MSc Program
Engineering Management

The New Business of AI Software Vendors in the European Manufacturing Industry - An Empirical Study on Business Models of Entrepreneurial AI Software Vendors

A Master's Thesis submitted for the degree of
“Master of Science”

supervised by
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Vienna, 23.03.2021

Affidavit

I, **ROBERT NIKLAS FIP**, hereby declare

1. that I am the sole author of the present Master's Thesis, "THE NEW BUSINESS OF AI SOFTWARE VENDORS IN THE EUROPEAN MANUFACTURING INDUSTRY - AN EMPIRICAL STUDY ON BUSINESS MODELS OF ENTREPRENEURIAL AI SOFTWARE VENDORS", 75 pages, bound, and that I have not used any source or tool other than those referenced or any other illicit aid or tool, and
2. that I have not prior to this date submitted the topic of this Master's Thesis or parts of it in any form for assessment as an examination paper, either in Austria or abroad.

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Abstract

This thesis's topic is the business model analysis of entrepreneurial companies that provide artificial intelligence solutions to the manufacturing industry. Additionally, the thesis provides an overview of state-of-the art AI technologies and applications common in the manufacturing industry.

In virtue of the 4th industrial revolution, Artificial Intelligence (AI) technologies have found their way into the manufacturing industry. The technology revolutionizes production in a range of applications, from predicting machine downtime to assuring quality through computer vision. With various deployment possibilities, the opportunities of AI in manufacturing are manifold. In many cases this technology is provided by a multitude of vendors that specialize in manufacturing-specific AI software. The vendors range from large technology incumbents to upcoming technology startups. Especially entrepreneurial AI software vendors have been emerging over the last decade, imposing direct competition to well-known technology companies. However, it is yet unclear how entrepreneurial AI vendors employ their offerings to the manufacturing firms and whether there are any identifiable patterns that have emerged. To bring clarity into this uprising research field, a qualitative content analysis was adopted to study the business models of entrepreneurial AI software vendors. The vendors are registered in the crowdsourced Dealroom database and were sampled according to predefined criteria. The business model information was primarily extracted from the websites of those companies and systemized according to a conceptual framework proposed in this thesis.

The result of this thesis yielded in a typology of entrepreneurial vendors. The typology provides valuable insights into the emerging world of AI vendors in the European manufacturing industry. Moreover, the thesis recommends a need to further understand the various type of vendors by extending the sample size to a global level and verify the application of the proposed framework.

Table of Abbreviations

AI – Artificial Intelligence

AIVA – Artificial Intelligence Vendor Analysis

BMC – Business Model Canvas

CNN – Convolutional Neural Network

DaaS – Data as a Service

DL – Deep Learning

MaaS – Model as a Service

ML – Machine Learning

NN – Neural Network

IoT – Internet of Things

PM – Predictive Maintenance

PaaS – Platform as a Service

SaaS – Software as a Service

QC – Quality Control

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1. Introduction

1.1. Problem Statement

Over the last years, the term Artificial Intelligence (AI) has become pervasive in many scientific works and is broadly discussed in various newspaper articles, panel discussions, and company presentations. It has become a polarizing symbol for the technological progress of the 21st century. With the advances in data collection and aggregation as well as computational power and algorithms, scientists have made significant breakthroughs in artificial intelligence. Major established companies, innovative startups, and many researchers are working relentlessly on new computational solutions that bolster efficiency and productivity gains in various use cases. In virtue of the 4th industrial revolution, Artificial Intelligence (AI) technologies have found their way into the manufacturing industry. The technology revolutionizes production in a range of applications, from predicting machine downtime to assuring quality through computer vision. With various deployment possibilities, it is an immense challenge for industrial managers to overview the opportunities and challenges of this technology. Albeit that AI technology is an inherent part of the digitalization roadmap of most manufacturing companies to stay competitive in a globalizing industrial world.

In many cases AI technology is procured from a multitude of vendors that have specialized in developing industry-specific AI software. The vendors range from large technology incumbents to upcoming technology startups and in most cases offer software products or services for a wide variety of application fields. Especially entrepreneurial AI software vendors have been emerging over the last decade, imposing direct competition to well-known technology companies such as Google, Amazon AWS, IBM, and others.

With this acceleration of AI adaption and the increase in the supply of AI solutions by entrepreneurial businesses, the research body of knowledge has been growing. While it mainly offers evidence about the technicality of artificial intelligence technologies itself or the impact on the manufacturing side, the business case of entrepreneurial AI software companies (or startups) remains broadly untouched. Only a few management consultancies conducted surveys with manufacturing executives or deduct opportunities and challenges from aggregated case studies about Industrial AI applications and their vendors (Chui M., 2017). This quantification of AI in the manufacturing industry is also followed by business intelligence agencies (Dealroom, 2020; Crunchbase, 2020) which start to categorize data on AI technology companies in the manufacturing industry. However, it is yet to be determined what the characteristics of a successful AI startup in the manufacturing world, and beyond, look like.

