic. *Food Science and Technology (Brazil)*, 42, doi:10.1590/fst.35421.

Chen, Yan, Cai, Kezhou, Tu, Zehui, Nie, Wen, Ji, Tuo, Hu, Bing, Chen, Conggui and Jiang, Shaotong (2018). Prediction of benzo[a]pyrene content of smoked sausage using back-propagation artificial neural network. *Journal of the Science of Food and Agriculture*, 98(8), p. 3022–3030, doi:10.1002/jsfa.8801.

Cherns, Albert (1976). The Principles of Sociotechnical Design. *Human Relations*, 29(8), p. 783–792, doi:10.1177/001872677602900806/ASSET/001872677602900806.FP.PNG_V03.

Cho, Sarina, BCIT School of Health Sciences, Environmental Health and Heacock, Helen (2020). Is this too ugly for you? *BCIT Environmental Public Health Journal*, doi:10.47339/ephj.2020.29.

Christensen, Clayton M., Mcdonald, Rory, Altman, Elizabeth J. and Palmer, Jonathan E. (2018). Disruptive Innovation: An Intellectual History and Directions for Future Research, doi:10.1111/joms.12349.

Chung, Chia Lin, Huang, Kai Jyun, Chen, Szu Yu, Lai, Ming Hsing, Chen, Yu Chia and Kuo, Yan Fu (2016). Detecting Bakanae disease in rice seedlings by machine vision. *Computers and Electronics in Agriculture*, 121, p. 404–411, doi:10.1016/j.compag.2016.01.008.

Cramer, Sam, Kampouridis, Michael, Freitas, Alex A. and Alexandridis, Antonis K. (2017). An extensive evaluation of seven machine learning methods for rainfall prediction in weather derivatives. *Expert Systems with Applications*, 85, p. 169–181, doi:10.1016/j.eswa.2017.05.029.

Curto, Belén, Moreno, Vidal, García-Esteban, Juan Alberto, Blanco, Francisco Javier, González, Inmaculada, Vivar, Ana and Revilla, Isabel (2020). Accurate prediction of sensory attributes of cheese using near-infrared spectroscopy based on artificial neural network. *Sensors (Switzerland)*, 20(12), p. 1–16, doi:10.3390/s20123566.

Daneshjou, Roxana, Smith, Mary P., Sun, Mary D., Rotemberg, Veronica and Zou, James (2021). Lack of Transparency and Potential Bias in Artificial Intelligence Data Sets and Algorithms:

A Scoping Review. *JAMA Dermatology*.

Dellermann, Dominik, Ebel, Philipp, Söllner, Matthias and Leimeister, Jan Marco (2019). Hybrid Intelligence. *Business and Information Systems Engineering*, 61(5), p. 637–643, doi:10.1007/s12599-019-00595-2.

Deng, Li (2018). Artificial Intelligence in the Rising Wave of Deep Learning: The Historical Path and Future Outlook. *IEEE Signal Processing Magazine*.

Denney, Andrew S. and Tewksbury, Richard (2013). How to Write a Literature Review. *Journal of Criminal Justice Education*, 24(2), p. 218–234, doi:10.1080/10511253.2012.730617.

Dilmaghani, Saharnaz, R. Brust, Matthias and Danoy, Grégoire (2019). *Privacy and Security of Big Data in AI Systems: A Research and Standards Perspective*. Los Angeles: IEEE.

Dong, Yuan, Shi, Hongxi, Chen, Xin, Liu, Cong, Liu, Lingyan, Zhao, Nan, Cheng, Yingkun, Zhang, Yibo, Lin, Feng and Teng, Lirong (2012). Artificial Intelligence Based Optimization of the Extracting Process of Protein from DDGS Using Alkali Method. In: Zhu, Egui and Sambath, Sabo (eds.) *Information Technology and Agricultural Engineering*. Berlin, Heidelberg: Springer Berlin Heidelberg, p. 135–141. https://doi.org/10.1007/978-3-642-27537-1_18.

Duan, Yanqing, Edwards, John S. and Dwivedi, Yogesh K. (2019). Artificial intelligence for decision making in the era of Big Data – evolution, challenges and research agenda. *International Journal of Information Management*, 48, p. 63–71, doi:10.1016/j.ijinfomgt.2019.01.021.

Dwivedi, Yogesh K., Hughes, Laurie, Ismagilova, Elvira, Aarts, Gert, Coombs, Crispin, Crick, Tom, Duan, Yanqing, Dwivedi, Rohita, Edwards, John, Eirug, Aled, Galanos, Vassilis, Ilavarasan, P. Vigneswara, Janssen, Marijn, Jones, Paul, Kar, Arpan Kumar, Kizgin, Hatice, Kronemann, Bianca, Lal, Banita, Lucini, Biagio, Medaglia, Rony, Le Meunier-FitzHugh, Kenneth, Le Meunier-FitzHugh, Leslie Caroline, Misra, Santosh, Mogaji, Emmanuel, Sharma, Sujeet Kumar, Singh, Jang Bahadur, Raghavan, Vishnupriya, Raman, Ramakrishnan, Rana, Nripendra P., Samothrakis, Spyridon, Spencer, Jak, Tamilmani, Kuttimani, Tubadji, Annie, Walton, Paul and Williams, Michael D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, 57, doi:10.1016/j.ijinfomgt.2019.08.002.

Eisenhardt, Kathleen M. (1989). Building Theories from Case Study Research. *Academy of Management Review*, 14(4), p. 532–550, doi:10.5465/amr.1989.4308385.

Elbasi, Ersin, Mostafa, Nour, Alarnaout, Zakwan, Zreikat, Aymen I., Cina, Elda, Varghese, Greeshma, Shdefat, Ahmed, Topcu, Ahmet E., Abdelbaki, Wiem, Mathew, Shinu and Zaki, Chamseddine (2023). Artificial Intelligence Technology in the Agricultural Sector: A Systematic Literature Review. *IEEE Access*.

Eriksson, Mattias, Pano, Nathalie and Ghosh, Ranjan (2016). *Food Chain Sustainability in Sweden - Value Creation through Research?* Uppsala. https://pub.epsilon.slu.se/13495/1/eriksson_m_160703.pdf [Accessed: 2024-03-04].

von Eschenbach, Warren J. (2021). Transparency and the Black Box Problem: Why We Do Not

Trust AI. *Philosophy and Technology*, 34(4), p. 1607–1622, doi:10.1007/S13347-021-00477-0/METRICS.

Esmaeily, Rezvan, Razavi, Mohammad Amin and Razavi, Seyed Hadi (2024). A step forward in food science, technology and industry using artificial intelligence. *Trends in Food Science and Technology*.

Etzioni, Amitai and Etzioni, Oren (2017). Incorporating Ethics into Artificial Intelligence. *Journal of Ethics*, 21(4), p. 403–418, doi:10.1007/s10892-017-9252-2.

FAO (2023). *The State of Food Security and Nutrition in the World 2023*. The State of Food Security and Nutrition in the World 2023. FAO; IFAD; UNICEF; WFP; WHO; https://www.fao.org/3/cc3017en/cc3017en.pdf.

van der Fels-Klerx, H. J., van Asselt, E. D., Raley, M., Poulsen, M., Korsgaard, H., Bredsdorff, L., Nauta, M., Flari, V., d'Agostino, M., Coles, D. and Frewer, L. (2017). Critical review of methodology and application of risk ranking for prioritisation of food and feed related issues, on the basis of the size of anticipated health impact. *EFSA Supporting Publications*, 12(1), doi:10.2903/sp.efsa.2015.en-710.

Fielke, Simon, Taylor, Bruce and Jakku, Emma (2020). Digitalisation of agricultural knowledge and advice networks: A state-of-the-art review. *Agricultural Systems*, 180, p. 102763, doi:10.1016/J.AGSY.2019.102763.

Flores, Kristoffer O., Butaslac, Isidro M., Gonzales, Jon Enric M., Dumlao, Samuel Matthew G. and Reyes, Rosula S. J. (2016). Precision agriculture monitoring system using wireless sensor network and Raspberry Pi local server. In: *2016 IEEE Region 10 Conference (TENCON)*. IEEE, p. 3018–3021.

Fox, William M. (1995). Sociotechnical System Principles and Guidelines: Past and Present. *The Journal of Applied Behavioral Science*, 31(1), p. 91–105, doi:10.1177/0021886395311009.

Futagawa, Masato, Iwasaki, Taichi, Takao, Hidekuni, Ishida, Makoto, Sawada, Kazuaki, Takao, Hidekuni, Ishida, Makoto and Sawada, Kazuaki (2009). Fabrication of a multi-modal sensor with PH, EC and temperature sensing areas for agriculture application. In: *2009 IEEE Sensors*. IEEE, p. 2013–2016.

Gaikwad, Pramod, Devendrachari, Mruthyunjayachari Chattanahalli, Thimmappa, Ravikumar, Paswan, Bhuneshwar, Raja Kottaichamy, Alagar, Makri Nimbegondi Kotresh, Harish and Thotiyl, Musthafa Ottakam (2015). Galvanic Cell Type Sensor for Soil Moisture Analysis. *Analytical Chemistry*, 87(14), p. 7439–7445, doi:10.1021/acs.analchem.5b01653.

Galaz, Victor, Wilson, Erik and Janson, Sverker (2021). Al in the service of the climate - A survey of Swedish competence in an international perspective. *Vinnova*.

García, Rodrigo, Aguilar, Jose, Toro, Mauricio, Pinto, Angel and Rodríguez, Paul (2020). A systematic literature review on the use of machine learning in precision livestock farming. *Computers and Electronics in Agriculture*.

