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Artificial Intelligence in the Pulp and Paper Industry

Current State and Future Trends

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by

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Master of Science Thesis TRITA-ITM-EX 2020:271
KTH Industrial Engineering and Management
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Artificiell Intelligens i Massa- och Pappersindustrin

Nuläge och Framtida Trender

av

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Abstract

The advancements in Artificial Intelligence (AI) have received large attention in recent years and increased awareness has led to massive societal benefits and new opportunities for industries able to capitalize on these emerging technologies. The pulp and paper industry is going through one of the most considerable transformations into Industry 4.0. Integrating AI technology in the manufacturing process of the pulp and paper industry has shown great potential, but there are uncertainties which direction companies are heading. This study is an investigation of the pulp and paper industry in collaboration with IBM that aims to fill a gap between academia and the progress companies are making. More specifically, this thesis is a multiple case study of the current state and barriers of AI technology in the Swedish pulp and paper industry, the future trends and expectations of AI and the way organizations are managing AI initiatives.

Semi-structured interviews were conducted with 11 participants from three perspectives and the data was thematically coded. Our analysis shows that the use of AI varies, and companies are primarily experimenting with a still immature technology. Several trends and areas with future potential were identified and it was shown that digital innovation management is highly regarded. We conclude that there are several barriers hindering further use of AI. However, continued progress with AI will provide large benefit long term in areas such as predictive maintenance and process optimization. Several measures taken to support initiatives with AI were identified and discussed. We encourage managers to take appropriate actions in the continued work toward AI integration and encourage further research in the area of potential reworks in R&D.

Keywords

Swedish Pulp and Paper Industry, Manufacturing Processes, AI, Artificial Intelligence, ML, Machine Learning, Current State, Future Trends, Management, Digital Innovation Management, Augmentation, Automation, Organizing R&D

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Sammanfattning

Framgångarna inom Artificiell Intelligens (AI) har fått stor uppmärksamhet de senaste åren och ökad medvetenhet har lett till stora fördelar för samhället liksom nya möjligheter för industrier som tar vara på dessa nya teknologier. Pappers- och massa industrin genomgår en av de mest omfattande transformationerna mot Industri 4.0. Integreringen av AI-teknologi i industrins tillverkningsprocesser has visat stor potential, men också osäkerhet kring vilken riktning företag är på väg mot. Denna studie är en undersökning av den svenska pappers- och massaindustrin, i samarbete med IBM, som syftar till att minska gapet mellan akademin och framstegen företag inom industrin tar. Mer specifikt är denna uppsats en kombinerad fallstudie av det nuvarande läget, barriärerna till AI-teknik i den svenska pappers- och massa industrin, de framtida trenderna och förväntningarna på AI och metoderna företag använder för att stötta AI-initiativ.

Semi-strukturerade intervjuer genomfördes med 11 deltagare från tre olika perspektiv och datan var tematiskt kodad. Vår analys visar att användning av AI varierar och företag experimenterar huvudsakligen med omogen teknik. Flera trender och områden med potential för framtiden identifierades och det visades att digital innovationshantering är högt ansedd. Vi sammanfattar med att det finns flera barriärer som hindrar fortsatt användning av AI. Fortsatt arbete med AI-tekniken kommer leda till stora fördelar på lång sikt inom områden som prediktivt underhåll och fortsatt processoptimering. Flera åtgärder för att stötta AI-initiativ var identifierade och diskuterades. Vi uppmuntrar industrin att genomföra lämpliga åtgärder i det fortsatta arbetet mot AI-integration och uppmuntrar fortsatt forskning inom potentiella omstruktureringar inom FoU.

Nyckelord

Svenska pappers- och massa industrin, skogsindustrin, tillverkningsprocesser, artificiell intelligens, AI, ML, maskininlärning, nuvarande tillstånd, framtida trender, management, digitalt innovationsarbete, automatisering, förstärkning, organisering av FoU.

Foreword

This thesis project was conducted in 2020 and is part of the master's track Machine Learning within the master's programme Industrial Engineering and Management at the KTH Royal Institute of Technology.

This master's thesis is conducted in collaboration with IBM Sweden. The role of the thesis is to increase understanding of AI-technology and how this can be applied on issues in the pulp and paper industry.

The authors would like to extend gratitude to some of the people contributed particularly to this thesis project.

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Marcus Nystad

Lukas Lindblom

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Nomenclature

AI	Artificial Intelligence
ML	Machine Learning
IoT	Internet of Things
POC	Proof of Concept
R&D	Research and Development
ANN	Artificial Neural Network
CBR	Case-based Reasoning
FL	Fuzzy Logic
NLP	Natural Language Processing

Contents

1 Introduction

The rise of AI

Since the first industrial revolution, the nature of work has been drastically changing due to technological advancements. Historically, intellectual tasks dependent on human cognition have been left almost exclusively to skilled professionals, while automation has been targeted towards operational and manual tasks (Nascimento & Bellini, 2018). Recently however, the advancements in Artificial Intelligence (AI) have received serious attention as the possibilities for the technology to emulate human cognition have become more apparent. This has led to massive societal benefits (Nascimento & Bellini, 2018) and an increasing awareness that corporate value can be captured from these emerging technologies (Makridakis, 2017). This includes efficiency improvements and drastic changes to the way firms manage their business. Moreover, the computerization of complex and intellectual tasks in operations and strategy allows people to work on even more challenging or creative tasks (Nascimento & Bellini, 2018). As such, significant competitive advantage is expected for companies accepting entrepreneurial risk to capitalize on the opportunities of innovating product and service offerings with AI (Makridakis, 2017).

The field of Artificial Intelligence (AI) has been of human interest since the 1950s and originates from studies on the nature of intelligence provided by computers (Nascimento & Bellini, 2018). The term encompasses a larger number of technologies (Russel & Norvig, 2009) and a precise definition of AI remain difficult to pinpoint (Sweeney, 2003). In recent years, AI has made drastic progress by developing machines able to emulate intelligence that is either complementary or supplementary to humans (Simon, 1995). Today, AI is considered a field within cognitive science with roots of research in robotics, machine learning, image processing, natural language processing and automation (J. Lee et al., 2018).

The introduction of AI in manufacturing industries

As the advancements of AI emerge, the real impacts this technology will have on the next generation of industrial systems becomes more apparent. However, some suggest that AI-driven automation has not yet shown major impacts on productivity growth (K. Lee, 2016). The lack of sustainable effect on productivity also leads to a growing need for systematic development of these novel technologies (J. Lee et al., 2018). Moreover, there are still uncertainties regarding how and why companies should invest in AI. Identifying relevant business processes that can be effectively AI-enabled to capture business advantage remains difficult. On top of this, it is said that our understanding of how business value can be achieved is still lacking as researchers suggest that there is no simple definition of business value. As such, business value may be generated in different forms (Livesey, 2006) and the value extracted from AI may therefore differ greatly between industries.

Drawing upon industry specific issues can help contextualize the possibilities companies are able to capitalize on. As an example, the global manufacturing industry is characterized by highly competitive pressure Gröger et al. (2012). Consequentially, constantly improving the manufacturing processes to be more effective and efficient is a critical success factor for companies within this industry. Moreover, data quantity is considered one of the most important criteria for successful machine learning algorithms (Gröger et al., 2012) and large amounts of data are continuously being generated during the manufacturing processes (Mourtzis et al., 2016). These factors indicate that applications of AI could provide benefits in areas such as efficiency improvements, automatizing, risk management, supply chain management and big data analytics (J. Lee et al., 2018). As such, the possibilities of introducing AI technology into the manufacturing industry appear promising.

The transformation to Industry 4.0

AI is transforming industries into more efficient organizations and, according to some researchers, is on its way to produce an AI revolution that could take society into a new phase of the industrial revolution, Industry 4.0 (Makridakis, 2017). After the developments in the steam revolution, the electric power revolution and the digital revolution, the discussion on Industry 4.0 has opened the potential of integrating physical, digital and biological structures with large impacts on governments, people and businesses (Schwab, 2015).

Furthermore, the discussion on the relationship between AI and industry 4.0 introduces the ability of bringing radical change to current industrial companies (J. Lee et al., 2018). More specifically, the integration of AI with novel technologies such as big data analytics, cloud computing, cyber physical systems and Industrial Internet of Things (IIoT) and could facilitate flexibility, efficiency and sustainability in industrial operations. As such, the role of AI is shown to have promising opportunities for organizations aiming to study how to leverage intelligent technologies (Nascimento & Bellini, 2018).

Problematization

The role of AI within manufacturing industries present great opportunities for the research on the merging of intelligent technologies, developments in human skills, organizational adaptations, work routines and context-specific AI (Nascimento & Bellini, 2018). The advancements show that there is enormous potential to capitalize business value from these novel technologies. As it stands however, the adoption and utilization of the technology is still immature and may take many directions in the future. This creates a gap between the research and what the leading companies are currently doing. As such, this is an area encouraged for future research (Nascimento & Bellini, 2018). An increased understanding of how industries are adapting as a response to the continued development of AI would provide valuable knowledge to academia as well as aid the information spread and technological advancements in enterprises. In the long run, this will not only benefit companies but can also be proven helpful for the global economy and the progression of society.

In order to conceptualize these issues, a case study on a specific industry segment is necessary. As a result, the aim of this degree project is to map the current state and the future trends of AI in the Swedish pulp and paper industry. More specifically, this project will be contextualizing relevant issues related to the use of AI within the manufacturing processes of the Swedish pulp and paper industry, the main trends of AI that are believed to be most promising and in what ways companies within this industry manage AI. As such, this project is an investigation of to what extent AI is used in the manufacturing processes of the Swedish pulp and paper industry and what barriers hinder further use, what potential is expected of AI in the future and how companies are organized to support initiatives within AI. The context of AI and the pulp and paper industry is covered in more detailed further in the literature review section.

1.1 Purpose and research questions

The purpose of this study is to shed light on the current state of AI in the manufacturing processes of the Swedish pulp and paper industry, the advancements of AI that are currently being adopted into these processes and what barriers are hindering further use of AI. This investigation will provide a broader understanding of what progress has been made within the area of AI in their core business of manufacturing, but also what factors that need to be addressed to make further use of AI. These are important issues to investigate as one of the greatest challenges companies are facing today is understanding how to utilize the full benefits of AI (Makridakis, 2017).

Furthermore, this study will attempt to capture the trends of AI in the manufacturing processes in the Swedish pulp and paper industry. This will be done by investigating what aspects of AI the companies in the industry are currently focusing on and how they are organized to manage digital innovation and support initiatives related to AI. The purpose of this is to identify common themes in what is expected of AI technology in the future and how the industry plan to leverage this technology. Moreover, the organizational landscape supporting digital innovation is an essential part of the decision-making related to these technologies and play a large role in its further development. Because of this, the way companies manage digital innovation and support initiatives within AI is also an essential part of understanding the advancements that are being made. The exploration of these topics will create a better understanding of what areas of AI have the greatest potential of extracting business value for the industry and will help companies navigate in this field.

As such, this degree project has three research question.

RQ1: To what extent are companies in the Swedish pulp and paper industry using artificial intelligence in their manufacturing processes and what barriers hinder further use?

RQ2: What are the main future trends of artificial intelligence in the manufacturing processes of the Swedish pulp and paper industry?

RQ3: How do companies in the Swedish pulp and paper industry manage digital innovation and organize R&D to support initiatives in artificial intelligence?

1.2 Delimitations

This section presents the delimitations made within this study. This is an important aspect as it helps keep a clear line of thought throughout the study while narrowing the scope for a more focused analysis of the subject.

The term Artificial Intelligence (AI) is commonly used in various ways. This study will solely study the use of AI as defined in the literature review section as this will limit the scope of the applications investigated while ensuring clear definition in all contexts. Moreover, this study is delimited to applications of AI the manufacturing processes of this industry this is seen as one of the core areas of the business that could benefit from AI technology. Thus, this study will not investigate the adoption of AI in functions outside the manufacturing processes. An overview of the manufacturing processes is detailed in the literature review section.

This study will answer the research questions under the light of the Swedish segment of the pulp and paper industry. Although a discussion is made on the generalizability of this study into the Nordic pulp and paper industry, the context investigated in this study is focused on Swedish companies. Furthermore, the research conducted will be delimited to the overall organizational and strategic level of decision-making processes and will thus not primarily be centered towards other aspects of AI, such as ethics in-depth technical elements.

1.3 Limitations

This section provides a brief overview of potential limitations in the study.

Since this study will not have access existing information on issues related to the research questions is instead provided in various forms during the project. Thus, the study will be based on data provided solely from company representatives, researchers and experts. As a result, questions that will be asked throughout this project may have confidential elements that can be sensitive to publish. As such, confidentiality might have an effect the degree to which the research questions can be fully explored.

1.4 Outline of the thesis

This section provides a brief overview of the main points of the thesis with the aim of clarifying the structure and how different parts relate to each other.

Chapter 1 - Introduction

The thesis begins with an introduction to the issues of the study and the objectives of the thesis.

Chapter 2 - Literature review

The second chapter aims to provide necessary knowledge of the subject to the reader. This includes more in-depth information on artificial intelligence and the pulp and paper industry.

Chapter 3 - Theory

In this chapter the theoretical frameworks used as foundations for upcoming analysis are presented. This includes *Automation and Augmentation*, *Digital Innovation Management* and *Managing Innovation and Organizing R&D.*

Chapter 4 - Method

This chapter outlines the research methodology used to in the thesis and aims to explain the research design and strategy, data collection, data analysis and quality of research. The purpose of this chapter to provide transparency by showcasing and motivating the methods used to conduct the research.

Chapter 5 - Results

This chapter presents the results and finding made from the different data collection methods conducted throughout the study. The findings are presented in themes and the chapter is structured corresponding to each research question

Chapter 6 - Discussion

This chapter presents an analysis and points of discussion on the most critical themes discovered in the results. Similar to the results, the findings are presented corresponding to each research question.

Chapter 7 - Conclusion

This chapter presents the most critical findings and conclusions of the thesis. This chapter also presents suggestions for future research.

2 Background and literature review

This chapter aims to provide necessary knowledge of the subject to the reader. This includes more in-depth information on artificial intelligence and its role in the pulp and paper industry.

2.1 Artificial Intelligence

This section provides more in-depth background to AI technology, its core components and key concepts.