1.2. Objective

Drawing upon two streams of research, this thesis attempts to provide an overview about the fundamentals of artificial intelligence and how it is applied in the manufacturing industry. Secondly, this thesis aims to provide an understanding of entrepreneurial AI software companies that offer their products or services to the manufacturing industry. In addition to that, the thesis is trying to draw a picture about the type of entrepreneurial vendors and the business models they use in order to monetize their offerings. To do this, a qualitative analysis of AI software companies in the manufacturing industry will attempt to describe the nature of their business. The underlying hypotheses of this thesis is: H1) The analysis of the sampled data of this study, will reveal patterns around the business models of AI software vendors; H2) The majority of entrepreneurial AI software vendors in the European manufacturing industry are driven by service-centric business models instead of product-centric business models. To answer the hypotheses, the thesis suggests three major research questions as guidelines for the qualitative research:

Research Question 1: *What kind of entrepreneurial AI vendors operate in the European manufacturing industry, and is there a significant identifiable pattern that characterizes their business models?*

Research Question 2: *What factors influence an AI vendor's service- or product-centricity in the manufacturing industry?*

Research Question 3: *Which application fields and technologies are utilized by AI software vendors in the manufacturing industry?*

The research questions could help draw a clearer picture of how AI vendors operate in the manufacturing industry in Europe.

1.3. Relevance

As AI technologies emerge from pure theory to an industry-changing reality, there is an imminent need to systematically develop and implement AI for manufacturers to stay competitive. In fact, the accelerating adoption of AI technologies, also forces industrial managers to have a decent understanding on the business dynamics and value those vendors bring to the table. Thus, it is of utmost importance to understand how AI companies create and offer value to manufacturing companies. Therefore, this thesis should help industrial managers in manufacturing companies as well as founders of AI companies to grasp the characteristics and challenges from a business perspective.

1.4. Methodology

The methodological approach of this thesis consists of two parts. Firstly, a literature review based on current findings of AI technologies, application fields and business models will provide the reader with an overview of the latest research. Secondly, an empirical study based on qualitative data including a qualitative content analysis and a systematization of the results is done. The first part consists of a literature review to give an overview of AI technologies, their business models and their applications in the manufacturing industry. The second part will analyze a dataset from a crowdsourced research database (Dealroom.co, 2020) that comprises information about entrepreneurial AI vendors. This information includes general company data, profiles, growth, acquisitions, and investments. The data for the analysis were collected from the business websites as well as technology portals, whitepapers, and blog posts. To receive guidance for the empirical study, several interviews with experts in the field of applied artificial intelligence have been conducted.

1.5. Structure

The thesis embodies six main chapters. The first chapter presents the problem statement, the research questions, and a rough outline of the applied methodology. The second chapter reviews relevant literature to build the theoretical foundation of artificial intelligence and its application in the manufacturing industry. The third chapter examines the business model research and the framework that is applied for the analysis. The fourth chapter explains the methodology and elaborates on the data collection and analysis process. The fifth chapter discusses the results. In the last chapter, a conclusion is made while commenting on the limitations and emphasizing the thesis's practical contribution and motivation for future research.

1.6. Literature

The literature for this thesis compounds two themes. On the one side, I will examine the scientific works about Artificial Intelligence in general as well as its applications in the manufacturing sector. On the other side, I will research and present the literature available on business models in general and specifically for AI.

Research on general Artificial Intelligence has steadily grown over the last decades. The most recent contributions to the field of research were made by Samuel (1956), Nilsson (1996), Mitchell (2006), Nielsen (2015), LeCun et al. (2015) and Bengio et al. (2015; 2017). For their research on Deep Learning, an enabling sub-technology of Artificial Intelligence technology, LeCun and Bengio (2015) won the Turing award. Only very recently, researchers began to describe the applications of AI techniques in the manufacturing space. Most prominently, Lee (2018, 2020), a thought leader of AI in manufacturing, explains his findings in the book "Industrial AI" (2020) and serves as one of the core sources mentioned in this thesis. The field is furthered by studies that helped to investigate various applications of AI in manufacturing (Kordon, 2020; Schuh & Scholz, 2019; Wuest et al., 2016),

Concerning the fundamentals of business models, I could identify a fair amount of literature that helps understand the basic concepts (Magretta, 2002; Osterwalder et al., 2010; Gassmann et al., 2014). Only a little research on business models deals with the commercialization of artificial intelligence from a vendor's perspective (Corea F., 2017; Bader et al., 2019; L. Jia, 2020). However, I could not find adequate research that described AI vendors' profiles and business models in the manufacturing industry. This gap in literature also serves as a solid motivation to formulate the research questions mentioned above.

2. Artificial Intelligence: Theoretical Background and Literature Review

Artificial intelligence represents a broad set of technologies and is often misunderstood as technical terminology inflation increases. Since this thesis deals with application fields enabled by AI technologies such as computer vision and advanced analytics, it is essential to understand the underlying techniques such as Machine Learning that leverage the value of data in manufacturing. Therefore, this chapter tries to explain the technical and practical background of the rather complex technology environment, focusing on the manufacturing industry. The first part of this section will elaborate on the history of AI and explain the essential technological foundations of AI, including two computational methods. The second part of this section will give a brief overview of the most important application fields of artificial intelligence in manufacturing and describe the challenges this technology faces in this industry.