Georgopoulos, Vasileios P., Gkikas, Dimitris C. and Theodorou, John A. (2023). Factors Influencing the Adoption of Artificial Intelligence Technologies in Agriculture, Livestock Farming and Aquaculture: A Systematic Literature Review Using PRISMA 2020.

*Sustainability (Switzerland)*.

Ghosh, Shubhrangshu and Mitra, Pralay (2024). MaTPIP: A deep-learning architecture with eXplainable AI for sequence-driven, feature mixed protein-protein interaction prediction. *Computer Methods and Programs in Biomedicine*, 244, doi:10.1016/j.cmpb.2023.107955.

Goertzel, Ben (2014). Artificial General Intelligence: Concept, State of the Art, and Future Prospects. *Journal of Artificial General Intelligence*, 5(1), p. 1–48, doi:10.2478/JAGI-2014-0001.

Gorczyca, Michael T., Milan, Hugo Fernando Maia, Maia, Alex Sandro Campos and Gebremedhin, Kifle G. (2018). Machine learning algorithms to predict core, skin, and hair-coat temperatures of piglets. *Computers and Electronics in Agriculture*, 151, p. 286–294, doi:10.1016/j.compag.2018.06.028.

Górriz, Juan M., Ramírez, Javier, Ortíz, Andrés, Martínez-Murcia, Francisco J., Segovia, Fermin, Suckling, John, Leming, Matthew, Zhang, Yu Dong, Álvarez-Sánchez, Jose Ramón, Bologna, Guido, Bonomini, Paula, Casado, Fernando E., Charte, David, Charte, Francisco, Contreras, Ricardo, Cuesta-Infante, Alfredo, Duro, Richard J., Fernández-Caballero, Antonio, Fernández-Jover, Eduardo, Gómez-Vilda, Pedro, Graña, Manuel, Herrera, Francisco, Iglesias, Roberto, Lekova, Anna, de Lope, Javier, López-Rubio, Ezequiel, Martínez-Tomás, Rafael, Molina-Cabello, Miguel A., Montemayor, Antonio S., Novais, Paulo, Palacios-Alonso, Daniel, Pantrigo, Juan J., Payne, Bryson R., de la Paz López, Félix, Pinninghoff, María Angélica, Rincón, Mariano, Santos, José, Thurnhofer-Hemsi, Karl, Tsanas, Athanasios, Varela, Ramiro and Ferrández, Jose M. (2020). Artificial intelligence within the interplay between natural and artificial computation: Advances in data science, trends and applications. *Neurocomputing*, 410, p. 237–270, doi:10.1016/j.neucom.2020.05.078.

Goulding, K. W. T. (2016). Soil acidification and the importance of liming agricultural soils with particular reference to the United Kingdom. *Soil Use and Management*.

Government Offices of Sweden (2018). *National approach to artificial intelligence*. https://wp.oecd.ai/app/uploads/2021/12/Sweden_National_Approach_to_Artificial_Intelligence_2018.pdf [Accessed: 2024-03-04].

Grewal, Dhruv, Hulland, John, Kopalle, Praveen K. and Karahanna, Elena (2020). The future of technology and marketing: a multidisciplinary perspective. *Journal of the Academy of Marketing Science*.

Grinblat, Guillermo L., Uzal, Lucas C., Larese, Mónica G. and Granitto, Pablo M. (2016). Deep learning for plant identification using vein morphological patterns. *Computers and Electronics in Agriculture*, 127, p. 418–424, doi:10.1016/j.compag.2016.07.003.

Gummesson, E. (1988). *Qualitative Methods in Management Research: Case Study Research, Participant Observation, Action Research-action Science, and Other "qualitative Methods" Used in Academic Research and Management Consultancy*. Studentlitteratur. https://books.google.se/books?id=ViUAQQAACAAJ.

Haefner, Naomi, Parida, Vinit, Gassmann, Oliver and Wincent, Joakim (2023). Implementing and scaling artificial intelligence: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 197, doi:10.1016/j.techfore.2023.122878.

Hassani, Hossein, Silva, Emmanuel Sirimal, Unger, Stephane, TajMazinani, Maedeh and Mac Feely, Stephen (2020). Artificial Intelligence (AI) or Intelligence Augmentation (IA): What Is the Future? *AI 2020, Vol. 1, Pages 143-155*, 1(2), p. 143–155, doi:10.3390/AI1020008.

Hassoun, Abdo, Jagtap, Sandeep, Garcia-Garcia, Guillermo, Trollman, Hana, Pateiro, Mirian, Lorenzo, José M., Trif, Monica, Rusu, Alexandru Vasile, Aadil, Rana Muhammad, Šimat, Vida, Cropotova, Janna and Câmara, José S. (2023). Food quality 4.0: From traditional approaches to digitalized automated analysis. *Journal of Food Engineering*.

Helm, J. Matthew, Swiergosz, Andrew M., Haeberle, Heather S., Karnuta, Jaret M., Schaffer, Jonathan L., Krebs, Viktor E., Spitzer, Andrew I. and Ramkumar, Prem N. (2020). Machine Learning and Artificial Intelligence: Definitions, Applications, and Future Directions. *Current Reviews in Musculoskeletal Medicine*.

Helmy, Mohamed, Elhalis, Hosam, Liu, Yan, Chow, Yvonne and Selvarajoo, Kumar (2023). Perspective: Multiomics and Machine Learning Help Unleash the Alternative Food Potential of Microalgae. *Advances in Nutrition*, 14(1), p. 1–11, doi:10.1016/j.advnut.2022.11.002.

Holmström, Jonny (2022). From AI to digital transformation: The AI readiness framework. *Business Horizons*, 65(3), p. 329–339, doi:10.1016/j.bushor.2021.03.006.

Horani, Omar Mohammed, Al-Adwan, Ahmad Samed, Yaseen, Husam, Hmoud, Hazar, Al-Rahmi, Waleed Mugahed and Alkhalifah, Ali (2023). The critical determinants impacting artificial intelligence adoption at the organizational level. *Information Development*, doi:10.1177/02666669231166889.

Hu, Haijiang, Pan, Leiqing, Sun, Ke, Tu, Sicong, Sun, Ye, Wei, Yingying and Tu, Kang (2017). Differentiation of deciduous-calyx and persistent-calyx pears using hyperspectral reflectance imaging and multivariate analysis. *Computers and Electronics in Agriculture*, 137, p. 150–156, doi:10.1016/j.compag.2017.04.002.

Hyman, Mikell (2019). Computers Can't Override America's Antipathy Towards the Poor - Virginia Eubanks, Automating Inequality: How High-Tech Tools Profile, Police, and Punish the Poor (New York, St. Martin's Press, 2018). *European Journal of Sociology / Archives Européennes de Sociologie*, 60(3), p. 406–411, doi:10.1017/S0003975619000225.

InData Labs (2023). *THE STATE OF GLOBAL AI ADOPTION IN 2023*. https://indatalabs.com/research-papers/state-of-ai-adoption [Accessed: 2024-02-12].

Issa, Helmi, Jabbouri, Rachid and Palmer, Mark (2022). An artificial intelligence (AI)-readiness and adoption framework for AgriTech firms. *Technological Forecasting and Social Change*, 182, doi:10.1016/j.techfore.2022.121874.

Javaid, Mohd, Haleem, Abid, Singh, Ravi Pratap and Suman, Rajiv (2021). Substantial capabilities of robotics in enhancing industry 4.0 implementation. *Cognitive Robotics*.

Jiang, Fei, Jiang, Yong, Zhi, Hui, Dong, Yi, Li, Hao, Ma, Sufeng, Wang, Yilong, Dong, Qiang, Shen, Haipeng and Wang, Yongjun (2017). Artificial intelligence in healthcare: past, present and future. *Stroke and vascular neurology*, 2(4), p. 230–243, doi:10.1136/SVN-2017-000101.

Johan, Carl, Carlberg, Casten and Jerhamre, Elsa (2021). *Artificial Intelligence in Agriculture - Opportunities and Challenges*. https://urn.kb.se/resolve?urn=urn:nbn:se:uu:diva-443576 [Accessed: 2024-03-22].

Jöhnk, Jan, Weißert, Malte and Wyrtki, Katrin (2021). Ready or Not, AI Comes— An Interview Study of Organizational AI Readiness Factors. *Business and Information Systems Engineering*, 63(1), p. 5–20, doi:10.1007/s12599-020-00676-7.

Jordbruksverket (2023). Follow-up and evaluation of the food strategy - Annual report 2023.

Kamalapuram, Sishir K. and Choudhury, Deepak (2024). Industry 4.0 technologies for cultivated meat manufacturing. *Food Bioengineering*, 3(1), p. 14–28, doi:10.1002/FBE2.12080.

Katiyar, Sapna, Khan, Rijwan and Kumar, Santosh (2021). Artificial Bee Colony Algorithm for Fresh Food Distribution without Quality Loss by Delivery Route Optimization. *Journal of Food Quality*, 2021, doi:10.1155/2021/4881289.

Kiger, Michelle E. and Varpio, Lara (2020). Thematic analysis of qualitative data: AMEE Guide No. 131. *Medical Teacher*, 42(8), p. 846–854, doi:10.1080/0142159X.2020.1755030.

Kim, Pauline (2021). AI and Inequality. *Forthcoming in The Cambridge Handbook on Artificial Intelligence & the Law, Kristin Johnson & Carla Reyes, eds.(2022), Washington University in St. Louis Legal Studies Research Paper*, (21–09), p. 03.

Koc, A. Bulent, Heinemann, P. H. and Ziegler, G. R. (2007). Optimization of whole milk powder processing variables with neural networks and genetic algorithms. *Food and Bioproducts Processing*, 85(4 C), p. 336–343, doi:10.1205/fbp07074.