2.1.1 Origin and definition

The term of Artificial Intelligence (AI) is said to be coined back in 1956 and encompasses a large number of technologies and frameworks (Russel & Norvig, 2009). As such, a precise definition of AI remains difficult to pinpoint for those disseminating the applications and concepts of AI (Sweeney, 2003). Because of this, the importance of accurately characterizing what aspects of AI is referred to is critical. The sections below will present the definition of AI used throughout this project, together with some of the key concepts behind AI. In many cases, the term Machine Learning (ML) would provide a more precise description of the concept described. However, the intelligent applications undergoing transformation in this industry is established among professionals and the term of AI is therefore used.

This project will follow the definition of AI coined by Steven Finlay in his article from 2018 (Finlay, 2018):

"Artificial Intelligence (AI) is the replication of human analytical and/or decision-making capabilities."

The reasoning behind this definition is partly due to the nature of how AI is adopted in enterprises today (Finlay, 2018). The author argues that machine learning and AI are different fields of studies. However, almost all AI systems today relies heavily on machine learning. For this reason, this definition provides a simple working definitions to most companies today. As such, a large number of the AI applications that are considered successful are sophisticated applications of machine learning.

Moreover, the author makes a distinct separation between AI applications used in the industry today (Narrow AI) and the future systems of AI able to perform across a wide range of problems (General AI) (Finlay, 2018). This distinction is critical as it focuses the issue toward the current possibilities of AI in industrial companies rather than futuristic conceptions.

2.1.2 Core components of AI

As described by Finlay (2018), there are five core components that drive most of today's AI applications.

- **Data input**

  This is the process of reading sensory inputs and preprocessed data.

- **Data (pre)processing**

  This is the process of processing raw data input into standardized formats.

- **Predictive models**

  This is the process of generating predictive machine learning models using historic data.

- **Decision rules (rule sets)**

  This is the process of constructing rules that constrain the purpose of the model.

- **Response/output**

  This is the process of taking action upon decisions that have been made.

2.1.3 Key concepts of AI

This section covers the main applications of AI that are existing today, what they are typically used for and their pros/cons.

Machine learning (ML)

Machine learning, a part of artificial intelligence, uses the theory of statistics in building mathematical models that learn from experience (Alpaydin, 2020).

Artificial neural networks (ANN)

An artificial neural network, often called neural network, is a series of algorithms that attempt to recognize underlying relationships in a set of data via a process that mimics how the human brain operates (Bishop, 2006).

Decision trees

A decision tree is a flowchart-like structure, in which the internal nodes represents a "test" on a given attribute (e.g. whether it is sunny or not). Each branch of the decision tree is representing the outcome of the test, and all the leaf nodes represents a specific class label. All paths via the branches represent different classification rules that determine what the decision (class label) becomes given a specific input vector (Magee, 1964).

Natural language processing (NLP)

Natural language processing, NLP, is a branch of artificial intelligence which deals with the interaction between humans and computers by using the natural language. The objective for natural language processing is to understand, decipher, read, and make sense of the human languages (Alpaydin, 2020).

Speech recognition

Speech recognition is the ability of identifying phrases and words in spoken natural language and convert them to a machine-readable format (Bishop, 2006). Speech recognition is often done with neural networks in combination with hidden Markov models (Juang & Rabiner, 1991).

Classification

Classification refers to a predictive modelling problem, where a class label is predicted, given an example of the input data, in which the aim is to assign each input vector to one of a finite number of discrete categories (Bishop, 2006).

Case-based reasoning (CBR)

Case-based reasoning, CBR, is a paradigm of cognitive science and artificial intelligence that models the reasoning process as primarily memory based, by solving new problems by adapting previously successful solutions to new similar problems (Hammond, 2012).

Fuzzy logic (FL)

Fuzzy logic, FL, is a method of reasoning that resembles human reasoning (Adnan et al., 2015). The approach of FL is very similar to how we humans perform decision making and involves all intermediate possibilities between the value Yes and No. The conventional logic block that a computer understands, takes a precise input and produces a definite output as either 1, TRUE, or 0, FALSE, which corresponds to a human's YES or NO. Humans, unlike computes, use decision-making that includes a range of possibilities between YES and NO such as certainly yes, possibly yes, cannot say, possibly no and certainly no (Zadeh, 1983). As such, the fuzzy logic works on the different levels of input in order to achieve a definite output.

2.2 The pulp and paper industry

This section provides relevant literature for understanding results related to the pulp and paper industry.

This section presents the following parts:

- Industry overview: A brief overview of the industry and its importance
- Industry trends: Trends and transformations the industry is going through
- Manufacturing process: The core steps in the manufacturing process
- Central issues: Some of the issues in manufacturing the industry faces
- Entry of AI: Areas where the entry of AI has been previously discussed

2.2.1 Industry overview

The pulp and paper industry is considered one of the largest industries of the world. The industry has provided society with many powerful benefits within packaging and logistics, communication, security, education and hygiene (Forest Sweden, 2013; Parente et al., 2019). Out of the total consumption of pulp within the EU, around a quarter is manufactured in Sweden (Forest Sweden, 2013). Sweden is the world's second largest exporter of pulp, paper and sawn wood products combined and the Swedish forest industry as a whole plays an important part in the Swedish economy. Out of the Swedish pulp and paper production, close to 90 percent is exported (Forest Sweden, 2013). As the production is heavily export oriented, this also has a significant contribution to Sweden's trade balance. Because of this, the pulp and paper industry is considered one of the most important industries for the Swedish economy.

2.2.2 Industry trends

Through the years, the industry has faced several challenges. As an example, the demand for graphic paper declined for the first time ever in 2015, partly due to other products replacing it. Although the industry has faced a series of setbacks over the years, including increased pressure and a stagnated growth, the global industry for paper and forest-products is continuing to grow. Some claim that the pulp and paper industry is far from disappearing, but rather changing, developing and adapting to advancements in society (Berg & Lingqvist, 2017).

Over time, the strategic orientation of the industry has evolved. Some researchers describe the industry as a group of large multinational corporations in a global landscape struggling in phases characterized by ongoing transformation and conservation-based economies. (Kozak, 2013) It has been suggested that the phases the industry is going through can be characterized by four different stages: forestry orientation, production orientation, market orientation and sustainability orientation (Toppinen et al., 2013).

As society enters new phases of industry 4.0 and increased advancements in digitalization, it has been stated that the pulp and paper industry is perhaps going through one of the most considerable transformations in many decades. This includes changes in the industry structure, changes in the market segments, changes in the ways companies approach cost optimization, and overall new challenges for companies to stay competitive in the long term (Berg & Lingqvist, 2017).

An accumulation of incremental changes to company structures over the long term has led to distinct industry landscape changes (Berg & Lingqvist, 2017). Transitions toward digital media and paperless communication has led to slight contractions in the industry during the last years (Bajpai, 2016). At its core, the consolidation and grouping of companies has led to a general increase in segment concentration and a concentration of production to fewer actors (Berg & Lingqvist, 2017). Ultimately, this leads to uncertainties and forecasts predicting strong needs for structural changes in near future (Bajpai, 2016).

The demand for different product segments is changing, resulting in significant variations in demands of product segments depending on region and customer groups (Berg & Lingqvist, 2017). Some segments are growing faster than others, leading to uncertainties regarding how and where to target the products. As such, the industry now shifts focus toward sanitary products and packaging materials (Bajpai, 2016). How these trends translate into profitability is expected to be largely influenced by company supplier actions and operational excellence (Berg & Lingqvist, 2017).

2.2.3 Manufacturing process

This section cover a description of some of the most fundamental parts of the pulp and paper manufacturing processing. This is important to capture in order to fully grasp the results that are later presented and where AI can be implemented.

The pulp and paper manufacturing process has been described in Bajpai (2017) as a major part of the forest industry that not only produces paper products for a vast number of applications but also various by-product chemicals. Pulp and paper are manufactured using wood, agricultural residues and recycled paper. The general process of pulp and paper manufacturing has not changed much in the last 150 years Bajpai (2017) and an overview of this process has been illustrated in LI (1995) (see figure 1).

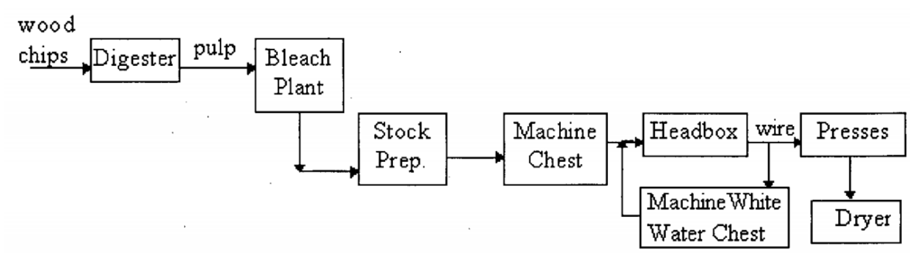

Figure 1: An overview of the the pulp and paper production process (LI, 1995).

To further simplify, this process can roughly be divided into and into four distinct steps: wood handling and debarking, pulping, bleaching, and papermaking (Biermann, 1996). An overview of these steps is summarized and presented, together with the general aim and potential actions performed, is presented in table 1.

Step	**Aim**	**Potential actions**
Raw material preparation	Preparing and handling the wood	Debarking, chipping, chip screening and chip handling
Pulping	Release and soften the cellulose fibers from the wood matrix	The use of chemical and/or mechanical forces
Washing and bleaching	Purifying the pulp to enhance quality and separate it from chemicals	The use of chemicals and washing machines such as rotary vaccuum washing
Stock preparation system	Removing water and preparing for papermaking	Pressing, drying, refining, sizing, coating, calendering, winding and cutting

Table 1: An overview of the steps in pulp and paper manufacturing process

Wood handling

In this process, wood chips are handled in a number of ways in order to prepare it for the pulping process. The specific chemical composition of wood depends on the type of tree, the location and other environmental conditions. Generally, however, the cellulose fibers in the wood are linked with hemicellulose and lignin and the wood chip quality is measured through size uniformity relative to the absence of contaminants.

Pulping

In the pulping process, chemical and/or mechanical forces are applied in order to extract the fibers from the wood. The extent to which lignin can be removed from the wood fibers vary and because of this there are different methods used to treat the fibers in the wood. As an example, recycled fibers are typically re-pulped through mechanical methods while virgin fibers from softwood and hardwood can be produced using either chemical or mechanical methods (Bajpai, 2017). As such, there are several pulping methods. However, the overall objective of extracting cellulose fibers from the raw materials is the same. The most common process of pulping is referred to as the "kraft pulping", described by Biermann (1996). This process is focused on treating wood chips into soft pulp that can be used in papermaking through the use of chemicals, heat and mechanical pulping.

Washing and bleaching

The pulp is mixed with different chemicals and diluted with water and the high amount of chemical use makes the recovery of chemicals essential (Bajpai, 2017). Because of this, proper removal of chemicals is not only important in order to maintain the quality of the pulp, but also to save resources and have less environmental impact.

Papermaking

The core steps of papermaking are the stock preparation, forming, pressing and drying of the pulp (Holik & Stetter, 2006). This is made possible through the use of paper machines and the quality of the stock determines the properties of the paper. A series of steps is conducted in order to further remove water, dry, press and coat the paper into its proper form. Other actions, such as sorting, cutting, counting and packaging of paper products (Bajpai, 2017).

2.2.4 Central issues

This section provides a description of some of the most central issues companies within the pulp and paper industry face regarding their manufacturing processes.

Paper web breakage

A web break in a paper machine is an event that occurs when the paper web breaks, and the end of the web is led to the paper roller (Ahalo, 2005). During this break, chopped paper is removed from the machinery and the equipment is cleaned. These events naturally occur when the strain on the web is greater than the strength of the paper and can be triggered from a number of causes such as excessive operating tension or poor formations in the paper web.

It has been noted that breakage of paper web is a critical issue for manufacturing processes of the pulp and paper industry, typically resulting in a 5-12% production loss and around 7% loss in total revenue (Bonissone et al., 2002). Given that the global pulp and paper industry produces world-wide revenues of around $63 billion dollars in 2018 (360 Market Reports, 2019), the web breakage issue alone translates to a loss in revenues of around $4 billion dollars yearly.

Machine maintenance

Continuous machine maintenance is a necessity for any pulp and paper mill. Typically, maintenance costs represent a significant investment for these factories and in many cases 20% of the total mill workforce is employees focusing on maintenance activities (Lu et al., 2009). Furthermore, it has been reported that mean maintenance budgets for pulp and paper companies could be around $5 million US dollars, where electrical and mechanical maintenance typically are the two areas requiring most resources (Lu et al., 2009). The continued development of industrial processes and increasing costs of maintenance have historically challenged traditional maintenance practices and companies are now encouraged to shift parts of the maintenance activities to operators.

Energy consumption

Energy consumption is considered a critical aspect for companies in the pulp and paper industry as there are several processes that are highly energy-intensive (Bajpai, 2016). In terms of energy usage, the pulp and paper industry is ranked fourth among all industries worldwide in total greenhouse gas emissions.

Two of the most significant energy consuming processes is the papermaking process and the pulping process. The papermaking process is considered the most energy-intensive processes and is responsible for around 45% of total energy consumption. Within the papermaking process, drying is the largest energy consumer, requiring about 4.5 GJ/t pulp of thermal energy and 0.6 GJ/t of electricity to evaporate water from the paper (Martin et al., 2000).

The second most energy-intensive process is pulping, where mechanical pulping is used to drive grinding equipment and chemical pulping is used for steam and electricity. Mechanical pulping consumes around 3.6–15.5 GJ per ton of air-dried pulp, while chemical pulping consumes around 7.5–16.5 GJ of thermal energy per ton of air-dried pulp and 2-3 GJ of electricity per ton of pulp (European Commission, 2013).

An upcoming trend is increased efforts to decrease power consumption while increasing power production (Bajpai, 2016). As a result, significant efforts are put into attempting to reduce the consumption of energy in the manufacturing processes and thereby reducing the costs. Although the industry has relatively low carbon dioxide releases (Bajpai, 2016), making efficiency improvements in the consumption will not only benefit companies but also frees up scarce bioenergy resources for other industries.