2.1. History of AI

It is worth taking a look at the roots of this relatively new field of research for better context. With the vision to build machines more intelligent than human beings, Artificial Intelligence has undergone several ups- and downturns since it has been first-coined at the Dartmouth Conference in 1956. From several "golden ages" to cold "AI winters", it seems that AI has taken a long way before becoming the global milestone in technology that it is today.

The first golden age of Artificial Intelligence can be dated back to 1965, when AI scientist Herbert A. Simon proposed that 20 years later, machines will be capable of doing any work a human can do. After this initial hype, the first "AI Winter" began in

1973 (Lee, 2020). It was initiated by a published report from Lighthill that provided deep insights into the gap between anticipation and reality of AI progress. With this, the initial optimism massively vanished and led to governments cutting their AI research funds. Thereafter, a second golden age ushered in when expert AI systems and Bayesian theory emerged in the 1980s (Lee, 2020). However, it became clear that software and algorithms imposed great challenges for the research community (Lee, 2020). Besides, new computing hardware developed rapidly and made AI-specialized hardware redundant, which ultimately led to increased investor uncertainty in the field. In the late 1990s, events like IBM's Deep Blue defeating the world chess champion Garry Kasparov and the successful implementation of AI in real-life gave it increased popularity and significance.

Furthermore, the value that AI generated for enterprises has accelerated rapidly through various breakthroughs in deep learning techniques (Lee, 2020). In 2012, AI scientist Geoffrey Hinton and his team could prove that deep learning technology outperforms conventional Machine Learning by far, shortening the length of training a model from several months to a few days or hours (Lee, 2020). In addition, Google created the deep learning model AlphaGo which was able to beat Go master Lee Sedol in 2016, accelerating AI to new public popularity. Beyond this public relation event, artificial intelligence has entered a new era in which it can bring real value to firms in a broad range of industries. However, it remains challenging to predict whether the current hype around AI the beginning of a new golden age is or already the climax of the technology. Nevertheless, from intelligent financial systems to smart manufacturing, the technology is already manifesting itself in unforeseeable ways to create value for the economy and society.

2.2. Theoretical Background of AI Technology

This paragraph explains the main technological methods behind artificial intelligence. First, this section is dedicated to explaining the AI technology ecosystem as well as its most critical computational methods for the manufacturing industry, namely machine learning (ML) and deep learning (DL) (Lee, 2020). Secondly, it will describe the challenges and limitations that AI faces when applied in real use-cases.

2.2.1. The AI Technology Ecosystem

Artificial intelligence is enabled by three core technologies: algorithms, big data technologies, and computing power technologies (Quan et al., 2019). Altogether, this collection of technologies unlocks the full potential of AI systems.

Firstly, algorithms refer to the different computational methods that help to build the software used to solve complex problems (Quan et al., 2019). Furthermore, big data technologies include data assessment, storage, management, and analysis technologies (Quan et al., 2019). Since algorithms need an enormous amount of data to learn from, it is vital to building a functioning data infrastructure around these technologies. In fact, data nurtures the core of the AI system with information. Finally, computer power technologies refer to the computational power needed to process the data with the algorithms (Quan et al., 2019). For instance, Intel's latest AI processing chips can run over 10 trillion calculations per second (Quan et al., 2019). Furthermore, computer power technologies can be differentiated between cloud computing and edge computing.

Cloud computing refers to an internet-based, central computational model that offers on-demand access to computational resources such as software applications, computer memory, or data centers (Kordon, 2020). It allows companies to outsource their computational power "outside" of the physical world and thus, bypass any complex infrastructure set-ups. "From a modeling perspective, cloud computing gives opportunities to use almost unlimited computational power and to interact with big data, with easy deployment on a large scale." (Kordon, 2020; p. 356). One widely discussed problem with cloud computing is privacy and latency. Here, privacy refers to the transmission of data to the internet. For manufacturing companies, which often handle sensible data, cloud computing is yet connected with significant concerns. Also, the transmission time from a data collection device (e.g. sensor) into the cloud is an opposing challenge for manufacturers who need to analyze specific equipment in real-time.

Edge computing, on the other side, refers to a decentralized computing infrastructure. In fact, with hardware exponentially decreasing in size, it has become possible to equip IoT devices (e.g., machine sensors) with strong computational abilities (Corea, 2017). In combination with AI algorithms, edge computing allows real-time analytics of data on the spot (Corea, 2017).

2.2.2. Machine Learning

There are two primary definitions of Machine Learning in research. Firstly, Arthur Samuel (1959), one of the pioneers in Machine Learning, described the subject as "the field of study that gives computers the ability to learn without being explicitly programmed." (A. Samuel, 1959) While the latter definition already dates back a while, a more modern description of ML has been expressed as "a computer program said to learn from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E." (TM Mitchell, 2006) In order to visualize this definition, one imagines a program that is programmed to learn or play chess:

"E = the experience of playing many chess parties

T = the task of playing chess

P= the probability that the program will win the game"