Kollia, Ilianna, Stevenson, Jack and Kollias, Stefanos (2021). Ai-enabled efficient and safe food supply chain. *Electronics (Switzerland)*.

Kumar, Indrajeet, Rawat, Jyoti, Mohd, Noor and Husain, Shahnawaz (2021). Opportunities of Artificial Intelligence and Machine Learning in the Food Industry. *Journal of Food Quality*, 2021, p. 1–10, doi:10.1155/2021/4535567.

Lakhankar, Tarendra, Ghedira, Hosni, Temimi, Marouane, Sengupta, Manajit, Khanbilvardi, Reza and Blake, Reginald (2009). Non-parametric methods for soil moisture retrieval from satellite remote sensing data. *Remote Sensing*, 1(1), p. 3–21, doi:10.3390/rs1010003.

Larsson, Stefan and Heintz, Fredrik (2020). Transparency in artificial intelligence. *Internet Policy Review*, 9(2), p. 1–16, doi:10.14763/2020.2.1469.

Leavitt, Harold J. (2013). Applied organizational change in industry: Structural, technological and humanistic approaches. In: *Handbook of Organizations (RLE: Organizations)*. Routledge, p. 1144–1170.

Lecun, Yann, Bengio, Yoshua and Hinton, Geoffrey (2015). Deep learning. *Nature*.

Lei, Zhenfeng, Yang, Shuangyuan, Liu, Han, Aslam, Saba, Liu, Jinyu, Tekle, Halefom, Bugingo, Emmanuel and Zhang, Defu (2018). Mining of Nutritional Ingredients in Food for Disease Analysis. *IEEE Access*, 6, p. 52766–52778, doi:10.1109/ACCESS.2018.2866389.

Leo, M., Medioni, G., Trivedi, M., Kanade, T. and Farinella, G. M. (2017). Computer vision for assistive technologies. *Computer Vision and Image Understanding*, 154, p. 1–15, doi:10.1016/j.cviu.2016.09.001.

Lezoche, Mario, Panetto, Herve, Kacprzyk, Janusz, Hernandez, Jorge E. and Alemany Díaz, Mª Mar Eva (2020). Agri-food 4.0: A survey of the Supply Chains and Technologies for the Future Agriculture. *Computers in Industry*.

Li, Francis G. N., Trutnevyte, Evelina and Strachan, Neil (2015). A review of socio-technical energy transition (STET) models. *Technological Forecasting and Social Change*, 100, p. 290–305, doi:10.1016/J.TECHFORE.2015.07.017.

Liakos, Konstantinos G., Busato, Patrizia, Moshou, Dimitrios, Pearson, Simon and Bochtis, Dionysis (2018). Machine learning in agriculture: A review. *Sensors (Switzerland)*.

Liu, Zhe, Wang, Shuzhe, Zhang, Yudong, Feng, Yichen, Liu, Jiajia and Zhu, Hengde (2023). Artificial Intelligence in Food Safety: A Decade Review and Bibliometric Analysis. *Foods*.

Lu, Yang (2019). Artificial intelligence: a survey on evolution, models, applications and future trends. *Journal of Management Analytics*.

Maione, Camila, Batista, Bruno Lemos, Campiglia, Andres Dobal, Barbosa, Fernando and Barbosa, Rommel Melgaço (2016). Classification of geographic origin of rice by data mining and inductively coupled plasma mass spectrometry. *Computers and Electronics in Agriculture*, 121, p. 101–107, doi:10.1016/j.compag.2015.11.009.

Makarius, Erin E., Mukherjee, Debmalya, Fox, Joseph D. and Fox, Alexa K. (2020). Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization. *Journal of Business Research*, 120, p. 262–273, doi:10.1016/j.jbusres.2020.07.045.

Manny, Liliane, Angst, Mario, Rieckermann, Jörg and Fischer, Manuel (2022). Socio-technical networks of infrastructure management: Network concepts and motifs for studying digitalization, decentralization, and integrated management. *Journal of Environmental Management*, 318, doi:10.1016/j.jenvman.2022.115596.

Mark, Ryan (2019). Ethics of Using AI and Big Data in Agriculture: The Case of a Large Agriculture Multinational. The ORBIT Journal, 2(2), p. 1–27,

Mavani, Nidhi Rajesh, Ali, Jarinah Mohd, Othman, Suhaili, Hussain, M. A., Hashim, Haslaniza and Rahman, Norliza Abd (2022). Application of Artificial Intelligence in Food Industry—a Guideline. *Food Engineering Reviews*.

McAfee, Andrew and Brynjolfsson, Erik (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies.* https://psycnet.apa.org/record/2014-07087-000.

McKinsey & Company (2023). *The state of AI in 2023: Generative AI's breakout year*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-state-of-ai-in-2023-generative-ais-breakout-year#/ [Accessed: 2024-02-11].

McPhearson, Timon, Cook, Elizabeth M., Berbés-Blázquez, Marta, Cheng, Chingwen, Grimm, Nancy B., Andersson, Erik, Barbosa, Olga, Chandler, David G., Chang, Heejun, Chester, Mikhail V., Childers, Daniel L., Elser, Stephen R., Frantzeskaki, Niki, Grabowski, Zbigniew, Groffman, Peter, Hale, Rebecca L., Iwaniec, David M., Kabisch, Nadja, Kennedy, Christopher, Markolf, Samuel A., Matsler, A. Marissa, McPhillips, Lauren E., Miller, Thaddeus R., Muñoz-Erickson, Tischa A., Rosi, Emma and Troxler, Tiffany G. (2022). A social-ecological-technological systems framework for urban ecosystem services. *One Earth*.

Mehryar Mohri, Afshin Rostamizadeh, Ameet Talwalkar (2018). Foundation of Machine Learning 2nd. *The MIT Press*, 4(1), p. 88–100.

Mengucci, Carlo, Ferranti, Pasquale, Romano, Annalisa, Masi, Paolo, Picone, Gianfranco and Capozzi, Francesco (2022). Food structure, function and artificial intelligence. *Trends in Food Science & Technology*, 123, p. 251–263, doi:10.1016/j.tifs.2022.03.015.

Miller, Katie (2020). A Matter of Perspective: Discrimination, Bias, and Inequality in AI. p. 182–202.

Mishra, Sagarika, Ewing, Michael T. and Cooper, Holly B. (2022). Artificial intelligence focus and firm performance. *Journal of the Academy of Marketing Science*, 50(6), p. 1176–1197, doi:10.1007/s11747-022-00876-5.

Misra, N. N., Dixit, Yash, Al-Mallahi, Ahmad, Bhullar, Manreet Singh, Upadhyay, Rohit and Martynenko, Alex (2022). IoT, Big Data, and Artificial Intelligence in Agriculture and Food Industry. *IEEE Internet of Things Journal*, 9(9), p. 6305–6324, doi:10.1109/JIOT.2020.2998584.

Miyazawa, Taiki, Hiratsuka, Yoichi, Toda, Masako, Hatakeyama, Nozomu, Ozawa, Hitoshi, Abe, Chizumi, Cheng, Ting Yu, Matsushima, Yuji, Miyawaki, Yoshifumi, Ashida, Kinya, Iimura, Jun, Tsuda, Tomohiro, Bushita, Hiroto, Tomonobu, Kazuichi, Ohta, Satoshi, Chung, Hsuan, Omae, Yusuke, Yamamoto, Takayuki, Morinaga, Makoto, Ochi, Hiroshi, Nakada, Hajime, Otsuka, Kazuhiro and Miyazawa, Teruo (2022). Artificial intelligence in food science and nutrition: a narrative review. *Nutrition Reviews*.

Mohammadi, Vahid and Minaei, Saeid (2019). Artificial Intelligence in the Production Process. In: *Engineering Tools in the Beverage Industry: Volume 3: The Science of Beverages*. Elsevier, p. 27–63.

Mohareb, Fady, Papadopoulou, Olga, Panagou, Efstathios, Nychas, George John and Bessant, Conrad (2016). Ensemble-based support vector machine classifiers as an efficient tool for quality assessment of beef fillets from electronic nose data. *Analytical Methods*, 8(18), p. 3711–3721, doi:10.1039/c6ay00147e.

Morales, Iván Ramírez, Cebrián, Daniel Rivero, Fernandez-Blanco, Enrique and Sierra, Alejandro Pazos (2016). Early warning in egg production curves from commercial hens: A SVM approach. *Computers and Electronics in Agriculture*, 121, p. 169–179, doi:10.1016/j.compag.2015.12.009.

Münch, Christopher, Marx, Emanuel, Benz, Lukas, Hartmann, Evi and Matzner, Martin (2022). Capabilities of digital servitization: Evidence from the socio-technical systems theory. *Technological Forecasting and Social Change*, 176, doi:10.1016/j.techfore.2021.121361.

Murray Alex, Rhymer, Jen and Sirmon, David G. (2021). Humans and technology: Forms of conjoined agency in organizations. *Academy of Management Review*, 46(3), p. 552–571, doi:10.5465/amr.2019.0186.

Neo, Yi Ting, Chia, Wen Yi, Lim, Siew Shee, Ngan, Cheng Loong, Kurniawan, Tonni Agustiono and Chew, Kit Wayne (2023). Smart systems in producing algae-based protein to improve functional food ingredients industries. *Food Research International*, 165, doi:10.1016/j.foodres.2023.112480.

Newell, Allen and A. Simon, Herbert (1976). Completer Science as Empirical Inquiry: Symbols and Search. *Communications of the ACM*, 19(3), p. 113–126, doi:10.1145/360018.360022.

Ng, Wei Long and Tan, Jian Song (2024). Application of machine learning in 3D bioprinting of cultivated meat. *International Journal of AI for Materials and Design*, 1(1), p. 3, doi:10.36922/ijamd.2279.