2.2.5 The entry of AI

In a paper from 1992 (Udo, 1992) it was said that advanced manufacturing systems are becoming too dynamic and complex. Because of this, the study surveyed the technology of neural networks on the application of manufacturing processes and concluded that many applications reported in the literature are either laboratory experiments or preliminary applications. In 1995, a paper studying the issues of sheet breaks in pulp and paper factories concluded that there were no ways of effectively predicting and preventing sheet breaks (LI, 1995). In another paper (Leiviskä, 2000), some of the intelligent applications receiving work during the latest years in a laboratory were discussed. The study concluded that there is a growing number of applications of intelligent methods in the pulp and paper industry, including expert systems, fuzzy logic, neural networks and genetic algorithms. Since the publication of these studies, a lot has happened within the development of improving manufacturing processes of the pulp and paper industry using AI algorithms.

Paper web break prediction

In a paper from 2002 (Bonissone et al., 2002), a set of researchers attempted to solve the issues of paper web breakage in paper-making machines using sensor data and various machine learning models. It was found that it is possible to build predictive models that accurately estimates time-to-breakage in paper-making machines and flags for web break tendencies in these machines. The authors further argued that these models could cover up to 50% of break with unknown causes with generalized models that ignore rule-based parameters.

The interest in increasing production of paper has led to an increasing number of studies on paper machine runnability in the last decades (Ahalo, 2005). One of the elements defining the current operating situation at the paper mills and which provides valuable information to operators is web break sensitivity. Predicting such events would allow operator time to react to changing operating situations and can therefore lead to increase production efficiency.

In a study from 2005 (Ahalo, 2005), an application for the evaluation of web break sensitivity in paper machines was presented. The study concluded that there is potential to build generally effective applications that use case-based reasoning and basic fuzzy logic. Other elements of AI that can be relevant in the prediction of these events are PCA, neural networks and decision trees. A paper published in 2017 (Kanawaday & Sane, 2017) explored the use of machine learning to predict possible failures and quality defects in the manufacturing process. It was concluded that IoT based machine learning has the potential to overcome major limitations in productivity and decrease maintenance costs associated with this.

Predictive maintenance

In order to avoid unexpected failures in machinery and lower maintenance costs, managers are looking to improve efficiency of the maintenance by capitalizing on the opportunities presented by new technology. As a result, there has been substantial efforts and progress in the areas of preventive maintenance and predictive maintenance during the last years. (Lu et al., 2009)

While preventive maintenance can be described as maintenance scheduled at regular intervals, predictive maintenance is centered around maintaining machinery as needed and based on asset conditions. As such, predictive maintenance is an approach related to equipment management focusing on the exploration of sensors, inspection, and maintenance data with the aim of forecasting future degradation states, the remaining useful life of a machinery or other parameters with connections to expected future performance (Miller & Dubrawski, 2019). Smart applications within predictive maintenance aims to enable intelligent planning in order to effectively and efficiently reduce the burden of equipment management and thus significantly decrease maintenance need, unplanned downtime and uncertainty (Miller & Dubrawski, 2019).

Due to the fact that the nature of available data and process constrains in implementations vary largely between industries, a large number of studies on predictive maintenance are focused on specific industry segments (Miller & Dubrawski, 2019). This tendency largely affects the nature of available studies in this area and limits the research on predictive maintenance specifically in the pulp and paper industry. However, in one study from 2019 the potential use of machine learning of automation system data in paper mills was investigated (Nykyri et al., 2019). It was concluded that predictive models were able to reach accuracies of up to 98,85%, while also being generalizable to other processes and scaled up using factory scale IIoT systems.

3 Theory

This chapter will present the theoretical frameworks that will be used to help understand the results gathered in this study. As such, this chapter will serve as a foundation for the data analysis by presenting relevant scientific theories related to the research questions.

Some key elements of that are unraveled in this theory are frameworks related to managing artificial intelligence, managing digital innovation and organizing R&D. The theory will mainly act to create a common understanding of some principles of reasoning between different purposes in AI integration, managing AI as an innovation, and relationships between organizational R&D and technological innovation. The aim of these theories is to create an understanding in how companies value automation in contrast to augmentation, to what extent digital innovation is used in the industry, and how companies are organized to support initiatives within AI. As a result, the following three main theoretical frames are used supplement the data analysis:

- Automation and Augmentation
- Digital Innovation Management
- Organizing R&D

3.1 Automation and Augmentation

This section covers a framework that help explain the management of AI through the trade-off between automation and augmentation.

In the article "Artificial Intelligence and Management: The Automation-Augmentation Paradox" by Raisch and Krakowski (2020) they explore the two concepts of augmentation and automation within the management domain. They define automation as the process of a machines taking over human tasks and augmentation as the process of collaboration between machines and humans in order to perform specific tasks.

In one of their books they advise companies to augment rather than automate. The authors put this in the following way: "don't automate, augment" (Davenport & Kirby, 2016, p. 59). Furthermore, they describe augmentation as: "the only path to sustainable competitive advantage" (Davenport & Kirby, 2016, p. 204). The message here is clear; they see larger potential in augmentation than with automation and encourage companies to adopt an augmentation strategy. Instead of fearing the effects of automation and seeing AI as technology that will replace labors, AI should be seen as a technology with potential to enhance the performance of humans in managerial tasks (Davenport & Kirby, 2016, pp. 30-31).

The exponential increase in the amount of data, new machine-learning techniques together with recent advances in computational power is now making it possible for companies to also use AI solutions for managerial tasks (Brynjolfsson & Mcafee, 2017). Taking a normative stance relying on three recent business books (Brynjolfsson & McAfee, 2014; Daugherty & Wilson, 2018; Davenport & Kirby, 2016) the conclusion and advice for organizations is to focus on augmentation since it leads to superior performance.

3.1.1 Paradox perspective

This theory section adopts a paradox perspective based on the definition of a paradox by Smith and Lewis (2011): *"We define paradox as contradictory yet interrelated elements that exist simultaneously and persist over time"*. This perspective is used to evaluate the tension between automation and augmentation. Paradox studies adopt a different approach to tensions, focusing on and exploring how organizations can attend to competing demands concurrently (Smith & Lewis, 2011). Although choosing among competing tensions might benefit short-term performance, a paradox perspective argues that in order to get long-term sustainability, continued efforts has to be made to meet multiple, divergent demands (Smith & Lewis, 2011).

3.1.2 Paradoxical tension

However, over-emphasizing either one of these applications fuels reinforcing cycles with negative societal and organizational outcomes. Because of this, the authors also argue that a one-sided approach might not be the most appropriate strategy in all scenarios. Instead, they present a more comprehensive paradox perspective. In this perspective they argue that, within the management domain, it is not possible to separate augmentation from automation. As the applications of automation and augmentation are interdependent across both space and time, this creates somewhat of a paradox. Thus, having a perspective where both augmentation and automation is prioritized will make companies able to realize synergy effects that benefit both the businesses as well as society.

The relationship between augmentation and automation is described as a trade-off decision by the authors of the above-mentioned books. They state that companies that want to implement and use AI technologies have the choice of either entirely automate the task or use an augmentation approach instead. Whether a specific task should be solved using an automation approach or augmentation approach depends solely on the nature of the task. Routine-tasks that are well structured can easily be automated while more complex tasks are much harder to automate and can be addressed via an augmentation approach instead (Brynjolfsson & McAfee, 2014). (Raisch & Krakowski, 2020) argue that the arguments provided by these books are hard to refute but emphasize that the perspective these books have is very limited to a specific point in time and a specific task.

Paradox theory, on the other hand, warns that taking such a narrow perspective will not represent the reality appropriately (Smith & Lewis, 2011). Using a paradox lens instead can help to increase the level of analysis for a more systematic perspective, which in turn allows companies to also see interdependencies between augmentation and automation and not only perceive contradictions (Schad & Bansal, 2018). The bottom line of the paradox is that augmentation and automation are both contradictory and interdependent according to Schad and Bansal (2018).

3.1.3 Management Strategies

The continued technological progress and the recent advancements toward digitalization has resulting in a high tension toward AI technology. Companies that face such tension tend to address the situation by applying different management strategies. According to the paradox theory these responses by management fuel reinforcing cycles and these cycles are by nature either positive or negative (Smith & Lewis, 2011). If organizations are unaware of that this tension between augmentation and automation exists, they might be inclined to apply only partial strategies which in turn might lead to vicious cycles that only escalate this tension. On the contrary, organizations that are aware and accept this tension as paradoxical could enable chains of positive events known as virtuous cycles (Schad et al., 2016).

3.1.4 Vicious cycles

Due to the promise of short-term cost savings and efficiency gains most organizations are likely to prioritize automation (Davenport & Kirby, 2016). Such a strategy also forces companies' competitors to pursue automation as well in order to stay cost competitive. According to Endsley and Kiris (1995) these organizations over time lose the human skills that are required to change their processes. Automation has been shown by previous research to be able to deskills humans, diffuse their sense of responsibility as well as make them self-satisfied (Parasuraman & Manzey, 2010). Even though automation can free up more resources for search activities, only focusing on automation is mostly associated with short-term thinking, lock-in effects as well as loss of human knowledge and expertise. Thus, automation can fuel reinforcing vicious cycles that makes it difficult for companies to implement such search-activities.

3.2 Digital Innovation Management

This section covers frameworks that help explain the concepts of digital innovation management and practical ways to support digital innovation.

All industries today, including the pulp and paper industry, are facing the challenges of digitalization where digital technology is becoming more important by the day for companies in achieving their business goals (Demirkan et al., 2016). Applying new technologies to transform and renew business models have become a crucial aspect to achieve competitive advantage for today's companies and leads us into the field of digital innovation management.

In the paper "Digital innovation Management: Reinventing innovation management research in a digital world" (Nambisan et al., 2017), the field of innovation management is under the microscope. Questioning of fundamental assumptions and an emphasis on the importance of novel theorizing on digital innovation management that draws on the rapidly and rich emerging research that can be found on digital technologies. The concept of digital innovation is referred to as the process of innovating using digital technology, where digital innovation can be used to describe the outcome of innovation.

3.2.1 Digital Innovation

Digital innovation has led to drastic and radical changes in both the nature and structure that products and services have today, generated novel value creation and value appropriations, together with enabling innovation collectives, produced new innovation processes and more or less transformed entire industries (Nambisan et al., 2017). In the quest of pursuing more encompassing theories of digital innovation, Nambisan et al. (2017) has presented a new conceptualization of digital innovation that aims at being both inclusive in its nature and inviting other disciplines that might not have been contributing to the field in the past. They conceptualize digital innovations as "the creation of (and consequent change in) market offerings, business processes, or models that result from the use of digital technology.". Following this conceptualization, digital innovation management refers to the different parts: practices, principles and processes that determine the effective composition of digital innovation.

The authors state that the definition captures three concurrent and very important phenomena (Nambisan et al., 2017). First of all, the definition includes a wide range of different innovation outcomes: e.g. new products, services and platforms and new customer experiences together with other value propositions, provided that these innovations are made through the use of digital technologies. An important aspect is that the outcome itself does not have to be digital. Secondly the definition includes a broad range of different digital tools and infrastructures (e.g. data analytics, 3D printing etc.) that are making the innovation process possible. The final phenomena that this definition captures the fact that the outcomes from digital innovation may both be diffused, assimilated or adapted to specific use contexts.

3.2.2 The digital innovation life-cycle

In the wake of new theory building on digital innovation, a theoretical framework has emerged by (Kohli & Melville, 2019). Building on the four stages presented by Fichman et al. (2014), Kohli and Melville (2019) have developed a theoretical framework of digital innovation which can be seen in figure 2. This framework helps explain parts of digital innovation management and the actions companies are taking in order to fully utilize the innovation.

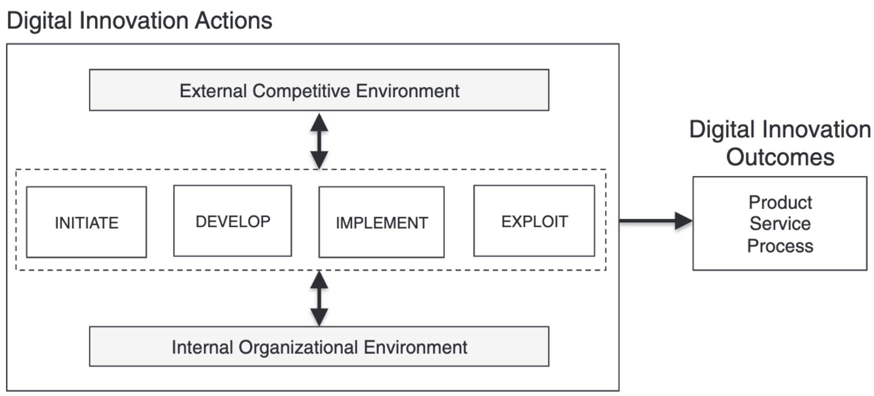

Figure 2: Theoretical framework of digital innovation (Kohli & Melville, 2019)

In the field of digital innovation, Kohli and Melville (2019) identified common patterns emerging from the literature. The first component they found was that the outcome of the digital innovations all includes IT-enabled products, services and processes. Furthermore, the idea that a key aspect of innovation is design and development, which includes both adoption and development of new artifacts followed by the implementation of these artifacts within the organization. Lastly, they identified the internal organizational environment as an important component. The internal organizational environment incorporates existing organizational structures, while culture and processes all are shaped by as well as shape the innovation process and affecting the final outcome.

Besides these four concepts of development, implementation, internal organizational environment and the product, process, and service outcomes (Kohli & Melville, 2019), adds three new components to make the model more complete. These components are:

- Initiation - the early stages of innovation
- Exploitation - the recombination and reuse of data and artifacts
- Internal organizational environment - organizational backdrops of strategies, cultures and operations
- External competitive environment - marketplaces in which firms operate

3.2.3 Digital innovation barriers

The concept of barriers to digital innovation was covered in the work by Ivanov (2018). In this paper, the authors have identified a barrier typology for digital innovation in manufacturing firms of physical products. This is an important aspect in order to fully understand the potential drivers and obstacles within organizations.

In the article *"Digital Innovation in Manufacturing Firms: a Grounded Theory Approach for Identifying a Barrier Typology."* by Ivanov (2018), the authors have identified a range of different barriers in the context of development of digital innovation in manufacturing firms. Six main types of barriers were defined together with subcategories (see table 3).