As a matter of fact, Machine Learning is the science of algorithms that learn and improve from experience. These algorithms analyze sample data, so-called training data, to build a model that can make predictions. In practice, Machine Learning algorithms are manifold. A straightforward machine learning algorithm is called *Naive Bayes* and can separate spam mail from legitimate mail (Bengio et al., 2017). Another machine learning algorithm is called *logistic regression* and can, for instance, recommend whether a cancer patient has a malignant or benign tumor. The success of those simple algorithms strongly depends on the representation of data they are given. For instance, when a logistic regression algorithm recommends a benign tumor, the subjected patient is not examined by an AI system itself. In reality, the doctor has to feed in the relevant data, such as the patient's lifestyle or health history. These pieces of relevant data are called features. The algorithm then learns how these features are correlating with various outcomes. The limit of those simple algorithms in Machine Learning is that they cannot define how those features are defined. Therefore, it becomes clear that the choice of representations can have an enormous impact on an algorithm's performance. Moreover, it becomes a complicated problem to solve, when there is no or limited understanding of what features should be extracted for a specific task (Bengio et al., 2017). A solution to this problem is called representation learning, an approach in which the system learns to map representations itself or in simple words: an algorithm for learning features (Bengio et al., 2017). In a more sophisticated representation learning version, also known as Deep Learning, the features can be abstracted by the algorithm on multiple layers to take out a concept's complexity. A good overview of the above-mentioned learning methods and their differences is shown in Fig. 1.

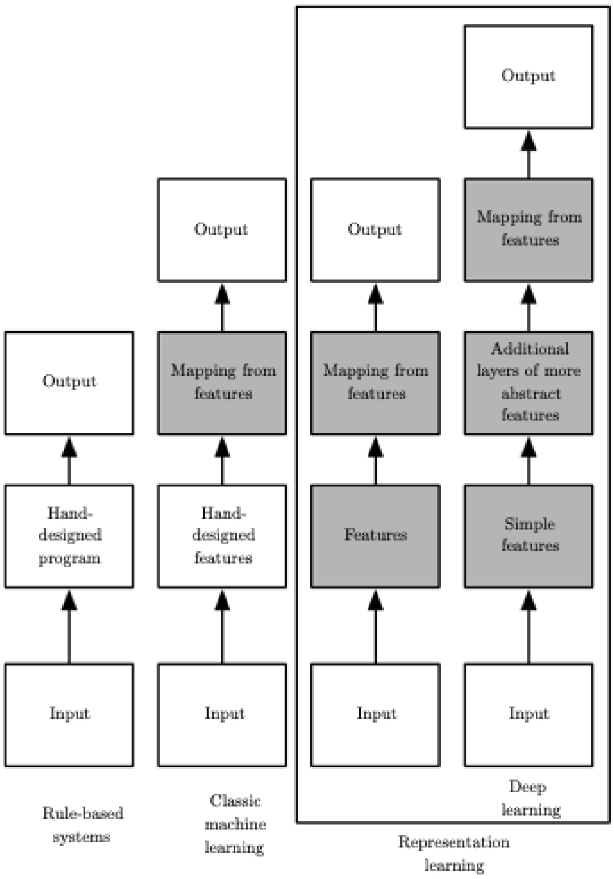

Figure 1: Flowchart of different parts of an AI system (Bengio et al., 2017)

In practice, machine learning developers often use these simple algorithms, like a logistic or linear optimization algorithm, to iteratively compute outputs and errors of a given input to find a good set of weights for it (LeCun, Bengio et al., 2015). This is also called model training. After the training, the model should be able to generalize its ability to produce outputs on new inputs that it has never seen before (LeCun, Bengio, et al., 2015). To create prediction models, one differentiates two main learning categories to which Machine Learning problems can be assigned to: supervised- and unsupervised learning.

Supervised learning works with a given sample data set for which the correct outputs are already defined or "supervised". It assumes that the user already has an idea about the relationship between input and output factors. In general, supervised learning can be categorized into "regression" and "classification" problems. While the latter is trying to classify input variables into discrete categories, the regression problem is trying to make predictions within a continuous output. To exemplify both a simple problem is described in the following:

"One imagines data about the production output of machines in the injection molding machine market and utilizes Machine Learning to predict their productivity. Productivity as the function of production output is a continuous output, meaning a regression problem. Similarly, this example can be put into a classification problem by defining our output about whether the machines production output is higher or lower than the required productivity, creating two discrete classes." (Own Example)

The other learning technique that ML problems can be assigned to is called unsupervised learning. In this approach, the data is unsupervised, i.e., there is no immediate feedback on whether the predictions are right or wrong. The system itself has to identify natural partitions of patterns within the unlabeled data (N. J Nilsson, 1998). With the help of algorithms, this approach gives structure to data where one only knows little or nothing about the relationship between input and output. The resulting data patterns have the ability to give deep insights beyond human computational abilities. Especially in an industrial context, unsupervised learning can be utilized to monitor machines' conditions or evaluate a system's health (J. Lee, 2020). In the next chapter, these much more complex deep learning models are explained in detail.

2.2.3. Deep Learning

As mentioned above, Deep Learning is a subclass of Machine Learning (LeCun et al., 2015). It enables computational models, composed of multiple processing layers, to learn representations of raw data with multiple abstraction levels (LeCun et al., 2015). This abstraction is necessary to simplify complex concepts and allows the model to process features in a more performant way. With this, Deep Learning creates a model that on its own defines characteristics to analyze and thus optimizes itself continuously. Therefore, the deep learning approach allows replacing any hand-engineered features with a self-trainable multilayer network. Deep learning has significantly accelerated the AI ecosystem by optimizing speech recognition, visual object recognition, detection, and many other domains of science (LeCun et al., 2015).