Nishant, Rohit, Kennedy, Mike and Corbett, Jacqueline (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management*, 53, doi:10.1016/j.ijinfomgt.2020.102104.

Obschonka, Martin and Audretsch, David B. (2020). Artificial intelligence and big data in entrepreneurship: a new era has begun. *Small Business Economics*, 55(3), p. 529–539, doi:10.1007/s11187-019-00202-4.

Onyeaka, Helen, Tamasiga, Phemelo, Nwauzoma, Uju Mary, Miri, Taghi, Juliet, Uche Chioma, Nwaiwu, Ogueri and Akinsemolu, Adenike A. (2023). Using Artificial Intelligence to Tackle Food Waste and Enhance the Circular Economy: Maximising Resource Efficiency and Minimising Environmental Impact: A Review. *Sustainability (Switzerland)*.

Oscar, T. P. (2017). Neural network model for thermal inactivation of salmonella typhimurium to elimination in ground chicken: Acquisition of data by whole sample enrichment, miniature most-probable-number method. *Journal of Food Protection*, 80(1), p. 104–112, doi:10.4315/0362-028X.JFP-16-199.

Pantazi, X. E., Moshou, D., Alexandridis, T., Whetton, R. L. and Mouazen, A. M. (2016). Wheat yield prediction using machine learning and advanced sensing techniques. *Computers and Electronics in Agriculture*, 121, p. 57–65, doi:10.1016/j.compag.2015.11.018.

Papageorgiou, E. I., Aggelopoulou, K., Gemtos, T. A. and Nanos, G. D. (2018). Development and Evaluation of a Fuzzy Inference System and a Neuro-Fuzzy Inference System for Grading Apple Quality. *Applied Artificial Intelligence*, 32(3), p. 253–280, doi:10.1080/08839514.2018.1448072.

Partel, Victor, Charan Kakarla, Sri and Ampatzidis, Yiannis (2019). Development and evaluation of a low-cost and smart technology for precision weed management utilizing artificial intelligence. *Computers and Electronics in Agriculture*, 157, p. 339–350, doi:10.1016/j.compag.2018.12.048.

Pathan, Misbah, Patel, Nivedita, Yagnik, Hiteshri and Shah, Manan (2020). Artificial cognition for applications in smart agriculture: A comprehensive review. *Artificial Intelligence in Agriculture*.

Patton, Michael Quinn (2002). Qualitative research and evaluation methods. *Qualitative Inquiry*, 3rd, p. 598, doi:10.2307/330063.

Peruzzi, Andrea, Frasconi, Christian, Martelloni, Luisa, Fontanelli, Marco and Raffaelli, Michele (2012). A new prototype to perform precision treatments of activated steaming to kill weed seed before sowing of organic vegetable.

Pomerol, Jean-Charles (1997). *Artificial intelligence and human decision making*. European Journal of Operational Research.

Priya, Arya (2021). Case Study Methodology of Qualitative Research: Key Attributes and Navigating the Conundrums in Its Application. *Sociological Bulletin*, 70(1), p. 94–110, doi:10.1177/0038022920970318.

Rahman, Sk Al Zaminur, Chandra Mitra, Kaushik and Mohidul Islam, S. M. (2018). Soil Classification Using Machine Learning Methods and Crop Suggestion Based on Soil Series. In: *2018 21st International Conference of Computer and Information Technology (ICCIT)*. IEEE, p. 1–4.

Rai, P., Majumdar, G. C., DasGupta, S. and De, S. (2005). Prediction of the viscosity of clarified fruit juice using artificial neural network: A combined effect of concentration and temperature. *Journal of Food Engineering*, 68(4), p. 527–533, doi:10.1016/j.jfoodeng.2004.07.003.

(Rami) Shani, A. B., Grant, Robert M., Krishnan, R. and Thompson, Eric (1992). Advanced Manufacturing Systems and Organizational Choice: Sociotechnical System Approach. *California Management Review*, 34(4), p. 91–111, doi:10.2307/41166705/ASSET/41166705.FP.PNG_V03.

Ramirez-Asis, Edwin, Bhanot, Astha, Jagota, Vishal, Chandra, B., Hossain, Md Shamim, Pant, Kumud and Almashaqbeh, Hashem Ali (2022). Smart Logistic System for Enhancing the Farmer-Customer Corridor in Smart Agriculture Sector Using Artificial Intelligence. *Journal of Food Quality*, 2022, p. 1–8, doi:10.1155/2022/7486974.

Ransbotham, Sam, Kiron, David, Gerbert, Philipp and Reeves, Martin (2017). Reshaping Business With Artificial Intelligence. *MIT Sloan Management Review*.

Reda, Rabie, Saffaj, Taoufiq, Ilham, Bouzida, Saidi, Ouadi, Issam, Kadmiri, Brahim, Lakssir and El Hadrami, El Mestafa (2019). A comparative study between a new method and other machine learning algorithms for soil organic carbon and total nitrogen prediction using near infrared spectroscopy. *Chemometrics and Intelligent Laboratory Systems*, 195, doi:10.1016/j.chemolab.2019.103873.

Rein, Dietrich, Ternes, Philipp, Demin, Rodion, Gierke, Jürgen, Helgason, Thrandur and Schön, Christiane (2019). Artificial intelligence identified peptides modulate inflammation in healthy adults. *Food and Function*, 10(9), p. 6030–6041, doi:10.1039/c9fo01398a.

Rong, Dian, Xie, Lijuan and Ying, Yibin (2019). Computer vision detection of foreign objects in walnuts using deep learning. *Computers and Electronics in Agriculture*, 162, p. 1001–1010, doi:10.1016/j.compag.2019.05.019.

Ryan, Mark (2023). The social and ethical impacts of artificial intelligence in agriculture: mapping the agricultural AI literature. *AI and Society*, 38(6), p. 2473–2485, doi:10.1007/s00146-021-01377-9.

Sadiku, Matthew N. O., Fagbohungbe, OmobayodeI and Musa, Sarhan M. (2020). Artificial Intelligence in Food Industry. *International Journal of Engineering Research and Advanced Technology*, 06(10), p. 12–19, doi:10.31695/ijerat.2020.3649.

Safdar, Nabile M., Banja, John D. and Meltzer, Carolyn C. (2020). Ethical considerations in artificial intelligence. *European Journal of Radiology*.

Sahni, Varsha, Srivastava, Sandeep and Khan, Rijwan (2021). Modelling Techniques to Improve the Quality of Food Using Artificial Intelligence. *Journal of Food Quality*, 2021, p. 1–10, doi:10.1155/2021/2140010.

Salwei, Megan E. and Carayon, Pascale (2022). A Sociotechnical Systems Framework for the Application of Artificial Intelligence in Health Care Delivery. *Journal of Cognitive Engineering and Decision Making*, 16(4), p. 194–206, doi:10.1177/15553434221097357.

Sandqvist, David and Bengtsson, Gustaf (2022). How does the Swedish farmers' union perceive the digital development within AI?

Sarker, Iqbal H. (2022). AI-Based Modeling: Techniques, Applications and Research Issues Towards Automation, Intelligent and Smart Systems. *SN Computer Science*, 3(2), doi:10.1007/s42979-022-01043-x.

Savaget, Paulo, Geissdoerfer, Martin, Kharrazi, Ali and Evans, Steve (2019). The theoretical foundations of sociotechnical systems change for sustainability: A systematic literature review. *Journal of Cleaner Production*.

Seyedzadeh, Amin, Maroufpoor, Saman, Maroufpoor, Eisa, Shiri, Jalal, Bozorg-Haddad, Omid and Gavazi, Farnoosh (2020). Artificial intelligence approach to estimate discharge of drip tape irrigation based on temperature and pressure. *Agricultural Water Management*, 228, doi:10.1016/j.agwat.2019.105905.

Shang, Gao, Low, Sui Pheng and Lim, Xin Ying Valen (2023). Prospects, drivers of and barriers to artificial intelligence adoption in project management. *Built Environment Project and Asset Management*, 13(5), p. 629–645, doi:10.1108/BEPAM-12-2022-0195.

Sharma, Abhinav, Jain, Arpit, Gupta, Prateek and Chowdary, Vinay (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive Review. *IEEE Access*.

Sharma, Poonam, Vimal, Archana, Vishvakarma, Reena, Kumar, Pradeep, de Souza Vandenberghe, Luciana porto, Kumar Gaur, Vivek and Varjani, Sunita (2022). Deciphering the blackbox of omics approaches and artificial intelligence in food waste transformation and mitigation. *International Journal of Food Microbiology*, 372, doi:10.1016/j.ijfoodmicro.2022.109691.

Shen, Yufeng, Zhou, Huiling, Li, Jiangtao, Jian, Fuji and Jayas, Digvir S. (2018). Detection of stored-grain insects using deep learning. *Computers and Electronics in Agriculture*, 145, p. 319–325, doi:10.1016/j.compag.2017.11.039.

Shin, Dong Hee, Choo, Hyunseung and Beom, Khisu (2011). Socio-Technical Dynamics in the Development of Next Generation Mobile Network: Translation Beyond 3G. *Technological*

*Forecasting and Social Change*, 78(3), p. 514–525, doi:10.1016/J.TECHFORE.2010.04.017.

Shin, Ju Young, Kim, Kyu Rang and Ha, Jong Chul (2020). Seasonal forecasting of daily mean air temperatures using a coupled global climate model and machine learning algorithm for field-scale agricultural management. *Agricultural and Forest Meteorology*, 281, doi:10.1016/j.agrformet.2019.107858.

Sittig, D. F. and Singh, H. (2010). A new sociotechnical model for studying health information technology in complex adaptive healthcare systems. *Quality and Safety in Health Care*, 19(Suppl 3), p. i68–i74, doi:10.1136/qshc.2010.042085.