Open coding	**Seed concepts/ Subcategories**	**Categories**
Perception of DI on a senior management level	***Cognitive***	Misunderstanding of Digital Innovation
Hesitation towards DI due to lack of experience		
Software engineers are not attracted by product-driven companies		
Lack of knowledge to develop DI		
Not harvesting the potential of DI		
Mindset as a barrier		
The industry structure is considered as a barrier	***Ecosystem***	Industry readiness for DI
Not existing ecosystem standards for DI connectivity		
DI is not scalable and network effects are not possible		
The industry trends are not yet developed in the direction of DI		
Personal data protection in EU will slow down the development of DI	***Legal framework***	Uncertainty due to governmental regulations
Decision making for DI investments made from product development perspective	***Innovation process***	No integration possible in the current framework
Requirements of quality of DI		
No dedicated process for DI development		
DI capitalization cannot be defined	***Capitalization***	Lack of tangible incentives to invest in DI
DI pace is very high and cannot fit the business model		
Lack of DI strategy	***Organization***	Blurred direction and lack of alignment towards the development of DI
Organizational change as a prerequisite for DI		
DI roadmap is challenging to develop		
Internal alignment can be improved		

Figure 3: Table of open coding (barriers) of digital innovation in manufacturing firms (Ivanov, 2018).

The cognitive barriers cover all barriers related to mindset, perception, understanding and knowledge (Ivanov, 2018). These types of barriers represent the current stage of digital innovation understanding considering beliefs, perception and assumptions while the other barriers are described as more self-explanatory.

The results from their study indicated that the context for development of digital innovation in manufacturing firms is volatile. This volatility leads to challenges for the companies during the integration of digital innovation activities into their existing processes. Furthermore, organizations implementing radical innovations do in general face more barriers than organizations that focus more on incremental innovation activities (D'Este et al., 2012). Moreover, Ivanov (2018) concludes that cognitive barriers play a key role in the development of digital innovation and therefore affects its implementation path.

3.3 Organizing R&D

This section covers frameworks that help explain different ways organizations can structure R&D units to facilitate work within digital innovation and to support digital innovations.

3.3.1 Decentralization of R&D, innovation and firm performance

In a study by Arora et al. (2011) the relationship between decentralization of R&D, innovation and firm performance was investigated. The tension between decentralization and centralization of R&D is explored, which depicts a tradeoff between responsiveness to immediate local business needs and research that could benefit the organization as a whole. Although business units might have superior local information about e.g. the needs of their customers, the managers of these units may be more likely to ignore the potential research could have provided for other parts of the organization (Nobel & Birkinshaw, 1998). This may be a result of lack of knowledge (Hitt et al., 1990) or a result of business unit managers being rewarded predominantly for their individual unit's performance, and not that of the organization as a whole. In contrary, centralized R&D is able to invest in projects associated with higher risk in longer periods and can incorporate "spillover research" better. However, centralized R&D risks losing information about their customers' needs. Moreover, Arora et al. (2011) found that decentralized research is more incremental in its nature, narrower in technical and organizational scope, and is also less likely to draw upon scientific research. As such, centralized R&D tend to be more scientific in its orientation.

Turning to the relationship between outcomes and decentralization, it was found that organizations with decentralized R&D invest less in in R&D and thereby also produce fewer patents, but also grow faster (Arora et al., 2011). Interestingly, it was also found that, although the existence of corporate labs is associated with a higher market value, the extent of decentralization is positively correlated with the market value of the organizations. This may reflect the efficiency of having decentralized R&D or the more incremental nature of an R&D that is decentralized. Although being associated with lower investments in R&D, decentralized R&D is associated with higher sales growth and market value. This phenomenon suggests that, although centralized research may be scientifically and technically superior, the private economic benefits of such R&D units are less clear.

Being more attentive to the immediate needs of the business, decentralized R&D are also less likely to advance in technology that is of a fundamental nature. In contrary, centralized R&D, though better at managing pioneering research, is more susceptible to careless expenditures on scientifically interesting projects, which have limited value for the organization. As a result, the authors suggest some organizations to adopt hybrid structures. The hybrid organizations are described in the following quotation: "[...] hybrid organizations, where R&D is performed centrally but the projects are those that the individual units and affiliates are willing to pay for, may be a useful compromise between the two pure forms." (Arora et al., 2011).

3.3.2 Integrated R&D network

The classical binary center-subsidiary relation of an R&D unit loses its significance in the integrated R&D network model as defined in (Gassmann & Zedtwitz, 1999). In the integrated R&D network model the central R&D involves into more of a competency center among interdependent R&D units, which all are closely interconnected by means of diverse and flexible coordination mechanism as can be seen in figure 4.

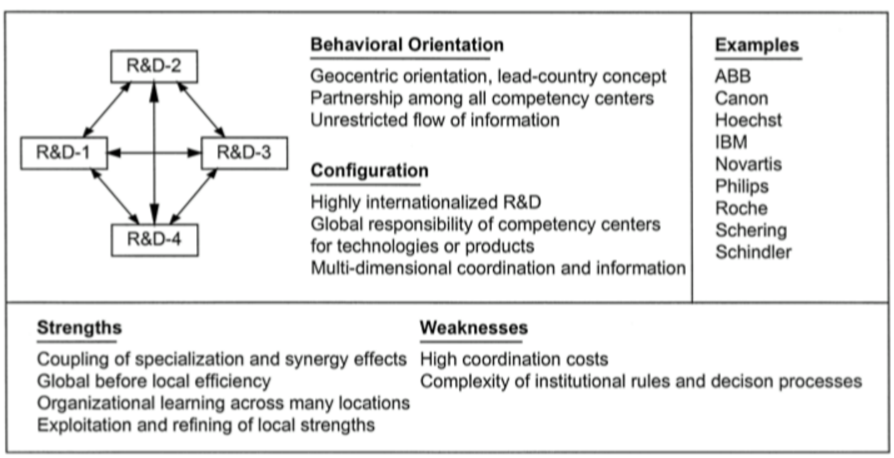

Figure 4: Illustration of the integrated R&D network (Gassmann & Zedtwitz, 1999)

Furthermore, the integrated R&D networks is characterized by authority for technology or component development based on the individual capabilities of the R&D units. The idea of the integrated model is to exploit the synergy between closely connected R&D units. Each unit in the network is specialized on a particular service, product, component or technology area. Since a unit accumulates knowledge in particular field of specialization, a specific unit assumes a leading role as a competency center.

4 Method

This chapter presents the methodological choices selected and why these were used in order to increases transparency, credibility and reliability of the study.

4.1 Research design and strategy

4.1.1 Exploratory approach

In order to collect relevant data for the examination of the research questions a qualitative research method was chosen together with an exploratory approach. This design has been proven suitable when the objective is to gain deeper understanding of a specific phenomenon, rather than a more generalized understanding derived from a large population (Bell et al., 2018; Saunders et al., 2000). This design is in line with the aim of this study.

4.1.2 Inductive approach

Furthermore, an inductive research approach was applied within this study. An inductive approach is used when a researcher begins with a data collection phase in order to explore a specific phenomenon, then formulating a hypothesis and finally developing theories from the data (Gioia et al., 2012; Saunders et al., 2000). The objective when using an inductive approach is to allow meanings to emerge from the collected data in order to identify relationships and patterns to build a theory. Although, it does not prevent the researcher from using existing theory to formulate the research questions or to identify concepts that are explored during the research process (Saunders et al., 2000)

Since the aim of this study is to gain deeper understanding of how AI is used and affects the manufacturing processes within a certain context, an analytical framework was used as a guide for analysis. However, the analysis was not fully restricted to the framework and thus had an open-minded viewpoint. As such, there may be empirical findings illustrating other aspects that do not fit into the existing theoretical framework which motivate an inductive approach.

4.1.3 Multiple case study

Moreover, this study was conducted as a multiple case study. According to Baxter and Jack (2008), a multiple case study constitutes as a tool to study a complex phenomenon within its context. A multiple case study is beneficial since the analysis can be made within a common context set by the industry, processes and technologies covered in this study.

For a multiple case study of this kind, the perspectives covered by the data collection is essential. The leading aim of this study is to investigate the main trends of AI within the manufacturing processes of the Swedish pulp and paper industry. Due to the nature of the topic qualitative data collection is required for this study to extensively investigate this area.

4.1.4 Triangulation

Triangulation is considered the practice of using two or more independent sources of data in order to ensure help the data is telling the information it is believed to present (Saunders et al., 2000). The use of triangulation helps confirm validity, credibility and authenticity of the research data, analysis and interpretation (Saunders et al., 2000). As such, the data collected in this project consists of three different viewpoints and perspectives of the issue. Covering several alternative views of the same issue is of high relevance. As such, the three relevant perspectives selected in this study are the following:

- **Pulp and paper perspective:**

  Organizations active within the Swedish pulp and paper industry

- **IT perspective:**

  Organizations with experience assisting digital transformations

- **AI expert perspective:**

  Experts with deep hands-on experience in AI implementations

The data collection covering these three perspectives is further described below.

4.2 Data collection

4.2.1 Data sources

The respondents and organizations interviewed in this study were selected according to defined inclusion criteria in accordance with purposive sampling (Bell et al., 2018). The data sources used for data collection will be motivated from the selected perspectives of this study. In order to collect data to cover these perspectives of the topic, three different sources were used for the data collection. In table 2, each of these perspectives are described and mapped to the data sources selected to represent the perspective.

Perspective	**Meaning**	**Selected data source**
Pulp and paper perspective	The perspective from companies in the swedish pulp and paper industry	Four major companies representing the swedish pulp and paper industry: SCA, BillerudKorsnäs, Holmen, Stora Enso
IT perspective	The perspective from IT organizations assisting the pulp and paper industry with digital transformations	Representatives from IBM with experience in the pulp and paper industry
AI expert perspective	The perspective from AI experts with deep hands-on experience in technology implementations	AI researchers and leaders of AI projects in the pulp and paper industry

Table 2: The triangulation of different perspectives their corresponding data sources

In the following sections, these data sources are further described together with their respective inclusion criteria.

The pulp and paper industry perspective

Data from the first perspective was collected from a subset of companies within the Swedish pulp and paper industry. The market share of this industry is split by a relatively small number of large companies. Because of this, four major actors were selected to represent the Swedish pulp and paper industry. The external interviews covered four major companies within the Swedish pulp and paper industry. The data was collected in the form of two semi-structured interviews with each company, resulting in eight external interviews in total. The companies that will represent the external perspective of the Swedish pulp and industry are Stora Enso, BillerudKorsnäs, Holmen and SCA.

The inclusion criteria for the interviewees were partly that people had adequate knowledge and experience applicable to answer questions regarding AI and digital transformation within the pulp and paper industry. Because the organizational structures and role responsibilities varies between companies, the most relevant representatives from each company also varied. A full list of the interviewee job titles can be found in table 3.

The IBM perspective

The data covering the second perspective was collected from IBM. IBM is one of the largest global IT companies in the world, has a strong history within the Swedish IT industry and has extensive experience with helping industrial companies with their technological advancements (Statista, 2020). Furthermore, IBM is currently active in several ongoing projects and collaborations with several companies within the Swedish pulp and paper industry. Because of this, they have a strong relationship and a good understanding of how these organizations operate to facilitate technical advancements. This study was conducted in collaboration with IBM and the methodology and inclusion criteria for the data collection from this perspective is described below.

The internal interviews covered IBM's perspective of the research area. IBM is as a giant actor within the Swedish IT industry, has valuable in-house knowledge and adds another, more general, layer of perspective on the given research question. In total, three internal interviews were held with IBM employees that have worked closely with the pulp and paper industry. These interviewees acted as an expertise panel on the trends and current status within the Swedish pulp and paper industry from the perspective of the IT industry.

The AI expert perspective

The data covering the final, more technical, perspective was collected through interviews with technical experts within the field of AI. The interviewees were AI experts with hands-on experience with implementing novel machine learning solutions in organizations and are thus at the forefront of technology. The methodology and inclusion criteria chosen for the data collection from this perspective is described below.

4.2.2 Sampling technique

When selecting organizations and respondents to interview, purposive sampling was used. Purposive sampling is a non-probability sampling technique that relies on the judgement of the researcher when selecting the units that are to be studied (Bell et al., 2018). The goal of purposive sampling is to sample in a strategic way; therefore, the respondents were chosen for their relevance to the research questions being posed (Bell et al., 2018). Furthermore, the researcher needs to choose relevant criteria that the respondents and organizations should fulfil in order to be included in the study. In purposive sampling, the researchers have a crucial role in choosing the cases that best suits the stated research questions. However, evidence that there can be bias and errors in judgment when choosing cases has been reported (Saunders et al., 2000). Therefore, the researchers have been meticulous when deciding which cases to include in the study in order to stay transparent and show awareness of the limitations of the methodology. In table 3, each interviewee job title is listed together with their perspective representation.

Perspective	**Job title**
IT	Global Lead, Forestry, Pulp & Paper Industry
IT	Digital Strategist and Business Development Leader
Pulp and paper	Head of digital innovation
Pulp and paper	IT Architect, Digital Innovation Department
Pulp and paper	Head of digital innovation
Pulp and paper	Director of IP management
Pulp and paper	Business development manager
Pulp and paper	CIO
Pulp and paper	Innovation manager
AI expert	Associate Professor
AI expert	CEO

Table 3: Job titles of the interviewees and their corresponding perspectives

4.2.3 Interview format

Strategy and structure

In total, 11 interviews were conducted covering both the pulp and paper perspective, the IT perspective, and the AI perspective. The empirical data was gathered through semi-structured interviews with people representing all of the above-mentioned perspectives Campbell et al. (2013). When taking an exploratory approach, it is argued that semi-structured interviews are advisable since they allow for open-ended, complex and follow-up questions (Saunders et al., 2000). A semi-structured interview gives the participants a chance to elaborate on and explore issues that they feel are essential (Longhurst, 2003). Furthermore, the semi-structured interviews allowed the respondents own thoughts and perceptions to be the primary guide for the conversation. This phenomenon could reduce the risk of an interviewer affecting and influencing the respondents' answers (Bell et al., 2018).

Moreover, the current use and future beliefs of AI cannot only consist of many complex opinions, emotions and behaviors but also be affected by a considerable diversity in experience. Using predetermined questions together with allowing the participant to elaborate on their answer allowed for a more transparent picture of the current situation. Before the interviews, an interview guide was constructed to be able to ensure greater transparency of the study. The interview guide emanates both from relevant theories and concepts depicted in the analytical framework as well as from other aspects connected to the research questions.