An important concept that allows the application of Deep Learning algorithms is called Neural Network (NN). While there are many NN variances in deep learning like convolutional neural networks (CNN), this thesis will only focus on the basic NN. As the name suggests, NNs are inspired by the human brain and can be broken down into artificial neurons. In Deep Learning neural networks use sigmoid neurons (Nielsen, 2015). As seen in Fig. 2 a sigmoid neuron has inputs (x_1,x_2, etc.) that can take on any values between 0.0 and 1.0. In addition, a sigmoid neuron has weights for each input

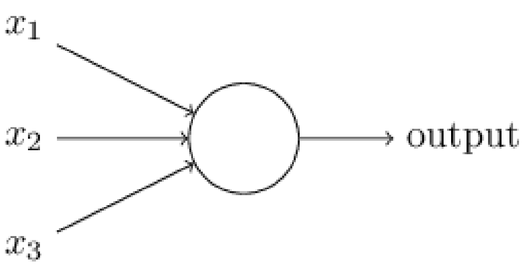

Figure 2: A sigmoid neuron based on Nielsen (2015)

(w_1,w_2) and an overall bias (b). The output of a sigmoid neuron is defined as $\sigma(w * x + b)$ where σ is called the sigmoid function:

$$(1) \quad \sigma(z) = \frac{1}{1 + e^{-z}}$$

To help visualizing, one imagines that the input is an image of a handwritten digit in greyscale. The generated output can be expressed as the average intensity of a single pixel of this image. The interconnected neurons can have a value between 0.0 and 1.0, with 0.0 representing white and 1.0 representing black. Accordingly, the output represents the neuron's intensity or analogically the greyscale, e.g. light or dark grey.

In a neural network, multiple sigmoid neurons can be found in three different types of layers (Nielsen, 2015). The first and leftmost layer is called the input layer and the neurons within this layer are called input neurons. The second and middle layer is called a hidden layer. The third and rightmost layer is called the output layer. Neurons in this layer are called output neurons. There is always one input and output layer. However, there can be multiple hidden layers. Many applications use a so-called feedforward neural network architecture that maps a fixed input (e.g., an image of a dog) to a fixed output (e.g., a dog eye). To transition from one layer to another, a weighted sum of inputs from the previous layer is computed by sigmoid neurons and passed through a nonlinear function, the sigmoid function (1), to the next layer.

As an example, Fig. 2 shows a three-layer NN that is programmed to recognize handwritten digits. The input for this network is a greyscale image of a handwritten digit with the size of 28 by 28 pixel (=784 neurons). As described above, the related input neurons can have a value between 0.0 and 1.0, with 0.0 representing white and 1.0 representing black. The output neurons represent the digits 0.0 to 9.0. If, for example, the fourth output neuron activates, it indicates that the input image is a handwritten three.

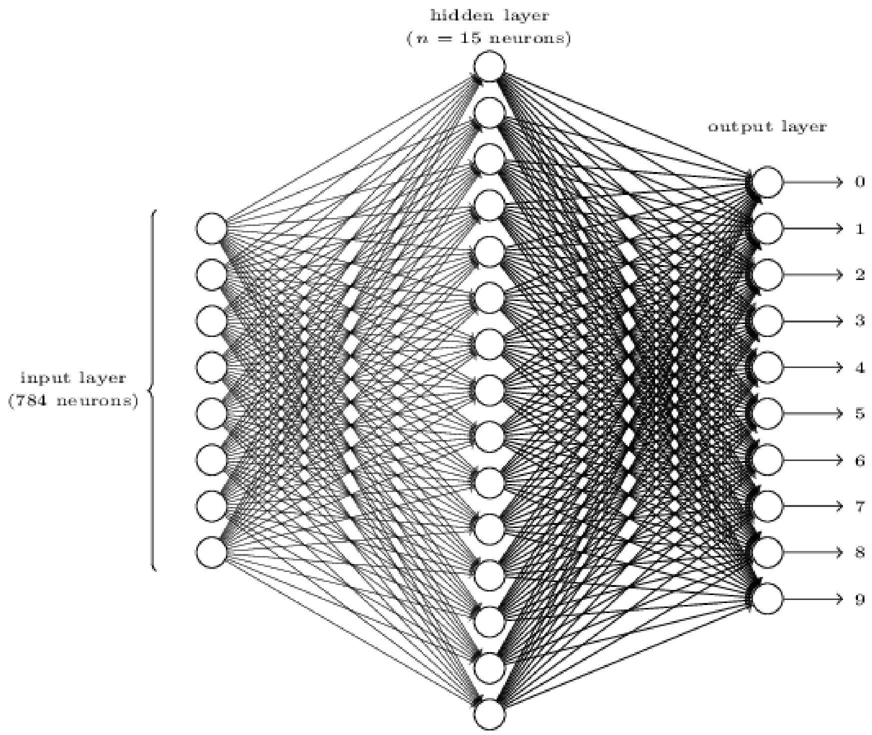

Figure 3: Depiction of a three-layer Neural Network with one hidden layer (Nielsen, 2015)