Sjödin, David, Parida, Vinit, Palmié, Maximilian and Wincent, Joakim (2021). How AI capabilities enable business model innovation: Scaling AI through co-evolutionary processes and feedback loops. *Journal of Business Research*, 134, p. 574–587, doi:10.1016/j.jbusres.2021.05.009.

Smith, Derek J., Helmy, Mohamed, Lindley, Nicholas D. and Selvarajoo, Kumar (2022). The transformation of our food system using cellular agriculture: What lies ahead and who will lead it? *Trends in Food Science and Technology*.

Sohail, Muhammad, Sun, Da Wen and Zhu, Zhiwei (2018). Recent developments in intelligent packaging for enhancing food quality and safety. *Critical Reviews in Food Science and Nutrition*.

Soltani Firouz, Mahmoud, Mohi-Alden, Khaled and Omid, Mahmoud (2021). A critical review on intelligent and active packaging in the food industry: Research and development. *Food Research International*.

Sony, Michael and Naik, Subhash (2020). Industry 4.0 integration with socio-technical systems theory: A systematic review and proposed theoretical model. *Technology in Society*, 61, doi:10.1016/j.techsoc.2020.101248.

Stanford University (2023). *AI Index Report 2023 – Artificial Intelligence Index*. https://aiindex.stanford.edu/report/ [Accessed: 2024-02-11].

Sun, Jie, Di, Liping, Sun, Ziheng, Shen, Yonglin and Lai, Zulong (2019). County-level soybean yield prediction using deep CNN-LSTM model. *Sensors (Switzerland)*, 19(20), doi:10.3390/s19204363.

Sundaravadivel, Prabha, Kesavan, Kavya, Kesavan, Lokeshwar, Mohanty, Saraju P. and Kougianos, Elias (2018). Smart-Log: A Deep-Learning Based Automated Nutrition Monitoring System in the IoT. *IEEE Transactions on Consumer Electronics*, 64(3), p. 390–398, doi:10.1109/TCE.2018.2867802.

Sweden Food Arena (2021). *The food chain as the development arena for sustainability and competitiveness*. https://swedenfoodarena.se/wp-content/uploads/Livsmedelskedjan-som-utvecklingsarena-slutrapport.pdf [Accessed: 2024-03-04].

Taddeo, Mariarosaria and Floridi, Luciano (2018). Regulate artificial intelligence to avert cyber arms race. *Nature 2021 556:7701*, 556(7701), p. 296–298, doi:10.1038/D41586-018-04602-6.

Tien, James M. (2017). Internet of Things, Real-Time Decision Making, and Artificial Intelligence. *Annals of Data Science*, 4(2), p. 149–178, doi:10.1007/s40745-017-0112-5.

Tilman, David, Balzer, Christian, Hill, Jason and Befort, Belinda L. (2011). Global food demand and the sustainable intensification of agriculture. *Proceedings of the National Academy of Sciences of the United States of America*, 108(50), p. 20260–20264, doi:10.1073/pnas.1116437108.

Tracy, Sarah J. (2010). Qualitative quality: Eight "big-tent" criteria for excellent qualitative research. Qualitative Inquiry, 16(10), p. 837–851, doi:10.1177/1077800410383121.

Tranfield, D. (2000). Some social and psychological consequences of the longwall method of coal getting. *Clinician in Management*, 9(4), p. 235–237, doi:10.1177/001872675100400101/ASSET/001872675100400101.FP.PNG_V03.

Turing, A. M. (1950). *Computing Machinery and Intelligence*. Source: Mind. https://www.jstor.org/stable/2251299.

Unal, Zeynep (2020). Smart Farming Becomes even Smarter with Deep Learning - A Bibliographical Analysis. *IEEE Access*, 8, p. 105587–105609, doi:10.1109/ACCESS.2020.3000175.

Varan Nath, Shyam, Dunkin, Ann, Chowdhary, Mahesh and Patel, Nital (2020). *Industrial Digital Transformation: Accelerate digital transformation with business optimization, AI, and Industry 4.0* .

Wang, Xinxin, Bouzembrak, Yamine, Lansink, AGJM G. J. M. O. and van der Fels-Klerx, H. J. (2022). Application of machine learning to the monitoring and prediction of food safety: A review. *Comprehensive Reviews in Food Science and Food Safety*.

Wang, Yuanyuan, Fu, Eugene Yujun, Zhai, Xinwei, Yang, Chunxi and Pei, Fengchun (2024). Introduction of Artificial Intelligence, p. 65–97, doi:10.1007/978-3-031-48161-1_4.

Weger, Kristin and Yeazitzis, Taylor (2023). Conceptualizing a Socio-technical Model for Evaluating AI-driven Technology. *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, 67(1), p. 1639–1644, doi:10.1177/21695067231192298.

Wester, Joel, Jacobsen, Rune Møberg, Jong, Sander de, Als, Naja Kathrine Kollerup, Djernæs, Helena Bøjer and Berkel, Niels van (2024). Theory of Mind and Self-Presentation in Human-LLM Interactions. *Proceedings of Workshop on Theory of Mind in Human-AI Interaction at CHI 2024 (ToMinHAI at CHI 2024)*. https://vbn.aau.dk/en/publications/theory-of-mind-and-self-presentation-in-human-llm-interactions [Accessed: 2024-05-12].

Whittlestone, Jess, Alexandrova, Anna, Nyrup, Rune and Cave, Stephen (2019). The role and limits of principles in AI ethics: Towards a focus on tensions. In: *AIES 2019 - Proceedings of the 2019 AAAI/ACM Conference on AI, Ethics, and Society*. Association for Computing Machinery, Inc, p. 195–200.

Wolfert, Sjaak, Ge, Lan, Verdouw, Cor and Bogaardt, Marc Jeroen (2017). Big Data in Smart Farming – A review. *Agricultural Systems*, 153, p. 69–80, doi:10.1016/J.AGSY.2017.01.023.

Woo Chaw Seng and Mirisaee, Seyed Hadi (2009). A new method for fruits recognition system. In: *2009 International Conference on Electrical Engineering and Informatics*. IEEE, p. 130–134.

Xie, Tiantian, Huang, Zhichuan, Chi, Zicheng and Zhu, Ting (2017). Minimizing amortized cost of the on-demand irrigation system in smart farms. In: *Proceedings - 2017 3rd International Workshop on Cyber-Physical Systems for Smart Water Networks, CySWATER 2017*. Association for Computing Machinery, Inc, p. 43–46.

Xing, Fei, Peng, Guochao, Zhang, Bingqian, Li, Shuyang and Liang, Xinting (2021). Socio-technical barriers affecting large-scale deployment of AI-enabled wearable medical devices among the ageing population in China. *Technological Forecasting and Social Change*, 166, doi:10.1016/j.techfore.2021.120609.

Yang, Meihua, Xu, Dongyun, Chen, Songchao, Li, Hongyi and Shi, Zhou (2019). Evaluation of machine learning approaches to predict soil organic matter and pH using vis-NIR spectra. *Sensors (Switzerland)*, 19(2), doi:10.3390/s19020263.

Yin, R. K. (2014). *Case Study Research*. SAGE Publications. https://books.google.se/books?id=Cdk5DQAAQBAJ.

Yousef AlShamsi, Abdulrahman (2022). Understanding Customer Behaviour in Restaurants based on Data Understanding Customer Behaviour in Restaurants based on Data Mining Prediction Technique Mining Prediction Technique. Rochester Institute of Technology. https://repository.rit.edu/theses.

Yun, Sunyoung and Lee, Joosung (2015). Advancing societal readiness toward renewable energy system adoption with a socio-technical perspective. *Technological Forecasting and Social Change*, 95, p. 170–181, doi:10.1016/J.TECHFORE.2015.01.016.

Zeevi, David, Korem, Tal, Zmora, Niv, Israeli, David, Rothschild, Daphna, Weinberger, Adina, Ben-Yacov, Orly, Lador, Dar, Avnit-Sagi, Tali, Lotan-Pompan, Maya, Suez, Jotham, Mahdi, Jemal Ali, Matot, Elad, Malka, Gal, Kosower, Noa, Rein, Michal, Zilberman-Schapira, Gili, Dohnalová, Lenka, Pevsner-Fischer, Meirav, Bikovsky, Rony, Halpern, Zamir, Elinav, Eran and Segal, Eran (2015). Personalized Nutrition by Prediction of Glycemic Responses. *Cell*, 163(5), p. 1079–1094, doi:10.1016/j.cell.2015.11.001.

Zhang, Guoquan, Li, Guohao and Peng, Jing (2020). Risk assessment and monitoring of green logistics for fresh produce based on a support vector machine. *Sustainability (Switzerland)*, 12(18), doi:10.3390/su12187569.

Zhang, Yudong, Phillips, Preetha, Wang, Shuihua, Ji, Genlin, Yang, Jiquan and Wu, Jianguo (2016). Fruit classification by biogeography-based optimization and feedforward neural network. *Expert Systems*, 33(3), p. 239–253, doi:10.1111/exsy.12146.