Time and place

All the interviews were conducted via video conference and by phone due to the Covid-19 pandemic and related recommendations for social distancing at the time of the interviews. Phone interviews have their limitations, such as losing face expressions, which could result in less trust from the respondent as well as the overall interpretation of the interviews (Bell et al., 2018). Nonetheless, phone interviews can have other advantages such as being perceived as less stressful by the respondent and also help the researchers to get easier access since a phone interview requires less effort from the respondents (Bell et al., 2018).

Each interview was held with one person interviewing the subject while another person took notes and was conducted in either English or Swedish depending on the respondents' native language. Furthermore, each interview was set to about 60 minutes depending on each respondent's situation, with the exception of the interviews with the AI experts that were set to about 30 minutes due to covering a smaller perspective of the study.

4.3 Data analysis

This section presents the methodological approach used to process and analyze the data collected in the interviews. The aim of this section is to guide the reader and provide transparency in how the results were retrieved, while also presenting explanations to why certain methods were chosen.

The analysis of the collected qualitative data was conducted through a rigorous mapping of reoccurring themes, with the aim of understanding the current situation and identifying future trends. The aim of this analysis is to bridge the gap between the practical use of AI in the pulp and paper industry and the scientific research area. For this to be possible, extensive and careful organizing of the semi-structured interview data is required. As the data analysis was conducted iteratively, this allowed earlier interviews to present insights for later interviews as well as deeper connections with the theoretical framework. However, the structure of the guiding interview questions remained the same throughout the data collection phase.

For clarity purposes, the full process is divided into two parts: the data processing operations and the data analysis operations. The processing operations describe how the data was stored, treated, condensed, and improved in order to ease the data analysis operations. The data analysis operations describe how the processed data was interpreted and the steps taken to extract insights from the data.

4.3.1 Processing operations

Data preparation is an essential part of data analysis. In order to process the qualitative data from its raw form to something more comprehensible, the first step conducted was the conversion of the qualitative data from oral form to word-processed text (Saunders et al., 2000). A common procedure that was used in this project was that all interviews were audio-recorded and subsequently transcribed. For each interview conducted, a transcribed document was saved. The second step involved data cleansing of these transcriptions, where the transcriptions were checked for grammatical and factual errors to validate the accuracy of the data. In order to further aid the data analysis, several procedures were taken to improve the qualitative data.

Interim summaries

The aim of the interim summaries was to detail the development of and thoughts that arose during the progress of the project. According to Saunders et al. (2000), conducting this during the data collection phase can create more nuanced foundations for increasing the confidence in upcoming interview findings.

Transcript summaries

The data transcriptions were then summarized into shorter and more comprehensible documents of the key notes and messages that emerged from the interview. According to Saunders et al. (2000), by re-phasing and making sense of what has been said researchers are able to compresses long statements into briefer ones and thus facilitate the analysis. The purpose was to reduce the amount of data to the most essential pieces of information. This is critical, as it enables deeper analysis to be made on the relevant pieces of data. Furthermore, this can help to identify relationships between themes.

These processing operations allowed the qualitative data to be transformed from its raw oral format into comprehensible interview summaries. The analysis that was conducted on these summaries and is described in the following section.

4.3.2 Thematic analysis

The methodological approach used to analyze the data collection is partially based on a the four-step process presented in Saunders et al. (2000). It is often encouraged to view data analysis in multiple levels. Following this process allows for a linear and hierarchical approach to building data interpretations that provide researchers with tools to involve multiple levels of analysis in parallel.

Analytical codification is used to better understand the content and context from speakers, allowing deeper analysis with the aim of finding patterns in the data. For this project, thematic analysis was applied to analyze the collected empirical data. This approach is argued to be a systematic yet flexible approach to analyze qualitative data (Braun & Clarke, 2006). The analysis is systematic since it provides an orderly and logical way to analyze the collected qualitative data. Furthermore, this analysis is flexible as it is not tied to a specific philosophical position and can be used regardless of your position (Saunders et al., 2000). The main purpose of this approach is to systematically search and identify patterns or themes that occur across a data set and that are related to the research questions. The procedure of conducting a thematic analysis consisted of four steps presented by Saunders et al. (2000):

1. Becoming familiar with the data
2. Coding the data
3. Searching for themes and recognizing relationships
4. Refining themes and testing propositions

4.4 Quality of research

The aim of this section is to evaluate, justify and discuss methodological choices related to the quality of research.

4.4.1 Validity and reliability criteria

One critical aspect in quality of research is the methodological discussion of validity and reliability. This discussion is based on the theories of validity and reliability criteria presented in Gibbert et al. (2008), Saunders et al. (2000).

Reliability

Reliability refers to the consistency and to the ability of replicating the study by using the same research design and achieving the same results. Furthermore, reliability can be divided into internal- and external reliability.

In qualitative research, internal validity, refers to aiming for consistency by assuring that the authors have agreed upon the interpretation of the collected data and the analysis (Saunders et al., 2000). In order to fulfill the internal reliability criteria, the authors have had a continuous dialog during the course of the study. Moreover, all sections of the thesis were written together to ensure internal reliability.

External reliability refers to whether the analytical procedures and data collection techniques would produce consistent findings if they were repeated by another researcher (Saunders et al., 2000). However, qualitative research is not necessarily intended to be replicated since it reflects interpretations, which are socially constructed (Saunders et al., 2000). Although there are a number of threats to reliability which were taken into consideration when conducting this study in order to ensure external reliability. On possible issues in this study is participant bias, which refers to any factor that induces a false response from the interviewee (Saunders et al., 2000). In this study, all of the respondents got the chance of being anonymous and therefore limiting the issue of participant bias. Furthermore, offering anonymity can heighten the transparency of the study according to Bell et al. (2018).

Validity

Validity refers to the appropriateness of the measures used, generalizability of the findings and the accuracy of the analysis of the results (Saunders et al., 2000). Furthermore, validity can be divided into internal- and external validity.

In qualitative research, internal validity refers to whether or not the researchers provide a plausible causal argument, logical reasoning that is compelling and powerful enough to defend the researcher's conclusions (Gibbert et al., 2008). In order to enhance internal validity theory triangulation has been used to enable verifying the findings by adopting multiple perspectives. This was done by adapting both the IT perspective and the Pulp and paper perspective to ascertain the validity, credibility and authenticity of the research data, interpretation and analysis (Saunders et al., 2000).

External validity refers to what degree the findings can be generalized within different settings, which means that theories must be shown to account for phenomena, not only in the setting in which they are studied, but also account for these phenomena in other settings (Gibbert et al., 2008). In qualitative research, external validity is often an issue, since sample sizes are often small and the research design takes the form of a case study, which makes generalization of the results difficult. Although a single case study or a multiple case study do not allow for statistical generalization but might provide a good basis for analytical generalization if the study consists of a cross-case analysis involving four to ten case studies (Gibbert et al., 2008). Analytical generalization is a separate process from statistical generalization and refers to generalization from empirical findings to theory, rather than a population (Gibbert et al., 2008). Therefore, this study might have the potential of analytical generalization since it covers four different cases in the pulp and paper industry, but no claims to either type of generalization is done in this study due to the difficulty of claiming generalizable findings in qualitative research.

4.4.2 Research ethics

Ethics, in the context of research, refers to the standards of behavior that guide the conduct in relation to the rights of the subjects of your study, or the people that are affected by the research (Saunders et al., 2000). There is always a risk that researches consciously or unconsciously may cross ethical boundaries when conducting research. Though this risk cannot be eliminated entirely, it can be considerably reduced by having awareness of these risks and follow recommendations to minimize these issues. The ethical aspects of conducting research have been taken into consideration in this study by following four commonly used ethical requirements; information, consent, confidentiality and usage (Dalen, 2015; Gustafsson et al., 2006).

To fulfill the first requirement of information, all of the respondents were presented with the purpose and reasons for conducting the study before they decided whether or not to participate. Secondly, in order to fulfill the consent requirement, the respondents were informed that participation in the study is completely voluntarily. Thirdly, to cover the requirement of confidentiality, which refers to how the collected data was handled, the respondents were asked if the interviews could be recorded. Recording the interviews also helped the authors to give their full attention to the respondents at the same time as ensuring that all relevant data was collected. Furthermore, the respondents were also given the opportunity to be anonymized in the study. Lastly, to follow the fourth requirement, which requires that the data collected is only used within the context of this study, the respondents were informed about this aspect prior to the interviews.

5 Results

The results retrieved from the semi-structured interviews reveal some emerging patterns. The observations made from the data will be presented in the form of themes as defined by Saunders et al. (2000). The themes will include reoccurring points of agreement or disagreement among the interviewees as well as patterns and trends related to the research questions. Furthermore, individual responses that were particularly significant to the stated research questions will be mentioned. In the following three sections, these themes will be presented from the perspective of the current state of AI, the future trends of AI, and the organizational efforts made to support AI.

5.1 Current state of AI

This section presents the results to research question 1: to what extent AI is used in the manufacturing processes of the Swedish pulp and paper industry and what barriers hinder further use.

The following themes are further described:

- The current use of AI in manufacturing processes varies
- The current approach to AI is primarily exploratory
- There are barriers hindering further use of AI

5.1.1 The use of AI in manufacturing processes varies

When asked about where AI is implemented today, the respondents tended to state that the current AI implementations are mostly found within enterprise business processes. Examples of enterprise business processes mentioned included overall IT and digitization environments, HR functions, finance and knowledge management systems. When asked to what extent AI is implemented in the manufacturing processes of the pulp and paper industry, there was a consensus that most companies have not implemented AI technologies in their manufacturing processes yet. However, this answer varied depending on which company the respondent was affiliated with. One IBM respondent noted that: *"All projects I am aware of are still in the pilot phase."* However, another responded explained that there are exceptions: *"there are exceptions where companies have embedded digitalization into their organization and have potentially implemented AI into their manufacturing processes."*

The divergence in AI adoption is demonstrated by the aforementioned examples but is also emphasized by a respondent representing the pulp and paper industry who explained their work with AI: *"AI is mostly implemented into supply chain and manufacturing [...] we are currently using AI in a few manufacturing processes and will be continuing to scale up and exploit the full benefits of AI in the future."* These responses highlight that there are differences in how far AI has been adopted in the manufacturing processes. It becomes clear that the extent to which AI is implemented in the manufacturing processes varies among the companies within the Swedish pulp and paper industry.

5.1.2 The current approach to AI is primarily exploratory

AI is an immature technology in the pulp and paper industry

When asked about the current progress of the AI technology for the manufacturing processes, there was an overwhelming agreement that companies are still exploring the possibilities of AI and are therefore still in early stages in terms of utilizing the technology. To exemplify, one of the pulp and paper respondents noted that: *"most companies view their work within AI as proof of concepts"*. The belief that AI technology is not yet fully mature in the industry is further emphasized by the fact that some of the terminology used to describe the current state of the AI development was "developing phase", "pilot phase", "exploratory phase", "immature", "testing phase", "proof of concept", and "experimentation phase". From these responses it is clear that most companies within the pulp and paper industry are currently not solving a large number of issues in the manufacturing processes using AI.

Companies have an exploratory approach toward AI

When asked about the future plans of using AI in the manufacturing processes there was an overwhelming agreement that most companies are interested in advancing their work with AI and scaling up ongoing projects. An IBM representative stated that: *"The biggest trend today is that everyone is experimenting with AI. [...] it will take some time before the technology becomes mainstream, but we will see faster implementations and more use cases in the future."* This stance was supported by a pulp and paper company representative explaining their continued work toward implementing AI: *"the company has been running several pilot projects and has the ambition to focus more on AI development in the future."* Similarly, another pulp and paper company representative highlighted the importance of learning: *"There have been recent attempts of implementing AI for process optimization [...] we have learned a lot from the project."* From these responses, it is clear that there is a strong belief in the possibilities of AI technologies in the manufacturing processes of the pulp and paper industry and companies are still attempting to learn how to effectively utilize them.

5.1.3 There are barriers hindering further use of AI

When asked about the main barriers for implementing AI and the main reasons why companies are currently not solving more issues using AI, three main barriers emerged: implications of scaling up project, issues of trust and lack of expertise.

Implications of scaling up projects

All of the respondents shared the belief that one of the main reasons for not solving more problems using AI within the manufacturing processes was due to issues related to scaling up pilot projects. For example, a company respondent stated the following when asked about how they scaled up an already existing AI solution: "As of today the project is too immature to produce enough value to be scaled up and implemented." Furthermore, another respondent from the pulp and paper industry also highlighted that their biggest problem within their innovation process is to scale up AI initiatives into live implementations: *"[...] handing over POCs to a given business unit is one of the toughest steps to do successfully"*. The phenomenon that companies have problems scaling up POCs is a view that is further strengthened by an IBM respondent: *"[...] companies are struggling with scaling up the pilot projects in the manufacturing processes."*. The fact that the biggest issues companies face when implementing AI is scaling up AI POCs is demonstrated by the aforementioned examples.

Issues of trust

An issue that became apparent from the interviews was having issues of trust in AI solutions. A clear example of the aforementioned issues came from one of the IBM employees: *"Companies are struggling with user acceptance, system friendliness and incorporating AI technologies into everyday work"*. Furthermore, all companies representing the pulp and paper perspective experienced having issues with trust related to AI solutions and their effectiveness. This phenomenon of lack of trust in AI from the company perspective is demonstrated by the following quotations:

"There is a lot of professional pride and letting something as undefined as an AI do what you have previously done is difficult."

"Trusting and believing in the algorithms are the biggest obstacles."

"In order to implement more AI in the future you need to convince people that AI can create value for your business"

It is clear from these responses that companies within the Swedish pulp and paper industry see trust as one of the biggest obstacles to overcome in order to be able to utilize the benefits of AI within the manufacturing processes in the future. Aside from having issues of trust, the respondents from both the pulp and paper perspective as well as from the IBM perspective identified incompatibility issues in the form of low user acceptance of new AI technologies as well as an unfitting mindset towards AI. Low user acceptance together with a reluctance to use new technologies was a phenomenon that all of the respondents identified within the industry. The following quotation from a company representative further underlines this issue: *"[We see a general] reluctance to use new technologies such as ML within the organization."*.