The design o a Neural Network architecture is considered straightforward and ultimately depends on the amount of input data and the desired number of outputs (Nielsen, 2015). For Neural Networks to function, a method called backpropagation is used (Nielsen, 2015). In short, the backpropagation algorithm calculates the gradient of the error function with respect to its weights. It is a form of feedback updating that enables the Neural Network to "think" intelligently. The backward name stems from the fact that it calculates the gradients of the output layer first and then updates its way back to the input layer weights until it has reached a certain probability. As already mentioned above, a subclass of Neural Networks in deep learning is the convolution neural network (CNN). They are often applied in computer vision applications. The name stems from the fact that the neural network layers apply a convolution operation to the input passing the result to the next layer. The convolution allows the network to analyze deeper with fewer features. In manufacturing, the integration of convolutional neural networks helps quality inspectors in manufacturing firms automatically inspect product quality.

As explained above, there are various types of AI methods within *Machine Learning* and *Deep Learning*. However, a detailed explanation of their technicalities would go beyond the scope of this thesis. Hence, the next chapter will focus on the advancements that those methods bring to the manufacturing industry.

2.3. AI in Manufacturing

2.3.1. Future of Manufacturing and Industrial AI

According to the Cambridge dictionary, manufacturing can be defined as "the business of producing goods in factories" (Cambridge dictionary, 2021). In recent years, the producing companies, or manufacturers, have been addressing the importance of enhancing processes and systems with a degree of "intelligence". With the emergence of the Internet of Things (IoT), Cyber-Physical Systems (CPS) and the increase in computational power through Cloud Computing (CS), industries are moving towards a new digital era. Nowadays, enterprises are equipped with the capability to generate, collect and process large amounts of data intelligently. For manufacturers, AI promises the potential to discover inefficiencies, improve outputs and adapt to new conditions fast (Schuh et al., 2019). As a game changer for manufacturing industries, it further promises rewards such as predictive maintenance, reduced downtime, 24/7 production, improved safety, lower operational costs, greater efficiency, quality control, and faster decision-making (Schuh et al., 2019).

This integration of information technologies, mainly AI, is also called Smart Manufacturing or Industry 4.0 (Thoben et al., 2016). In fact, AI software can support manufacturing processes and systems in three major dimensions (Schuh et al., 2019). Firstly, the technology allows to extract complex data representations from a large amount of data, giving immediate transparency into the interdependencies of a manufacturing system or machines. Secondly, AI enables the direct optimization of processes based on performance criteria. Thirdly, AI technology allows the manufacturers to make predictions based on historical data and provide or execute an instruction to optimize processes (Schuh et al., 2019). In recent literature, a new term, namely "Industrial AI" (Lee, 2018; Charrington, 2017) is coined to describe applied

AI in manufacturing industries. It is defined as *"[…] any application of AI relating to the physical operations or systems of an enterprise […]."* (Charrington, 2017) or as Lee (2020) defines it: *"a systematic discipline which focuses on developing, validating and deploying various machine learning algorithms systemically and rapidly for industrial applications with sustainable performance."*. While this term is only used in few research papers it emphasizes the application potential of artificial intelligence technology in an industrial context.

2.3.2. Adoption of AI in Manufacturing

In a recent study, Chui et al. (2017) surveyed over 3000 C-level executives on how they are using digital technology and AI in their companies. Only 20 percent of the participants said they use AI-related technology at scale, proving a slow adoption of AI among several industries (Chui et al., 2017). In fact, the financial services, telecom and high-tech industry are among the early adopters whereas other industries such as manufacturing still lack behind (Chui et al., 2017). These findings of the AI survey by Chui et al. (2017) are visualized in Figure 4 below. In another study conducted in 2018 by El-Jawahri et al. (2020), only nine percent of the surveyed 1155 manufacturing executives said that they have implemented AI in their operational processes (El-Jawahri et al., 2020). Furthermore, a paper by Burnstörm et al. (2021), is validating the slow adoption in the manufacturing industry where *"AI applications have not yet disrupted major parts of the manufacturing industry"* (Burnstörm et al., 2021, p.93) and *"[…] manufacturing incumbents are performing small-scale AI innovation in collaboration with various ecosystem stakeholders in order to identify a competitive edge through AI."* (Burnstörm et al., 2021, p.93).