# Appendices

## Appendix A: AI's market adoption

| Sector | Impact of AI | References |
|---|---|---|
| Healthcare | Significant effects expected, particularly in pharmaceutics. | (McKinsey & Company, 2023) |
| Finance | The banking sector could see up to 5% value addition from AI, indicating substantial impact. | (McKinsey & Company, 2023) |
| Technology | Technology companies are poised for the highest impact from gen AI—up to 9% of global industry revenue. | (McKinsey & Company, 2023) |
| Automotive and Manufacturing | Less disruptive effects expected due to gen AI's focus on knowledge work over physical labor. | (McKinsey & Company, 2023) |
| Overall Trends | Increasing integration across industries, with diverse applications from NLP to predictive analytics. | (Stanford University, 2023) |
| AI High Performers | Strategic use of AI in product/service development and risk management, focus on new business/revenue sources. | (McKinsey & Company, 2023) |

*Table 9. AI's market adoption (Own elaboration).*

## Appendix B: Classification of AI Challenges and Barriers

| Challenge | Description | References |
|---|---|---|
| Ethical Concerns | Issues related to algorithmic bias, decision-making autonomy, and ensuring fairness, accountability, and transparency in AI systems. | (Cave, Dihal and Dillon, 2020) |
| Data Privacy Issues | Concerns over privacy breaches and misuse of personal information due to AI's capability to analyze and infer insights from vast datasets. | (Dilmaghani, R. Brust and Danoy, 2019) |
| Regulatory Frameworks | The need for updated, comprehensive regulatory frameworks to address risks associated with AI, including ethical dilemmas, privacy concerns, and security vulnerabilities. | (Čerka et al., 2015) |
| Workforce Displacement | The automation potential of AI raises concerns about job displacement and the future of work, necessitating strategies for workforce transition and re-skilling. | (McAfee and Brynjolfsson, 2014) |
| AI Security | As AI systems become more integral to operations, they become targets for malicious use, requiring advanced security measures to protect against AI-specific threats. | (Taddeo and Floridi, 2018) |
| Interpretability and Explainability | The complexity of AI models, especially deep learning, poses challenges for understanding and explaining AI decisions, critical for trust and ethical considerations. | (von Eschenbach, 2021) |
| Socio-economic Inequalities | The uneven access and impact of AI technologies can exacerbate existing socio-economic inequalities, requiring policies to ensure equitable benefits. | (Hyman, 2019) |

*Table 10. Classification of AI Challenges and Barriers (Own elaboration).*

## Appendix C: AI development timeline

| Period | Era | Key Developments | Impact |
|---|---|---|---|
| 1950s-1970s | Foundational Years | Early AI research, Turing Test, development of basic AI algorithms. (Turing, 1950) | Laid the groundwork for AI, focusing on problem-solving and theoretical models. |
| 1980s-1990s | AI Winter & Revival | Expert systems, early neural networks, AI winter due to unmet expectations. (Newell and A. Simon, 1976) | Growth in understanding limitations and potential of AI, leading to more focused research. |
| 2000s-Present | AI Boom | Rise of deep learning, big data, and advancements in computational power leading to widespread AI applications across industries. (Lu, 2019) | AI becomes integral to many sectors, driving innovation, efficiency, and new capabilities. |

*Table 11. AI development timeline (Own elaboration).*

## Appendix D: Table: Swedish organization working on leveraging AI in Sweden.

| Organization | Summary of Activity | Section |
|---|---|---|
| The Swedish Government | The Swedish Government has recognized AI as a strategic area for the development of the country. It works on policies, regulations, and initiatives to promote AI research, development, and ethical guidelines. The government also collaborates with other national and international bodies to align AI advancements with societal needs and global standards. | Government |
| AI Sweden | AI Sweden is the national center for applied artificial intelligence, supported by the Swedish government, the public sector, the private sector, and academia. Its mission is to accelerate the use of AI for the benefit of Sweden's competitiveness and to address societal challenges. AI Sweden focuses on projects that provide shared resources, such as data factories and testbeds, and facilitates collaboration across sectors. | National AI Center (Public-Private Partnership) |
| VINNOVA | VINNOVA is Sweden's government agency for innovation. It supports research and development projects within various fields, including AI, with the aim of increasing Sweden's innovation capacity. VINNOVA funds projects that can transform the market and society, fostering collaboration between companies, universities, research institutes, and the public sector. | Government Agency (Innovation) |
| RISE | RISE is a Swedish research institute that collaborates with academia, industry, and the public sector to drive innovation and sustainable growth. Within AI, RISE focuses on applied research in areas such as machine learning, data science, and AI ethics. They offer expertise, laboratories, test and demo facilities for a wide range of industries and societal sectors. | Research Institute |
| KTH Royal Institute of Technology | KTH is one of Europe's leading technical universities and an important player in AI research in Sweden. It conducts cutting-edge research in machine learning, computer vision, robotics, and AI theory. KTH collaborates with industry and government to develop AI solutions that address complex real-world problems. | University (Education and Research) |

| | | |
|---|---|---|
| The Wallenberg AI, Autonomous Systems and Software Program (WASP) | WASP is Sweden's largest individual research program, funded by the Knut and Alice Wallenberg Foundation. It aims to advance Sweden's knowledge and capability in AI, autonomous systems, and software development. The program supports research projects, graduate education, and international collaboration. | Research Program (Funded by Private Foundation) |
| Governo | A Swedish management consultancy firm, known for its close collaborations with public sector organizations, e.g. VINNOVA | Government Agency |

*Table 12. Swedish organization working on leveraging AI in Sweden (Own elaboration).*

## Appendix E: Swedish companies as part of food system leveraging AI.

| Company | Summary of Activity | Section | Reference |
|---|---|---|---|
| Swegreen | Specializes in AI-driven in-store farming solutions for growing leafy greens and herbs sustainably. | Primary production | https://www.swegreen.com |
| Agronod | A platform for secure and easy sharing of Swedish agricultural data. | Primary production | https://www.agronod.com/ |
| Elvenite | Provides technology solutions for the food industry including ERP integration, data-driven decision making, and AI applications. | Supply Chain & Operations | https://elvenite.se |
| Cgrain AB | Offers AI technology for objective grain quality assessment and control. | Production & Quality Assessment | https://www.cgrain.se |
| Prediktera | Specializes in hyperspectral imaging software with AI for quality control in various industries including food. | Quality Control | https://prediktera.com |
| Arla | Uses AI-powered traceability systems to track the origin and journey of food products. | Supply Chain & Retail | https://www.arla.se |
| Greenfood | Implements AI in its Picadeli division for optimizing salad bar stock through the Arcorder system to reduce food waste. | Retail & Waste Reduction | https://greenfood.se |
| ICA | Collaborates with Whywaste on an AI tool for reducing food waste in stores through optimized management of food items. | Retail & Waste Reduction | https://www.icagruppen.se |
| Ekobot | Focuses on AI-supported field robotics for sustainable farming practices. | Production | https://www.ekobot.se |
| Agtira | Offers AI-driven solutions for urban agriculture and fish farming in customizable greenhouses. | Production | https://www.agtira.com |
| Animals.ai | Provides AI-driven solutions for livestock management, aiming at improving efficiency and animal welfare. | Production | https://www.animals.ai |
| Lodyn.ai | Develops an open mathematical platform for operational agriculture, optimizing decisions in farming through AI. | Production | http://lodyn.ai |
| Niftitech | Specializes in custom software solutions with a focus on agriculture, utilizing AI for crop growth optimization. | Production | https://niftitech.com |
| Agronod | a platform that allows farmers to control their data and share it securely. | | https://www.agronod.com |
| AFRY | Explores AI applications in the food industry to improve manufacturing processes, supply chains, and product development. | Production & Supply Chain | https://afry.com |
| Markkartering | Provides precision agriculture tools for soil mapping and control file creation for Swedish farms. | Production | https://markkartering.se |
| Geoanalysis Sweden AB | Specializes in remote sensing and earth observation for applications including forest and land monitoring. | Production | http://www.geoanalysis.se |
| SAS | Delivers agriculture analytics with embedded AI, supporting data-driven decisions for improved crop yields and sustainable practices. | Production & Analytics | https://www.sas.com |
| Väderstad | Develops AI-powered systems for precision agriculture, optimizing crop management. | Production | https://www.vaderstad.com |

| Company | Summary of Activity | Section | Reference |
|---|---|---|---|
| Scan AB | Implements AI systems for quality control and defect detection in food production lines. | Production and Processing | https://www.scan.se |
| Tetra Pak | Utilizes AI and machine learning for predictive maintenance, process optimization, and package design. | Production and Processing | https://www.tetrapak.com |
| Karma | Uses AI to predict and match excess food from restaurants and grocery stores with consumers. | Retail and Consumer Experience | https://karma.life |
| Lantmännen | Develops AI-driven traceability and food inspection solutions for quality assurance. | Production and Traceability | https://www.lantmannen.com |
| Oatly | Uses AI and machine learning to optimize plant-based milk production processes. | Food Production and Processing | https://www.oatly.com |
| Matsmart | Leverages AI for demand forecasting and inventory management in online grocery retail. | Retail and Consumer Experience | https://www.matsmart.se |
| Axfood | Explores AI applications in personalized grocery recommendations and supply chain optimization. | Retail and Consumer Experience, Supply Chain and Logistics | https://www.axfood.com |
| Coop | Utilizes AI for customer behavior analysis and targeted marketing in retail. | Retail and Consumer Experience | https://www.coop.se |
| Grönsakshallen Sortera | Uses AI-powered vision systems for sorting and grading fresh produce. | Food Production and Processing | https://www.grssortera.se |

*Table 13. Swedish companies as part of food system leveraging AI (Own elaboration).*

Table 13 reveals a strategic and multifaceted approach to AI adoption amongst Swedish food system companies. Far from isolated experiments, these initiatives demonstrate how AI is becoming a cornerstone for innovation and efficiency across the industry. Companies like Ekobot and Lodyn.ai are redefining production processes with AI. Ekobot employs AI-powered field robotics for sustainable farming, while Lodyn.ai uses advanced AI platforms to optimize decision-making, maximizing yields and resource efficiency. AI is also streamlining the supply chain and operations, as seen with Elvenite and AFRY. These companies integrate AI into their processes for data-driven decision-making, aiming to optimize logistics and manufacturing operations. The retail sector further illustrates the impact of AI adoption. Companies like Arla, Greenfood, and ICA demonstrate its practical use in strategic optimization and tackling industry challenges. Arla analyzes retail data with AI to optimize dairy shelf life, and both Greenfood and ICA collaborate with Whywaste, leveraging AI to combat food waste. Even beyond traditional production and retail, Animals.ai demonstrates AI extending into livestock management with solutions designed to enhance efficiency and improve animal welfare. Notably, sustainability is a recurring theme. Companies like Swegreen spearhead sustainable food production practices with AI-controlled vertical farming and urban agriculture systems. This aligns with a growing emphasis on eco-conscious practices within the Swedish food industry. This table reveals that AI adoption isn't simply a trend within the Swedish food system, but rather a strategic tool. Companies aren't just utilizing AI; they are thoughtfully integrating it into critical aspects of their operations, from ensuring quality control at the source (Cgrain AB's AI-powered grain analysis) to the complexities of retail supply chains. This showcases a maturing relationship between the Swedish food industry and AI technology, one that promises continuous innovation and transformative potential for this vital sector.