Moreover, a respondent representing the IT perspective stated that companies need to adopt a more top down approach where the top management is more involved in the investments related to AI in order to fully understand the importance of change towards using more AI solutions. This change in mindset regarding the approach to AI was also emphasized by respondents representing the different pulp and paper companies: *"Companies have made progress within this area, but in order to advance further it would require a totally new type of thinking or way of working."*. It becomes clear that issues of trust are a phenomenon that both industry parties as well as the IT industry see as barriers that need to be managed to fully capture the value of AI within the manufacturing processes.

Lack of expertise

Another barrier to implementing AI was the lack of expertise within the field of AI, which was demonstrated by all the respondents. Taking an IT industry perspective, the respondents stated that there is a big spectrum when it comes to the understanding of AI within the manufacturing processes, where the AI maturity varies among companies. One respondent from IBM argued that companies are using AI because someone has told them to implement it, but that they do not really know how or where to use it.

The experience with lack of expertise was also shared by the respondents from the pulp and paper perspective. One respondent claimed that their company does not have any extensive AI competency and that they are in need of future recruitment of competent staff, in order to continue their work toward using more AI within their manufacturing processes.

A lack of understanding of the overall manufacturing processes was another common response in the interviews. Many consultancy experts that are trying to implement AI, experience difficulties in understanding the overall manufacturing processes of the pulp and paper industry and therefore struggle to come up with good AI solutions. The following quotation highlights this aspect: *"most experts in the field of AI lack the proper understanding of the manufacturing processes needed to fully exploit the potential of AI within the industry."*.

It is clear from the responses that there exists a lack of expertise within AI in the industry, and that this needs to be addressed in the future, if the Swedish pulp and paper industry wants to gain the full advantages of AI. Ending with a quotation from a company representative demonstrating that they see future potential in AI: *"[We see a lot of potential in AI and we are] convinced that the technological possibilities of AI will develop to a large extent in the future, but it is difficult to pinpoint in what direction"*.

5.2 Future trends of AI

This section presents the results to research question 2: what the main future trends of AI are in the Swedish pulp and paper industry.

When asked about the main future trends of AI in the manufacturing processes of the pulp and paper industry, some of the themes that emerged were directly related to the technological advancements of AI while other themes were related to the approach and vision the industry has towards AI in the future.

The following themes are further described in this section:

- Process optimization and quality control
- Predictive maintenance
- Energy optimization
- Paper web break prediction
- Safety management
- Augmenting employees and automating factories are both important objectives of AI
- Increased human-robot collaboration is prioritized
- Further automation can be valuable in the long term

5.2.1 Process optimization and quality control

When asked about the major technological trends of AI in the manufacturing processes, the respondents tended to agree that there are two major areas where AI has shown great potential for the future: process optimization and predictive maintenance. One respondent motivated these areas as the most important ones in the short term: *"this is where most effort is made and where most money is being spent. [...] we believe these areas can generate most profit in the short term."* From this response it is clear that the area of process optimization shows great potential with the introduction of AI. Moreover, this area was also described as quite mature in relation to the adoption of AI, as one respondent noted that: *"Process optimization is quite mature when it comes to AI adoption."*

When asked what constitutes process optimization, one respondent explained that there are several parts of the production included in this area: "This area includes the flow of the manufacturing processes, the efficiency of production, measures to decrease input material into the system and different methods of scenario analysis." When asked about what process optimization issues the companies are trying to solve with AI, the respondents tended to believe that that there are two major issues they are trying to solve within this area that ultimately lead to loss of efficiency: variability in the manufacturing process and poor quality output.

One interviewee explained that continuing to innovate the manufacturing process and optimizing the production facility is a critical part of the business. Currently, companies are sending raw materials with varying characteristics to a factory. The characteristics of these raw materials, how maintenance is conducted and how operators control the process are all aspects that can affect the variance and quality output. The main objective is to decrease the variance in the process while also maintaining high quality in the output. According to one respondent, this is a promising area for AI as there is a lot of data and sensors in the production facilities that companies are currently not using.

Example: Quality insight systems

As of today, some efforts are made to account for these issues without AI. However, when the quality is lacking or varies AI could have great potential. One respondent explained an example where AI could be used to create quality insight systems that help us understand the production better:

"Every human operator operates a factory differently. By building an AI system to understand the interaction between the machine and operator you can find best practice on how to operate the machine."

Example: Digital twins

One case where the integration of AI in process optimization has been attempted is using digital twins. The digital twins act as a copy of the real production facility and allow a company to model and simulate scenarios for optimal production and track changes in the system without interfering with the production. A respondent highly involved in a project where this was recently tested explained that the digital twin was built from AI models trained on the live systems using data from the machines sensors and was developed using reinforcement learning. The aim of this project was to investigate how to optimize the use of different boilers by optimizing the use of steam in the manufacturing process and reducing the use of fossil fuel.

Example: Visual inspection of raw materials

Another case where using AI for process optimization has been proven successful is through visual inspection of raw materials. According to one respondent, there are several promising applications where AI could prove useful. As an example, visual inspection of wood in an AI system could provide guidance on the process that certain pieces of wood should undergo for optimal quality output depending on the characteristics of the wood. As of today, the process of determining how to process different raw materials is done manually with the help of lab tests. As such, an AI system could be used to analyze the compositions of raw materials and design custom design instructions for the optimal process. This could also be applied when analyzing the pulp and paper processes by investigating characteristics of the raw material such as brightness or amount of fibers and thus recommend the most suitable process to use using AI.

5.2.2 Predictive maintenance

As mentioned in the section above, the respondents tended to agree that predictive maintenance is one of the major technological trends of AI in the manufacturing processes. Moreover, the respondents tended to agree that this of one of the areas where most effort is put since they believe it can generate most profit in the short term. When asked about the progress being made within predictive maintenance, one respondent explained that one of the main objectives companies are aiming for is incorporating AI into the process: *"The work in this area started 15 years ago but companies are now trying to incorporate AI."*

When asked why this is considered one of the major trends, the respondents tended to agree that this is an area where the incorporation of AI is relatively easy. One respondent explained this in the following way: *"Predictive maintenance [...] is the easiest application of AI within this domain and also where most companies are starting."* This response was strengthened by another respondent who explained why they also believe predictive maintenance will be an area with extensive adoption of AI in the near future: *"I believe that predictive maintenance will be an area where we will use AI within our everyday business in a near future since it is a field that is easy to understand."*

When asked what constitutes predictive maintenance, the respondents tended to agree that predictive maintenance are smart techniques used to predict the conditions of a given machinery and then taking appropriate actions from these insights. When asked about what main objective companies are expecting to achieve within predictive maintenance, the respondents tended to believe that the main objective is to find anomalies in the machinery and predict or forecast breakdown of equipment. One IBM respondent explained the motive for the pulp and paper industry in the following way: *"Companies are effectively trying to minimize shutdown time using effective shutdown planning. Planned shutdown is more efficient than unplanned shutdown."*. It is clear from this response that there is a strong belief that the effects predictive maintenance could have on cost savings in the manufacturing processes could increase in the future.

When asked about the future potential of incorporating AI into predictive maintenance, the respondents tended to agree that that AI can help their companies increase their predictive capabilities and thus improve the maintenance work in the mills. Another interviewees explained that the role of AI in predictive maintenance is a critical step forward as it increases the efficiency of the maintenance procedures: *"A next step within this domain would be to look at when maintenance is needed and what is the best maintenance routine is. Applying AI to advice in this stage is the most likely next step of using AI within maintenance."* A pulp and paper respondent explained how they would like AI to advise their operators through predictive maintenance: *"We want the physical production line to understand when the time for maintenance would be most suitable and then alert operators of this. The system would signal flags for potential issues and inform operators on how long it will take before maintenance is required."*

5.2.3 Energy optimization

Another theme that emerged was the trend that AI can be an important technology for the future of energy optimization in the pulp and paper mills. When asked what issues companies are attempting to solve in this area, the respondents tended to agree that the central manufacturing processes within the pulp and paper factories are consuming large amounts of energy. Because of this, making smarter use of these resources have great potential of reducing operational costs in the factories. This was explained by one of the respondents in the following way: *"Well maintained equipment will use less energy, resulting in smaller carbon footprints and more energy efficient production [...] AI could be used to analyze data to better estimate how to best optimize different variables to reduce the total energy consumption."* It is clear from this response that there is future potential in integrating AI to optimize the use of energy.

When asked what progress has been made within the area of energy optimization, the respondents tended to agree that the work toward energy optimization has been in progress for many years. However, most processes are rule-based and have not yet adopted AI to further improve the process. This was exemplified by one respondent in the following way: *"All steps done today within for example the process of boiling fibers in digesters are rule-based."* The belief that the introduction of AI in this setting has potential was further strengthened by a pulp and paper company representative in the following statement: *"There is a desire to optimize other parameters in the manufacturing processes, such as green electricity [...] we are convinced that it is possible to make the energy consumption more efficient and thus increase profit using AI and smart systems in the future."* It is clear from this response that there is a belief in great future potential of integrating AI in energy optimization in the pulp and paper industry.

5.2.4 Paper web break prediction

One theme that emerged was the potential to use AI to predict failure modes. When asked how this can be applied to the industry, an area mentioned was paper machine web break prediction. When asked what issue this area is attempted to be solved, it was explained that sheet and web breaks are of concern since they reduce efficiency and reliability of the production process. When asked what AI could provide within this area, it was explained that the objective with paper machine web break prediction is to predict, explain and prevent breaks in the machinery in order to improve product quality and productivity.

One respondent explained why this is a critical area for the industry in the following way: *"This is an important aspect for companies as predicting breaks in the paper machines can save break time in the production. This can translate into enormous savings for companies, as the number of products sold is directly based on the hourly production."* Thus, by reducing or preventing tears in the production of pulp and paper the downtime can be reduced, resulting it a more efficiently run paper mill. Signaling for potential breaks can also enable operators to take appropriate actions in a quicker manner, ultimately reducing the risk to operators and increasing safety.

When asked what progress has been made within this area, one respondent noted that there have been large efforts focused on paper machine breaks prediction the last years: *"This is the only area within my knowledge where an AI pilot project has been taken into production as of today."* These responses show that the areas of predicting web breaks in the manufacturing processes of the pulp and paper industry show great potential for the future.

5.2.5 Safety management

Another theme that emerged during the interviews was that AI has the potential to be a natural part of the safety management in the manufacturing processes. According to the pulp and paper respondents there are several promising applications where AI can be valuable in safety management. The respondents from the pulp and paper industry were all convinced that safety is an important area where AI has the potential to be valuable in the future. This potential was further emphasized by one respondent who gave the following example of where AI could be used to manage safety in the manufacturing processes: *"[Using AI in order to] understand where breakage happens the company could help prevent dangerous incidents and increase the safety for our employees"*.

Furthermore, another common response from the interviews was that the respondents saw great potential in combining AI technology with camera surveillance in the factories. This possibility of using AI technology together with cameras to increase safety in the factories was further explained by one of the pulp and paper representatives: *"[...] for instance warning operators if they are located in an area with moving machinery. This is an area we are currently looking into."*. As another example one respondent explained that using AI for image prediction, focusing on predicting events in the factory, such as collisions and other hazardous events would be a perfect area of use for this technology. As such, the potential of AI in safety management in the manufacturing process was clearly demonstrated by the respondents as well as that fact that the industry believes that this is an area where AI most likely will be used more in the future.

5.2.6 Augmenting employees and automating factories are both important objectives of AI

All of the respondents shared the belief that both enhancing operator performance and increasing the degree of automation will be important roles for AI in the future. One of the respondents representing a pulp and paper company stated that it is generally difficult to distinguish between automation and augmentation in the manufacturing processes. Another respondent from one of the pulp and paper companies supported this stance in the following statement: *"It is hard to distinguish between automation and augmentation since it all comes down to creating more efficient processes and that can be done by giving the operator better tools, which can ultimately lead to the operator becoming expendable."*. Furthermore, augmentation and automation were described by the company respondents as approaches that need to coexist in order to utilize the full potential of AI in the manufacturing processes. A quotation from one of the company respondents strengthens the importance of both augmentation and automation: *"Our purpose with AI as of today is to both augment and automate our manufacturing processes in order to be more efficient and profitable."* The fact that all respondents tended to view augmentation and automation as important in regard to the future of AI in the pulp and paper industry is clearly demonstrated by the aforementioned examples.

5.2.7 Increased human-robot collaboration is prioritized

Although all respondents agreed that both augmentation and automation of AI are important, they also emphasized that the most useful AI solutions in the short term will be based on augmentation. One of the IBM representatives emphasized this in the following way: *"In the close future the industry might focus more on augmentation."*. The respondents described the focus of such an AI system in an initial setup to be enhancing the operator's ability to make good decisions rather than trying to fully replace a human operator in the manufacturing processes. A respondent from a pulp and paper company elaborated on this topic and stated the following: *"Beginning with augmentation in the process control would be the most suitable choice until you can trust the AI system and then make the process fully automated."*. It is clear from this response that AI systems with the objective to augment operators in the existing processes will be of higher priority in the short term. Augmentation was seen as the number one priority when talking about how to utilize AI in the manufacturing processes in the short term by both representatives from the IBM perspective as well as the companies representing the industry.

Reason 1: Automation is already extensively used

The fact that automation already exists in a lot of the manufacturing processes and therefore not being as important in the short term was another common response in the interviews. The following quotation highlights this aspect: *"[...] the paper machine is operated by one single operator, everything else is already fully automated."*. Another company respondent described this fact in more detail: *"Automation has been around for many years in the manufacturing processes of the pulp and paper industry. Because of this, our work is mostly focused on augmentation as the company believes this aspect is closer to digitalization and their work with AI."*. It is clear from this response that augmentation is considered more important in the beginning from a company perspective.

Reason 2: Managing expertise will increase efficiency

The importance of managing the existing expertise within the industry as well as giving guidance to the operators was another common view that emerged during the interviews. An IBM representative elaborated on the importance of managing and capturing the knowledge that exists within the pulp and paper companies which is exemplified by the following quotations:

"Human intelligence will never be replaced."

"[...] how to capture this knowledge will be a big challenge for the future."

"sustaining and maintaining the expertise is one key area where AI could be used in the future."