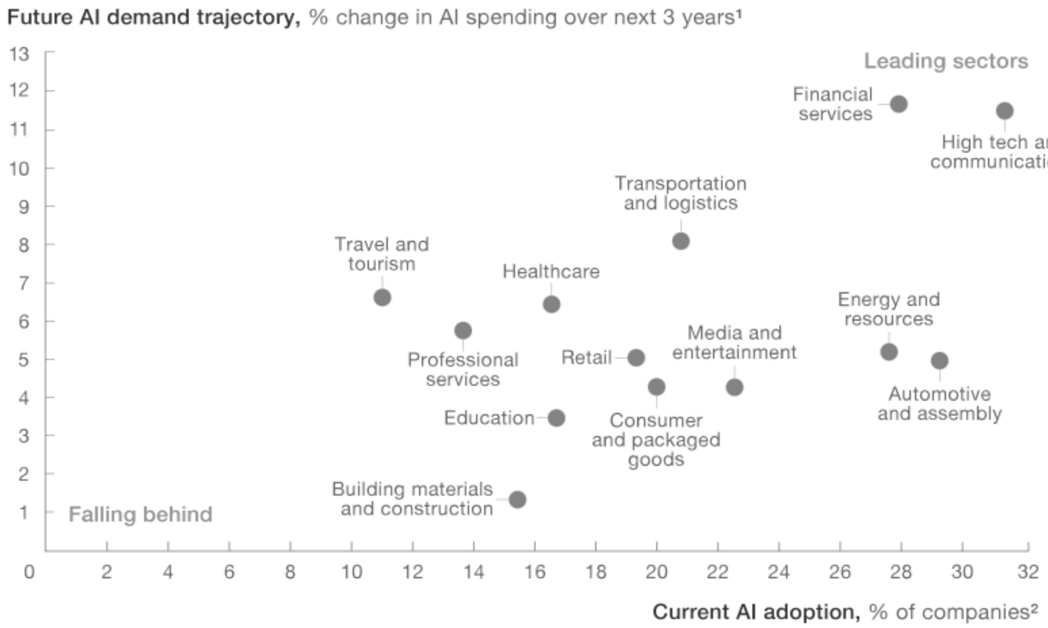

Figure 4: AI Adoption Matrix (Source: McKinsey Global Institute AI adoption and use survey)

2.3.3. AI Applications in Manufacturing

Artificial Intelligence applies to a broad range of manufacturing activities. The methods in which the technology is applied can strongly vary. This is due to the fact that every method has its own disadvantages and advantages for different application fields. In an attempt to understand which AI methods are used most in manufacturing, Fahle et al. (2020) reviewed 58 papers on deployed AI applications published between 2015 and 2020. They found that the majority of techniques are in the category of supervised learning using the method of Neural Networks outranking every other method (Fahle et al., 2020). While the interpretation of this is manifold, it clearly draws a picture of Deep Learning's aforementioned potential in manufacturing applications.

According to Charrington (2017), the manufacturing industry's various applications can be divided in three categories: monitoring, optimization, and control.

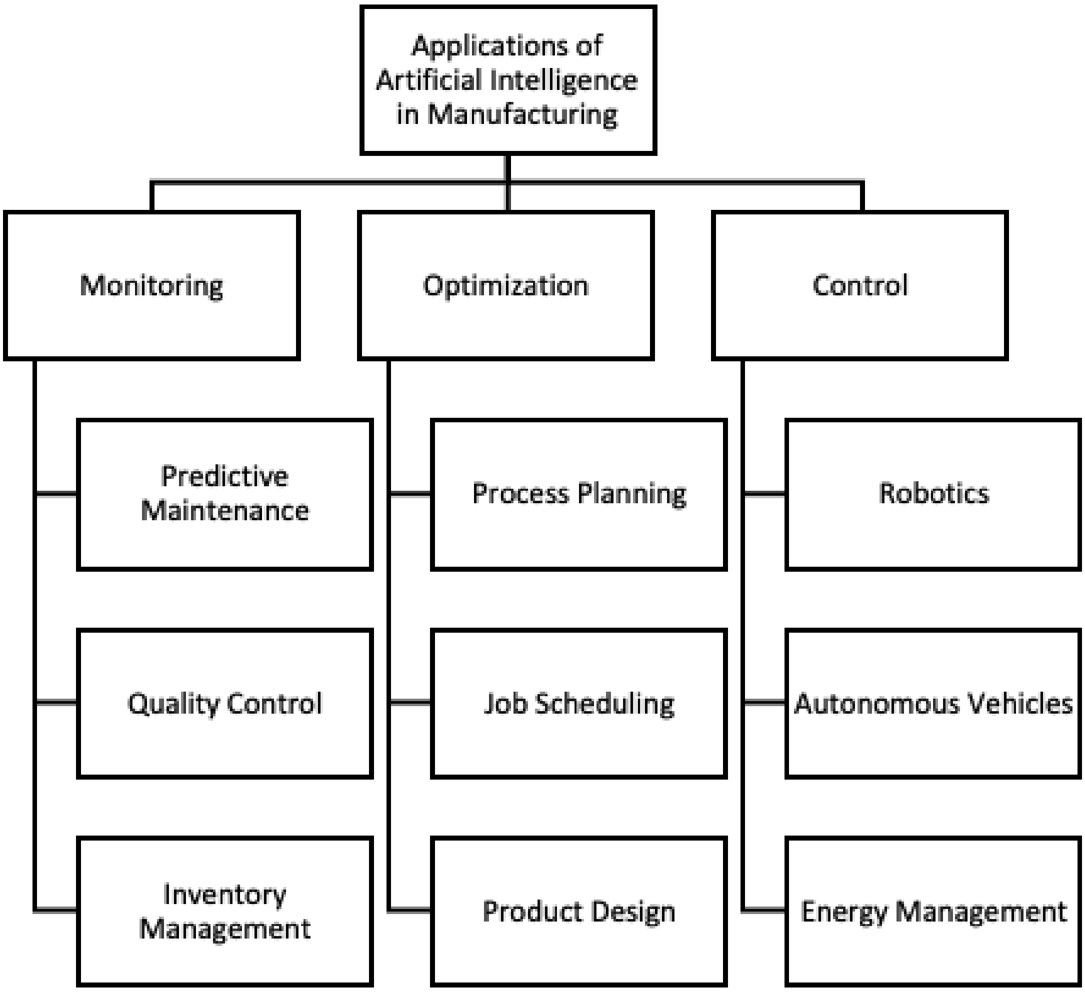

Figure 5: Own graphic of AI applications in manufacturing based on Charrington (2017

The first category includes applications connected to monitoring activities such as predictive maintenance, quality control, and inventory management (Charrington, 2017).