## Appendix F: Swedish research organizations related to food industry

| Institute | Summary | Website | Category |
|---|---|---|---|
| RISE Agrihub | Agrihub Sweden is an innovation hub aimed at increasing digitalization within the agricultural sector, focusing on supporting companies in agricultural production and small-scale food processing through regional nodes in Skåne, Uppsala, Västra Götaland, and Östergötland. | ri.se | Government |
| SLU (Swedish University of Agricultural Sciences) | SLU is involved in various aspects of the agri-food policy and trade, focusing on optimal performance of agricultural and food markets in Sweden and globally. It covers themes such as agricultural and food policies, rural develo0pment, and trade markets. | slu.se | Academia |
| AgriFood Economics Centre | A cooperation platform between SLU and Lund University, providing policy makers with independent and scientifically supported analyses in the fields of agriculture, food, and fishing within Swedish and international contexts. | agrifood.se | Government |
| SIANI (Swedish International Agricultural Network Initiative) | A network-based communications platform focusing on food security and agricultural development, facilitating inclusive dialogues and knowledge sharing across academia, private sector, public authorities, and civil society. | siani.se | Non-profit |
| SLU Centre for Organic Food and Farming (EPOK) | Focuses on research and development in organic farming and food systems, aiming to contribute to sustainable agricultural practices. | slu.se | Academia |
| Food and Landscape at SLU | Offers education and research opportunities focusing on the relationship between food, people, and landscapes, aiming to contribute to sustainable food systems and practices. | slu.se | Government |
| The Swedish Institute for Food and Biotechnology (SIK) | Research institute owned by RISE, focusing on food innovation and processing. | - | Food industry |
| Livsmedelsföretagen (The Swedish Food Federation) | Industry organization representing Swedish food producers and processors | https://www.livsmedelsforetagen.se/ | Food industry |
| The National Food Agency (Livsmedelsverket) | Government agency responsible for food safety and control. | https://www.livsmedelsverket.se/en | Food industry, food trade |
| The Swedish Board of Agriculture (Jordbruksverket) | Government agency responsible for agriculture and food policy. | - | Primary production |

*Table 14 Swedish research organizations related to food industry (Own elaboration).*

## Appendix G: Interview Guide

Introduction:

- Could you please give a short introduction about your work experience and your work now?

Opening Questions

- When you think of artificial intelligence, what comes to mind first? Is it opportunities, concerns, or something else entirely?
- Could you describe a recent work situation where you encountered AI, or had the potential to use AI?
- What is your overall perspective on the role of AI technologies in transforming industries and society?
- Can you share your experiences or your organization's experiences with implementing AI technologies so far? What has worked well, and what have been the main challenges?

Swedish Context

- Do you think Sweden is particularly well-positioned, or faces unique challenges, in adopting AI into the food system compared to other countries?
- Are there any unique opportunities or challenges for AI adoption in the Swedish context (e.g., policies, infrastructure, cultural factors, etc.)?

AI Priorities

- When considering AI for the food system, what's most important to you: efficiency gains, improved sustainability, or ensuring overall fairness? Why?
- From your perspective, which aspects of AI technologies (e.g., machine learning, computer vision, robotics, etc.) hold the most significant potential for the Swedish food system, and why?

Data and AI Governance

- From your perspective, what's the best way to make data useful for AI innovation in the food system, while still safeguarding [choose one: consumer privacy, producer interests, etc.]?
- Some say AI could benefit the biggest companies most. Do you agree? Why or why not?
- How can we make sure AI helps the whole food system, not just a few?

Tracing the Food System

- In which specific sectors of the Swedish food system (primary production, processing, distribution, consumption, etc.) do you see the most promising use cases for AI technologies?

- What are the potential impacts (positive or negative) of AI adoption on different stakeholders (e.g., farmers, food industries, consumers, etc.) within the Swedish food system?

Ending Question

- What steps or strategies do you think are necessary to ensure the responsible and beneficial integration of AI technologies throughout the Swedish food system?
- How do you envision the role of AI in the Swedish food system in future?
- What's the perfect picture you can imagine for the AI application in the Swedish food system?
- If you were me, what questions would you ask?

## Appendix H: The structure of themes and codes

| Codes | Themes | Layers |
|---|---|---|
| AI Application | 1- AI Capabilities and Applications | Technical - level |
| Automation | | |
| Data Management | 2- Data Challenges | |
| Data Sharing and Connectivity | | |
| Data Collection | | |
| Data and Knowledge Management | | |
| Data connectivity | | |
| Data processing | | |
| Data limitation | | |
| Data quality | | |
| Data Platform | | |
| Lack of comprehensive data | | |
| AI based Business plan | 3- Economic Drivers | Economic - level |
| Data as a Commodity | | |
| Costs of AI | | |
| Profitability and Resource Management | | |
| economies of scale | | |
| Economic Rationality as a Driver | | |
| Technology cost | 4- Commercializing AI Technology | |
| Marketing AI products | | |
| Entrepreneur Mindset | | |
| Funding | | |
| AI Perception - understanding | 5- Human-Centered AI Design | Social - level |
| UI/UX | | |
| Technology maturity | 6- AI Development | |
| AI for efficiency | | |
| Skepticism | | |
| AI optimization | | |
| User adoption | | |
| Food security | 7- Swedish context | |
| Swedish Food System Dynamics | | |
| Sweden's Unique factors | | |
| Food system complexity | | |
| Unequal negotiation | | |
| Supply chain disconnection | | |
| Natural factors | | |
| Power dynamics | | |
| Different Nature of sections | | |
| Swedish Innovation | | |
| Human-AI Collaboration | 8- Harmonized Integration | |
| Need for Standardization | | |
| Disconnected systems | | |

| Codes | Themes | Layers |
|---|---|---|
| Focus on Practicality | **8- Harmonized Integration** | |
| Accessibility of AI | | |
| Collaboration and Partnerships | | |
| Uneven Adoption | | |
| Data Ownership | **9- Ethical Considerations of Data** | **Ethical - level** |
| Data sharing resistance | | |
| Sustainability | **10- AI and Sustainable Food Systems** | |
| Green washing | | |
| Food Waste | | |
| Role of government in AI adoption | **11- Governance** | |
| Ethical Concerns | **12- Ethical concerns** | |
| Transforming human roles | | |
| Inequitable Power Dynamics | | |
| Privacy concerns | **13- Security and Privacy** | |
| Security and Traceability | | |