"You want to create a better decision basis for an operator by enhancing the operator controlling a specific process by using AI."

It becomes clear there are tendencies for companies in the pulp and paper industry to highly value the existing knowledge of the employees and therefore approach AI technology a means of ensuring that the intellectual property is not lost. Guiding the operators by using AI in an advisory role in order to enhance the operators' decision-making was described by the respondents as more important before they try to use AI to fully automate their processes. One respondent representing the pulp and paper perspective had the following belief regarding augmentation and automation: *"I believe that AI in advisory roles focusing on giving guidance on how to set different process parameters are the best way to use AI today"*. Furthermore, another company representative explained that augmentation also provides room for more creativity among the employees: *"Decision making support still allows the freedom of creativity among the employees"*. The belief that augmentation is more important in the short term was a general view that emerged during the interviews, both from respondents representing the IBM perspective as well as the pulp and paper perspective.

5.2.8 Further automation can be valuable in the long term

While augmentation is seen as most important in the short term, the respondents tended to believe that automation will be most important in the long term. All the respondents agreed that using AI technology for augmentation purposes and improving human performance will most likely be the natural starting point for AI. However, it was also emphasized that when AI has been used in the manufacturing processes to support the operators for some time, further automating the processes through AI solutions will be easier to achieve in the long term. A respondent from the pulp and paper industry explained that when the augmented AI solutions become good enough, they will turn into fully automated AI systems: *"if the AI solution becomes good enough you will be able to replace the operator"* Another quotation from a pulp and paper representative further emphasized the belief that AI will be able to automate more of the manufacturing processes in the future: *"In the long term we hope that AI will provide possibilities of replacing the human and automate the business even more. This is an important issue as there are difficulties replacing the older generation of operators at the mills."*.

Furthermore, one of the respondents from one of the pulp and paper companies talked about that the future most likely will bring new use cases of AI for automation. Hence, making automation a more viable option in the future. Another aspect highlighted by the respondents from the pulp and paper perspective was that the processes that have not yet been optimized are where they expect to see most success with integrating AI in the future. It becomes clear from the aforementioned examples that most respondents see great value in using AI for augmentation, but that automation has the potential to be more important in the long term.

5.3 Managing innovation and organizing R&D

This section presents the results to research question 3: how companies within the Swedish pulp and paper industry manage digital innovation and organize R&D to support initiatives within AI.

The following themes will be further described in this section:

- Digital innovation is highly valued
- AI initiatives are embedded in digitalization agendas
- AI initiatives are supported by digital innovation departments

5.3.1 Digital innovation is highly valued

One of the themes that emerged in relation to companies managing innovation was the strong support and engagement in staying innovative. When asking company representatives to what extent their organization is working with innovation to support AI initiatives, the respondents tended to agree that their company has a positive attitude toward innovation and that innovation is highly regarded in their business. This included both innovation in relation to product and process innovations as well as pure digital innovative work. On top of this, there was a strong consensus that innovation is a critical competitive advantage. One respondent noted that: *"It is important to have a good attitude towards innovation to stay competitive. Innovation is something that we work actively with and the board expects us to deliver."* It is clear from this response that active work with innovation is highly valued within the Swedish pulp and paper industry. One IBM representative elaborated on this topic and explained that: *"Nordic countries are pioneers in this area and are generally more innovative."* This theme was further strengthened by a strong belief that AI and digitization have the potential to create value for these companies in the future, supporting the efforts made to increase digital innovation.

Example: The use of innovation activities

When asked what specific efforts are made to support the digital innovations, some companies emphasized some form of reoccurring innovation activity being conducted in order to focus the innovative work. A key feature in these activities is facilitating innovation through interactive workshops. One respondent explained the main objective of the workshops in the following way: *"[...]competency is collected to tackle issues and taking concepts closer to realization than we are usually able to."* It is clear from this response that these activities are partly seen as a tool to work with innovative technologies such as AI.

Example: The use of digital innovation life-cycles

Another key example of managing innovation was the tendency to work with some form of digital innovation process to funnel ideas and concepts. When asked about their process of tackling AI-related ideas, the respondents tended to refer to some process defined within the company to help guide novel ideas into mature digital implementations. Most of these processes were described as some form of digital innovation life-cycle, where most ideas are tested through different steps and valued depending on the strength of their case in each step. As an example, one of the company respondents described their innovation process in five distinct phases:

- Find - Open ideas or targeted campaigns are gathered from the business
- Expand & exclude - Ideas are expanded with information and potentially clustered
- Initiatives - Ideas are sent into initiatives with hypothesis being created and stakeholders identified
- Experiment - Prototype building and hypotheses testing in six-week trials
- Projects are handed over to development organization or put on hold

From this innovation process it is clear that one of the main objectives having an open-minded approach toward new ideas and quickly evaluating the feasibility of these projects in order to maximize the efficiency.

5.3.2 AI initiatives are embedded in digitalization agendas

One theme that emerged in relation to the management of innovation is the that companies tend to not have specific strategies related to AI. Instead, companies tend to have digitalization agendas that are not directly embedded in their core business and where work within AI does occur. As an example, one IBM respondent noted that: *"[...] digitization and AI is not on the everyday agenda for the pulp and paper companies"*. This stance was explored further by a respondent from the pulp and paper perspective who explained how they manage AI innovations: *"We do not have a technology specific agenda, meaning that the role of AI is not the focus. Instead, we focus on solving issues by asking the right questions within the digital agenda. If AI is seen as a suitable tool to solve this problem, it will be used."* From these responses it is clear that companies tend to not have specific AI strategies but instead rely on digitalization agendas when managing technological innovations.

When asked for the reasons behind opting for this approach, the respondents tended to agree that the industry will not take a lead within AI technology and is therefore better off adapting to existing trends. One respondent motivated this stance in the following way: *"AI strategy is not necessary today since people know too little about AI. Because of this, it is important to begin implementing at a small scale and let the technology mature while the company is building a stronger knowledge base of what can and can't be done."* This response was strengthened by another company representative who explained their view on the issue: *"I do not believe that the pulp and paper industry will take the lead when it comes to AI. We believe we can take a holistic perspective since we own the whole value chain. Rather, the industry will pick up the existing trends and try to take advantage of already existing technology."* These responses emphasize the belief that the core business approach of the pulp and paper is not directly dependent on technological advancements and that the industry would benefit more from conservatively evaluating and adopting technological trends.

5.3.3 There are specific functions driving digital initiatives

One noticeable theme that appeared in relation to the support of AI initiatives was the organizational structures of R&D. When asked about how companies organize their R&D units to specifically support initiatives within AI, the respondents tended to agree that there is a function designed to support digital innovations separated from the traditional R&D departments. "Digital innovation center", "digital innovation department", "center of excellence", "advanced analytics hub" and "digitalization network" were examples of names used to describe these functions.

These departments, functions or teams were described to have similarities to traditional R&D departments but with less focus on product development and more focus on driving and assisting digital initiatives in the organization forward. One respondent explained the purpose of this function in the following way: *"The purpose of the department is to drive initiatives depending on the needs and requests of the business. These departments focus more on the existing technology that is out there and try to figure out how to use it."* Another company respondent described the roles of their department in the following way: *"This team drives cross-organizational efforts, provides technical expertise and knowledge to the company, helps different business areas find the right partners and coordinates respective lines of business to own their own digitalization ideas."* It is clear from these responses that companies tend to have a department that works closely with different business units and fulfils the role of testing and supporting digital initiatives within the company. As the function is less focused on specific product developments and more focused towards exploring technology and finding possible use cases, this naturally leads part of their work toward applications of AI.

It was also clear that these departments tended to be described as a relatively small network of people with one of the top priorities of supporting enterprise-wise technological initiatives that can be applied to various locations in the organization. One respondent explained that: *"We have digitalization network of around 10 people who supports the journeys within digitalization and works with solutions that will benefit the entire company, while also having other responsibilities not related to digitalization."* From this response it is clear that one of the focus areas is targeting solutions that could be useful for multiple parts of the organization.

Another theme that emerged is the fact that these departments tended to be described as having decentralized activities taking place in different business units together with having a centralized function in order to take R&D decisions that affect the entire organization. One respondent motivated the reasoning behind this structure in the following way: *"Questions surrounding digitalization and AI make it essential that the issues are handled over the entire organization and that the business units and digital departments work closer than they have before."* This description was supported and further explored by another company respondent in the following way: *"The department is physically distributed in the organization and tied to different business units, while being centralized organizationally. Because of this, we see the organizational structure as centrally decentralized."* These responses highlights that the specific departments are have wide networks within the organization by working closely with different business units, while still supporting solutions that benefit the entire company.

When asked how these departments typically operate to facilitate the continued work within AI, the respondents tended to agree that the work is conducted iteratively in small sprints. One respondent from the pulp and paper perspective explained how the overall objective of these sprints is efficiently identifying potential projects to scale up: *"The AI initiatives are done in sprints over about 6-8 weeks we they try to find POCs and analyze the opportunities as well as costs in terms of time and money."* This approach of working was supported by another company representative: *"This team is working through digitization projects at a fast rate and has worked through around 150 digitization projects in the last 3-4 years."* These responses highlight that one of the objectives of these teams is to work through ideas at a fast rate to quickly find proof of concept with large potential and eliminate concepts that would be too time-consuming or costly.

A full list of the themes that emerged from the interviews can be found in table 4.

Theme category	**Theme**
Current state of AI	The current use of AI in manufacturing processes varies
	The current approach to AI is primarily exploratory
	There are barriers hindering further use of AI
Future trends of AI	Process optimization and quality control
	Predictive maintenance
	Energy optimization
	Paper web break prediction
	Safety management
	Augmenting employees and automating factories are both important objectives of AI
	Increased human-robot collaboration is prioritized
	Further automation can be valuable in the long term
Managing innovation and organizing R&D	Digital innovation is highly valued
	AI initiatives are embedded in digitalization agendas
	AI initiatives are supported by digital innovation departments

Table 4: Summary of themes emerging in the results

6 Discussion

This section presents an analysis and multiple points of discussion on the most critical themes discovered in the results. The discussion is divided into three subsections corresponding to their respective research question: "Current state of AI", "Future trends of AI" and "Managing innovation and organizing R&D".

6.1 Current state of AI

In this section, the most critical results from research question 1 are discussed and reflected upon.

6.1.1 The use of AI is developing through exploration

As can be seen from the themes that emerged from the results, the extent to which AI is used in the manufacturing processes in the pulp and paper industry greatly varies between companies. These themes suggest that the use of AI is currently not particularly developed in the manufacturing processes of the Swedish pulp and paper industry and that AI remains a relatively immature technology. One interesting theme to note is the way companies are approaching their AI development. As can be found in the results, the current approach companies are having toward AI development is primarily exploratory. This means that, instead of making large investments in a few selected areas, there is a tendency for companies to explore the possibilities of AI in order to find useful and worthwhile projects. Exploration, idea-creation, problem formulation, hypothesis testing and experimentation are key points on the agenda.

To help understand this concept further we can analyze the exploratory approach from the context of the digital innovation life-cycle presented in Kohli and Melville (2019). In the digital innovation life-cycle, a digital innovation outcome is achieved after going through the initiate, develop, implement and exploit phases of the life-cycle. In this case, the digital innovation outcomes are improvement in the manufacturing processes, and it is clear that many projects that go through these steps are put on hold before extensive implementation takes place. This is an interesting approach, as it results in a large number of projects being left at an early stage without extensive follow-up. The benefits of working with a vast number of projects is that the companies are developing their competence in the area and are learning the possibilities of the technology at a much faster rate. On top of this, the risk of spending large sums of money on projects that will not progress to the manufacturing process is decreased.

There is no doubt that the technology, although immature, is developing. There is a strong belief that digital innovation will provide value for the industry and companies are showing a clear desire to progress in this field. Companies are continuously putting efforts into exploring the possibilities that AI has the potential to provide in terms of efficiency improvements in the factories. As presented in Nambisan et al. (2017), digital innovations have led to changes in the way companies operate and manage their resources and produce new innovation processes, and this can potentially lead to transformations in industries as a whole. It is clear that companies within the pulp and paper industry agree that these are promises that could be provided by the introduction of AI in the manufacturing processes. Thus, it is fair to believe that the use of AI technologies in the manufacturing processes is a highly regarded digital innovation that is far from fully mature. However, the continued exploration of the AI technology and the value it might bring to the industry highlight that the industry is making progress. As such, it is believed that the continued development will allow value creation to become more apparent in the future.

6.1.2 There are several barriers that need to be overcome

In order to make further progress in the area of AI, the industry should consider common barriers that hinder further development of these novel technologies. As can be seen from the results, one of the themes that emerged is that there are some barriers that decrease or even prevent the speed of which companies are able to introduce AI into the manufacturing processes. Three distinct barriers were identified: implications of scaling up projects, issues of trust and lack of expertise. In the following section we reflect on these issues individually.

Implications of scaling up projects

The findings suggest that one of the biggest barriers companies in the Swedish pulp and paper industry face when working with AI in the manufacturing process are issues related to scaling up their projects. This primarily includes early stages of a project, often referred to as a POC or pilot project. This is a central issue since it hinders the potential of taking AI projects into full scale implementations in the manufacturing processes and thus affects the advantages that can be derived from AI.

In order to be successful with AI implementations companies have to make solutions that are viable in their everyday business, as well as scale up their POCs to live implementations in the manufacturing processes. Scaling up AI POCs is a critical part for companies' digital innovation process of AI and is important to manage. This barrier of implications with scaling up digital innovation projects has also been discussed in Ivanov (2018), where the barrier for developing digital information in manufacturing firms was described as "Digital innovation is not scalable and network effects are not possible" (see table 3). This barrier was categorized as industry readiness for digital innovation and relating this to the pulp and paper industry one could argue for that the industry is not ready to scale up its AI POCs. According to Ivanov (2018), the low degree of scalability of services based on digital innovation is a big challenge and will lead to negative impacts on the speed of diffusion of digital innovation. In the case of the Swedish pulp and paper industry this means a negative impact on the speed of diffusion of AI in these companies. Therefore, companies in the industry must try to overcome these issues by making their industry more mature regarding the new AI technology in order to limit the effect of this barrier in the future.