*Table 15. Table of the thematic analysis of interviews (Own elaboration).*

## Appendix I: Ethical Level, connections to other levels, according to the extended STST

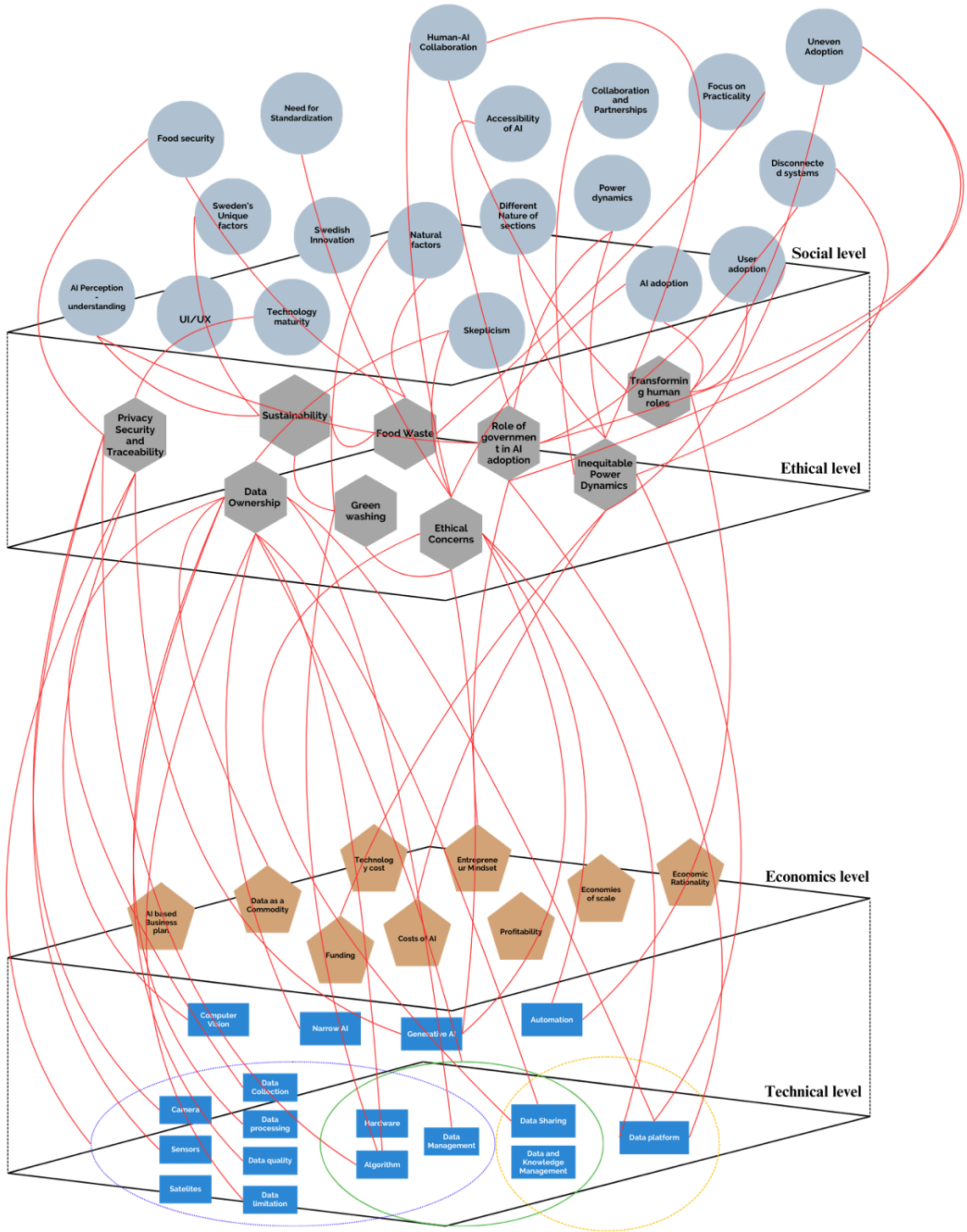



*Figure 20. Ethical Level, connections to other levels, according to the extended STST (Own elaboration).*

## Appendix J: Technical Level, connections to other levels, according to the extended STST

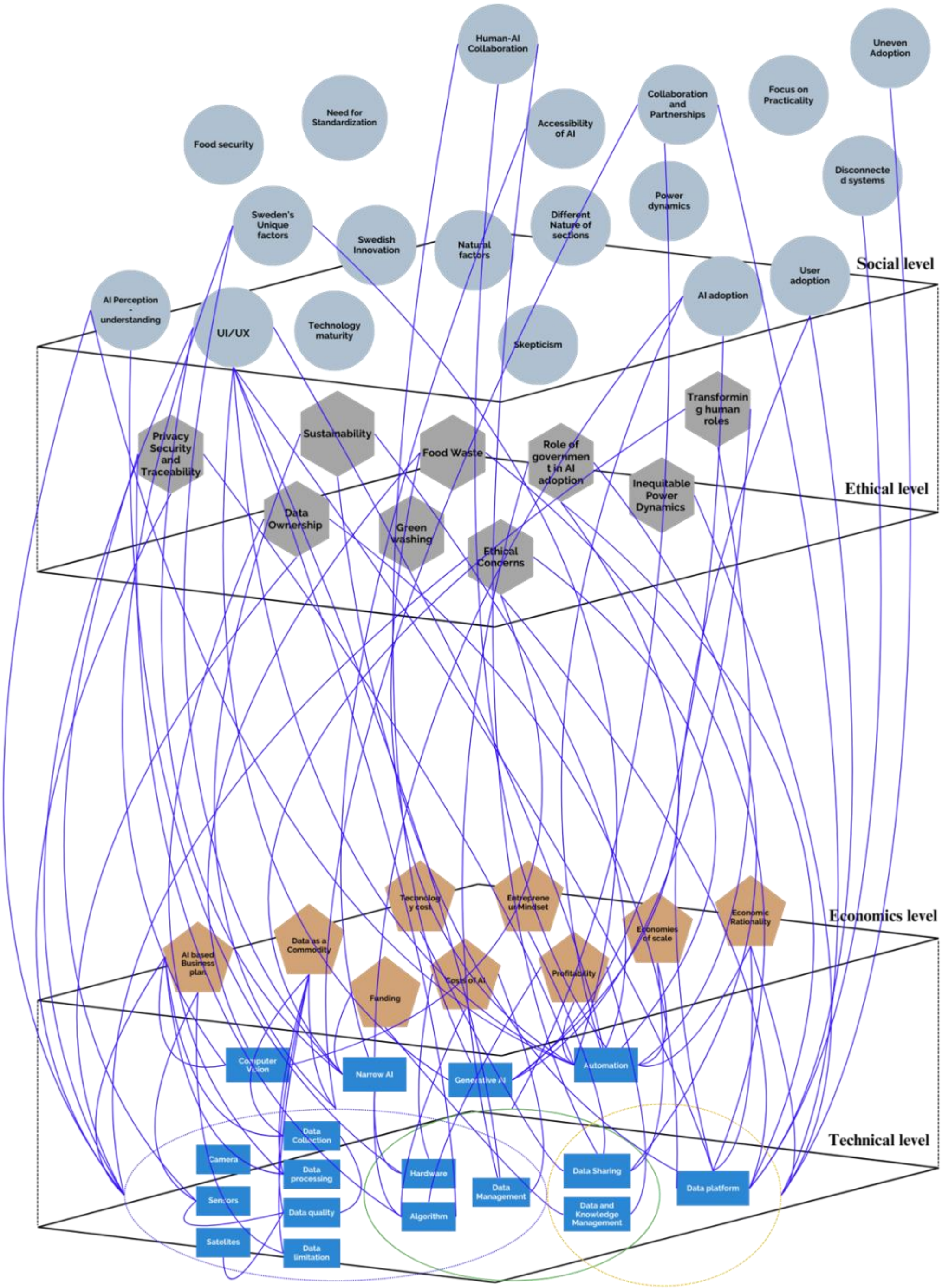



*Figure 21. Technical Level, connections to other levels, according to the extended STST (Own elaboration).*

# Appendix K: Economic Level, connections to other levels, according to the extended STST

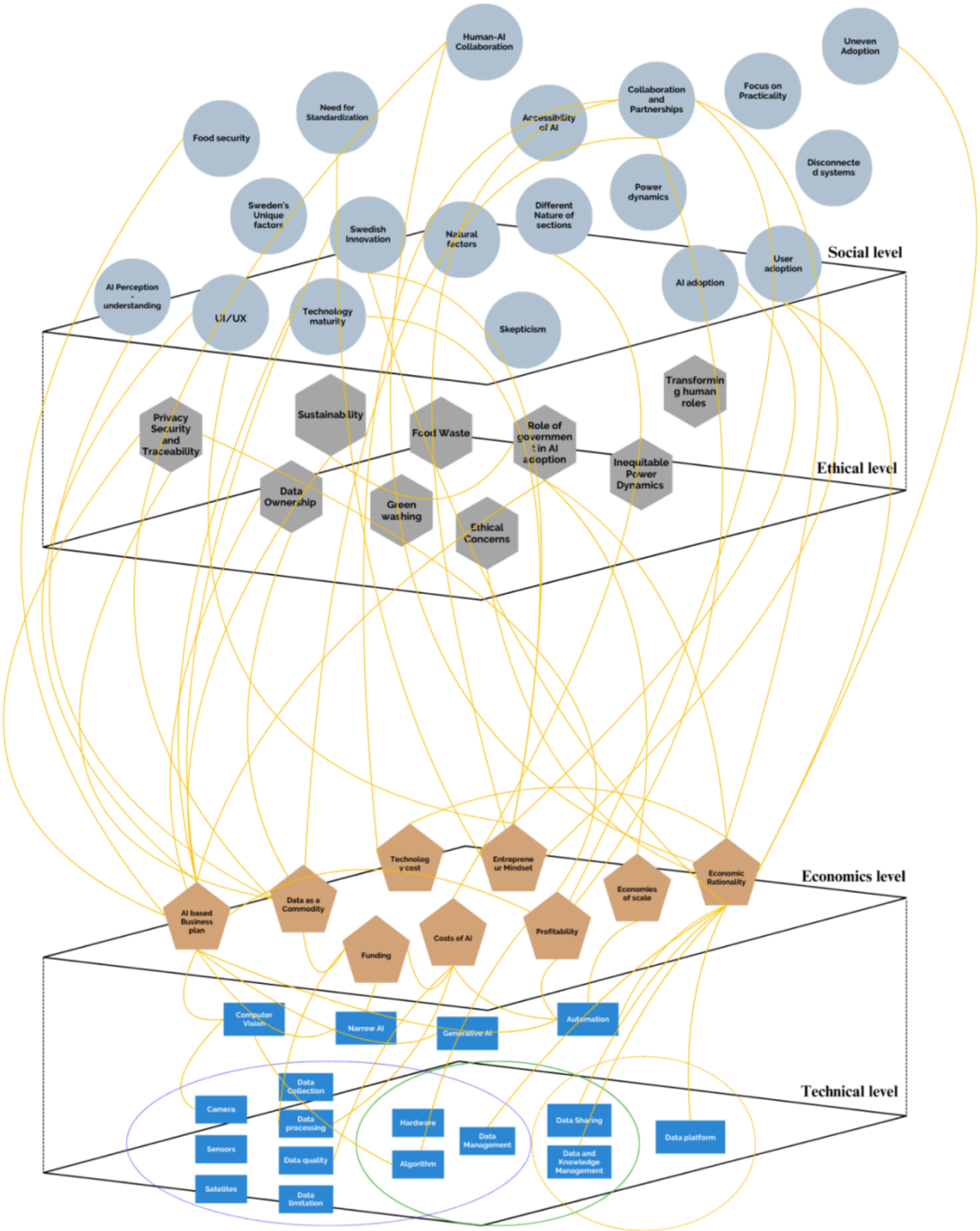



*Figure 22. Economic Level, connections to other levels, according to the extended STST (Own elaboration).*