Issues of trust

The findings suggest that companies are struggling with having issues of trust when it comes to solutions based on AI technologies. This can be related to the study made by Ivanov (2018), who defined a subset of barriers named cognitive barriers for developing digital innovations. The cognitive barriers were named: mindset as a barrier, not harvesting the potential of digital innovation and hesitation towards digital innovation due to lack of experience.

The experienced issues related to trust ranged from a difficulty in believing in an immature technology to an uncertainty of the capabilities of AI. Furthermore, issues related to professional pride, unfitting mindsets towards AI and difficulties in trusting the results from AI algorithms were the main problems seen in the companies of this study 4. These are all issues of a cognitive nature, relating to understanding, mindset and perception of AI. The issues of trust that the pulp and paper companies are facing can also be seen in the study by Ivanov (2018). To be able to solve these issues companies have to try to build a better understanding of the concepts of AI and try to showcase for their employees that AI can bring value to their manufacturing processes. Adapting a strategy where the focus is to change the mindset of the workers by increasing knowledge about the technology as well as changing legacy mindsets could provide a good platform for limiting the effects of these barriers in the future.

Lack of expertise

A lack of thrust was another theme that clearly emerged in the interviews, see table 4. Having the right expertise to manage a new technology such as AI was described as one of the most important aspects to be able to successfully implement AI in the manufacturing processes. The pulp and paper industry with its long and traditional history has developed for decades, even centuries in some cases. The processes has been optimized and evaluated through rule-based process optimization for a very long time. This makes the task of using AI to become more efficient even harder since an AI engineer must be able to truly understand how the processes work in order to outperform an already optimized system. The result that the companies experience issues with lack of expertise in this study is in line with further research on the topic which also found lack of expertise as a barrier for developing digital innovation: "Lack of knowledge to develop digital innovation" see figure 3.

In order to be successful with AI in the future, the pulp and paper companies should try to increase their expertise in the field of AI by hiring talented AI experts as well as starting to educate their staff about AI.

6.2 Future trends of AI

In this section, the most critical results from research question 2 are discussed and reflected upon.

6.2.1 Continued human-computer collaboration is prioritized in the short term

The general approach towards integrating AI in a business and the objectives that are desired is a fundamental aspect of managing AI. Raisch and Krakowski (2020) talk about automation as the biggest priority in the short term for most organizations due to the associate cost savings and efficiency gains that often comes with automation. However, the findings of this study points in the opposite direction when it comes to the companies in the pulp and paper industry, as they are more focused on augmentation. Why do these companies not focus on automation with AI like most other companies? This phenomenon could be explained by the fact that the representatives from the industry stated that they already have a large part of their manufacturing processes automated. Since most of their manufacturing processes are already automated the efficiency gains that one might expect from using AI for automation in the short term are most likely harder to achieve in the pulp and paper industry compared to other industries.

Automation has the ability to deskill humans and tend to lead to loss of human expertise and knowledge (Parasuraman & Manzey, 2010). This is another aspect that the pulp and paper industry seem better at handling in the short term by choosing to focus on augmentation. Automation can, according to (Raisch & Krakowski, 2020), fuel reinforcing vicious cycles that makes it harder for organizations to fully take advantage of the intellectual property and human expertise in the organization. We see the risk of entering a vicious cycle much smaller in the pulp and paper industry since companies are not focusing on using AI for automation in the short term. We believe that by focusing on augmentation instead of automation is making the companies in the pulp and paper industry less prone to enter vicious cycles, giving them better abilities to keep their human knowledge and pass it on to the next generation of workers in the future.

The findings clearly show that companies in the Swedish pulp and paper industry value both augmentation and automation in their manufacturing processes. In the article *"Artificial intelligence and Management: The Automation-Augmentation paradox"* Raisch and Krakowski (2020) argue that you cannot separate augmentation from automation. They emphasize the importance of having a perspective where organizations working with AI focus both on augmentation and automation. This is also in line with the findings in this study. The companies do not solely focus on either one of these two concepts but tries to incorporate AI solutions in their manufacturing processes by both using augmentation and automation. According to (Raisch & Krakowski, 2020) this is the right strategy to have and will lead to positive organizational outcomes for these companies in the future. Furthermore, it will also lead to positive societal effects on the Swedish society since the pulp and paper industry plays an important part in the Swedish economy (Forest Sweden, 2013; Parente et al., 2019). By using both augmentation as well as automation companies will be able to realize these synergy effects in the future.

6.2.2 Increased automation can be valuable in the long term

The findings of this study also show that further automation has the potential to be valuable in the future. Focusing on automation with AI in the future, when the technology has become more mature, decreases the risk of entering the above-mentioned vicious cycles of deskilling of humans. Using this strategy companies will experience fewer negative consequences related to automation. Moreover, when AI has been used in the manufacturing processes to enhance and support the decision making of the operators for some time, AI solutions for automation is regarded easier to achieve.

The approach of leaving most automation with AI for the future seems wise since the companies described that most of their processes already are automated today and that these rule-based automation systems have been developed and optimized for decades. Taking on this approach instead of focusing on automation directly, which was suggested to be a more likely approach according to Davenport and Kirby (2016), could be explained by the fact that these companies already have developed high quality rule-based automation systems. Trying to use an immature technology to optimize automation in the manufacturing processes, that has been improved and evaluated for such a long time, does not align with a well-defined digital innovation strategy.

6.3 Managing innovation and organizing R&D

In this section, the most critical results from research question 3 are discussed.

6.3.1 Digital innovation is highly valued

Digital innovation is an important factor for the industry

The results showed a clear tendency that innovation is highly regarded among the pulp and paper companies. Another interesting aspect was that digital innovation was partially seen as a critical aspect of competitiveness. As defined by Nambisan et al. (2017), digital innovation captures the process of innovating using digital technology. The pulp and paper industry is an old industry and many processes are not changing drastically. Yet, it is interesting to note that the continued work toward process innovation is seen as a vital element of the industry. As emphasized by Demirkan et al. (2016), many industries are today facing issues of digitalization while digital technologies are becoming more important in order to achieve business goals. The results show that there is a strong belief that AI has the potential to create value for these companies in the future. With this in mind, it fair to believe that the work within digital innovation is also considered an important factor for the pulp and paper industry.

Digital innovation is managed through innovation activities

Another interesting aspect of digital innovation management theory that appeared in the results is the tendency for companies to support and facilitate innovative thinking through specific innovation activities. The innovation activities are arranged to interactively and collectively tackle concepts that are otherwise difficult to work on. These activities can partly be seen as a tool to work with innovative digital technologies such as AI. Thus, one way companies in the Swedish pulp and paper industry manages digital innovation is through their innovation activities. Moreover, a key aspect of these activities are collaboration and experimentation with new technology fast-paced contexts. As previously discussed regarding the development of AI through exploration, the innovation activities can in this sense be seen as a part of the exploratory approach toward further use of AI within the manufacturing processes.

Digital innovation is managed through digital innovation life-cycles

When further analyzing the aspects of digital innovation management, the process that companies follow to guide their innovations came to surface. It is interesting to note that, from the results, there was a trend that companies have defined processes for working with digital innovation. In these processes, a set of predefined steps funnel the projects from ideas to fully exploited solutions. Through this process, ideas are tested and evaluated on their strength as a potential business case and quickly dismissed if the potential value appears to be low. Although companies have different processes to tackle digital innovation, in a sense they can all be seen as a form of the digital innovation life-cycle presented by Kohli and Melville (2019), altered for company-specific needs. Within the digital innovation life-cycle, technological advancements are created through steps in a process of digital innovation actions. As such, it is clear that elements from this model are also present in the processes used to funnel digital innovations within the Swedish pulp and paper industry. Thus, it is fair to believe that one of the ways companies within the Swedish pulp and paper industry manage digital innovation is through different forms of a digital innovation life-cycles.

6.3.2 AI is supported through digitalization agendas

From the results, it was clear that companies tended to not have specific strategies or targets regarding the use of AI. This choice can be understood from the motivation that technology-specific strategies is not in line with the overall business strategy and the belief that the industry will not take a lead within AI technology. However, a common theme is that most companies tend to have a strategy or agenda related to digitalization and it is within this agenda that AI initiatives are brought to light. This is an interesting approach as it shifts the approach of staying in the front line of AI development toward absorbing the most appropriate existing trends on the market that already have been proved successful. It can be argued that another reason for this motivation is a lack of expertise. As previously discussed regarding barriers hindering further use of AI, lack of expertise within AI was a main issue within the pulp and paper companies. Because of this, it seems reasonable to take small leaps in the progress of integrating AI in the manufacturing processes instead of investing heavily into uncertain technologies. From the results, this was motivated in an interesting way: *"[...]it is important to begin implementing at a small scale and let the technology mature while the company is building a stronger knowledge base of what can and can't be done."* This statement summarizes some of the reasons not opting for AI specific targets. As such, it is fair to believe that AI initiatives are primarily not driven through specific technology targets but instead are an important part of the digitalization agenda.

6.3.3 AI is supported through digital innovation departments

R&D with focus on digital innovation

One key theme that emerged from the interviews was in regard to the organizing of R&D supporting initiatives within AI. It is highly noticeable that companies within the Swedish pulp and paper industry tend to have specific departments, functions or teams that drive digital initiatives. Although it is difficult to pinpoint one common name for these functions as they vary between businesses, the overall purpose and objective within digital innovations remained largely similar. For this purpose, we will for simplicity sake make an interpretation of this function and refer to these as "digital innovation departments". We find this name most suitable as it was used by some of the companies and roughly summarizes the role of this department.

Supporting enterprise-wide AI

As presented in the results, the purpose of the digital innovation departments tended to be centered towards researching, developing, driving and assisting digital initiatives that primarily benefit large parts of the organization. The use of AI in the manufacturing processes is a critical part of this work. Through a tightly connected network of people the digital innovation department is able to identify what AI technologies can be used to increase process efficiency and coordinate how these can be scaled up at different business units. They are also able to help the organization face issues within their AI initiatives, such as a lack of expertise. As such, the digital innovation department can be seen as a form of an R&D department, with less focus on product development and more focus process development. In order to further understand the context of the digital innovation departments, we can analyze how these are organized within companies of the Swedish pulp and paper industry from different organizational theories.

Integrated R&D Network

The theories behind international R&D organizations can help us further understand the nature of the digital innovation departments. In the paper by Gassmann and Zedtwitz (1999), we learn of the five major trends that drive the evolution of international R&D organizations. Although this theory is primarily based on organizations with extensive international networks, it is fair to believe it would work similarly on large pulp and paper companies with paper mills spread across the country (and in many cases in several countries). Even through this model simply attempts to explain reality and the digital innovation departments are relatively small, it is reasonable to observe the similarities between the digital innovation departments present in the pulp and paper industry and the "Integrated R&D Network" described by the authors.

Above all, the integrated R&D network is described as a competence center among many closely units interconnected through flexible coordination mechanisms. This structure roughly reflects the inner workings of the digital innovation departments present in the pulp and paper industry. In the digital innovation department, sharing technical expertise, giving guidance and coordinating the work in AI projects with different business units and R&D teams at is a central task. On top of this, the digital innovation departments are typically distributed at different paper mills with close organizational connection and collaboration. These properties can similarly be seen with the integrated R&D network, where there is unrestricted flow of information and multi-dimensional coordination.

From this analysis, we can learn more about the properties of the digital innovation departments, their strengths and weaknesses in relation to supporting AI initiatives. As such, the organizational structure can be described as a highly dispersed while the behavioral orientation can be seen as a synergistic integration of international R&D units, presented by Gassmann and Zedtwitz (1999).

7 Findings and conclusion

In this section the most critical findings and conclusions of the thesis are presented. This will be done by summarizing the results that most accurately answer and each research question. Lastly, this section presents suggestions for future research.

7.1 Research question 1

RQ1: To what extent are companies in the Swedish pulp and paper industry using artificial intelligence in their manufacturing processes and what barriers hinder further use?

The current use of AI technology in the manufacturing processes is immature and the extent to which these are used varies between companies. Although it is too early for companies to be able to capture full potential of AI, companies have an exploratory approach that ensures the continued development of the technology. In order to make further progress in the area of AI, companies must tackle three barriers that currently hinder this effort, i.e. implications of scaling up projects, issues with trust and lack of expertise.

7.2 Research question 2

RQ2: What are the main future trends of artificial intelligence in the manufacturing processes of the Swedish pulp and paper industry?

There are several trends within the use of AI that appear promising for the manufacturing processes of the Swedish pulp and paper industry. These include five areas that are believed to benefit from the introduction or continued use of AI technology, together with overall approaches toward continued work with AI. The most prevailing trends are the integration of AI in process optimization and quality control, predictive maintenance, energy optimization, predicting web breaks and safety management. Furthermore, continued human-computer collaboration by augmenting mill operators with AI will be prioritized in the short term, while an increased focus on AI-integrated automation has the potential to be valuable in the long term.

7.3 Research question 3

RQ3: How do companies in the Swedish pulp and paper industry manage digital innovation and organize R&D to support initiatives in artificial intelligence?

It was shown that innovation is highly regarded in the Swedish pulp and paper industry. Companies tend to manage digital innovation both through innovation activities and digital innovation life-cycles. Companies do not have specific strategies directly related to progress within AI. However, AI initiatives are instead supported through digitalization agendas that formulate digital objectives. The main effort to support AI initiatives is concentrated on digital innovation departments that provide expertise in AI projects and act as integrated R&D networks.

7.4 Future research

One noteworthy takeaway from the interviews is the tendency for respondents to generalize the current state of the pulp and paper industry with regard to digital innovation and use of AI. From the results, it appears that there is a belief that the pulp and paper industry in the Nordic countries is ahead compared to other regions of the world in terms of their digital innovation and progress within AI. Perhaps this aspect suggests that that the findings of this study can be generalized to not only the Swedish pulp and paper industry, but the entire Nordic industry as well. It is outside the scope of this study to make this claim, but it could be an indication of the reality and be a promising area for further research.

This thesis showcases the potential of integrating AI in the manufacturing process of the pulp and paper industry. It was shown that there is great potential for AI technology in this context. However, companies must face the barriers of making further use of AI technology. These takeaways suggest that there is potential for further research both in areas of developing different AI technologies using data from specific processes, but also research on how companies within the pulp and paper industry should work with change management in order to overcome these barriers and restructure their organizations to better suit the growing advancements in AI. As such, we strongly encourage authors to continue the research within these areas.

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