Predictive Maintenance (PM). As the demand for real-time asset visibility grows, predictive maintenance becomes one of the most prominent use cases. In short, it allows enterprises to detect equipment failures before they happen and thus, optimizes the reliability of operations as well as the lifetime of assets. For this, Machine Learning algorithms are analyzing massive amounts of data from sensors, the enterprise resource planning system (ERP) and other manufacturing management systems (Lee, 2020). The techniques allow to analyze the relationship between a data record and the labeled output and then create a data-driven model to predict those outcomes. For manufacturers, PM's value is manifold and consists of a reduced downtime of machines, better maintenance planning, increased production and reduced operation costs (Lee, 2020). According to a study, an increase of 10 to 15 percent in machine availability and a reduction in maintenance costs can be achieved based on the introduction of Deep Learning algorithms (Bauer et al., 2016). Moreover, Fig. 6 provides a detailed overview of the application process of PM.

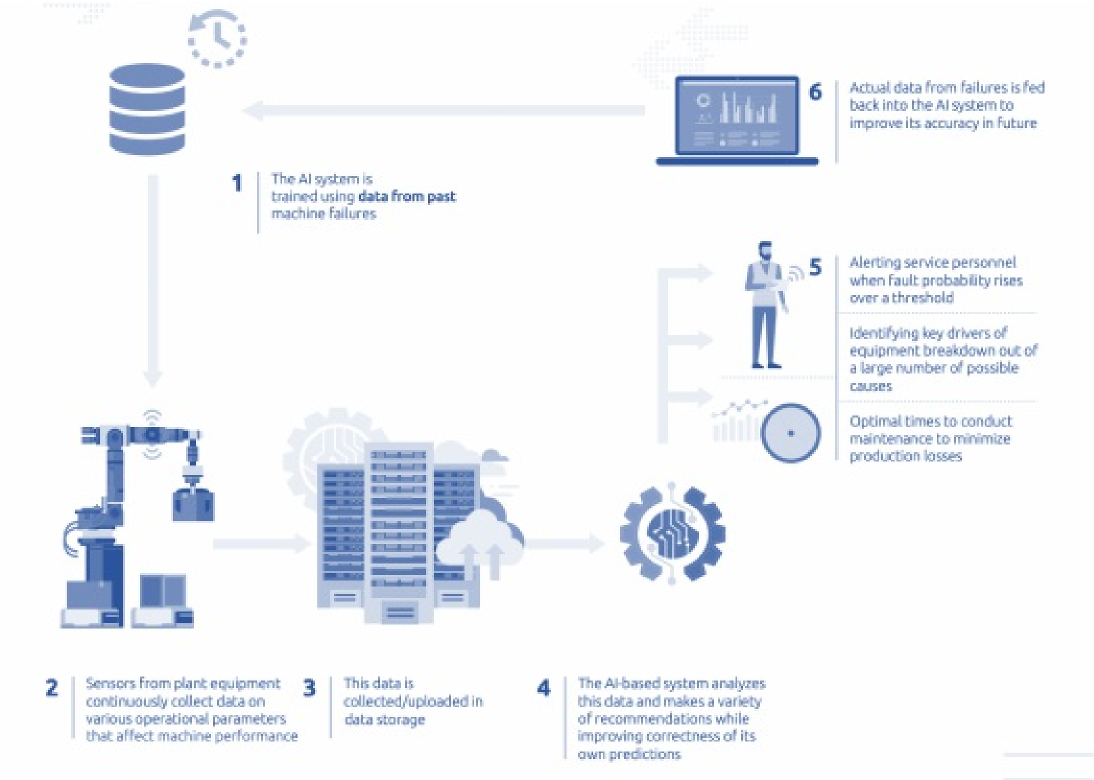

Figure 6: Predictive Maintenance process explained (Source: Capgemini Research, 2019)

Quality Control (QC). Another critical application field is Quality Control, especially of processes. In the manufacturing industry, quality is crucial for understanding a factory's production capacity (Lee, 2020). As quality output in production is dependent on various factors, engineers often have difficulties finding abnormalities and their root causes (Lee, 2020). With AI and the relevant algorithm, a relationship between quality and multiple variables can be detected. This helps to extract quality-related rules in production and ultimately supports enterprises to solve potential quality issues (Lee, 2020).

Furthermore, QC is also applied to visually inspect items on a production line with sensory technologies such as computer vision (Charrington, 2017). It allows production to have an automatically inspected product output according to the quality-based standards of the manufacturer. Thus, it reduces operational costs and leads to increased productivity. Moreover, Fig. 7 provides a detailed overview of the application process of QC.

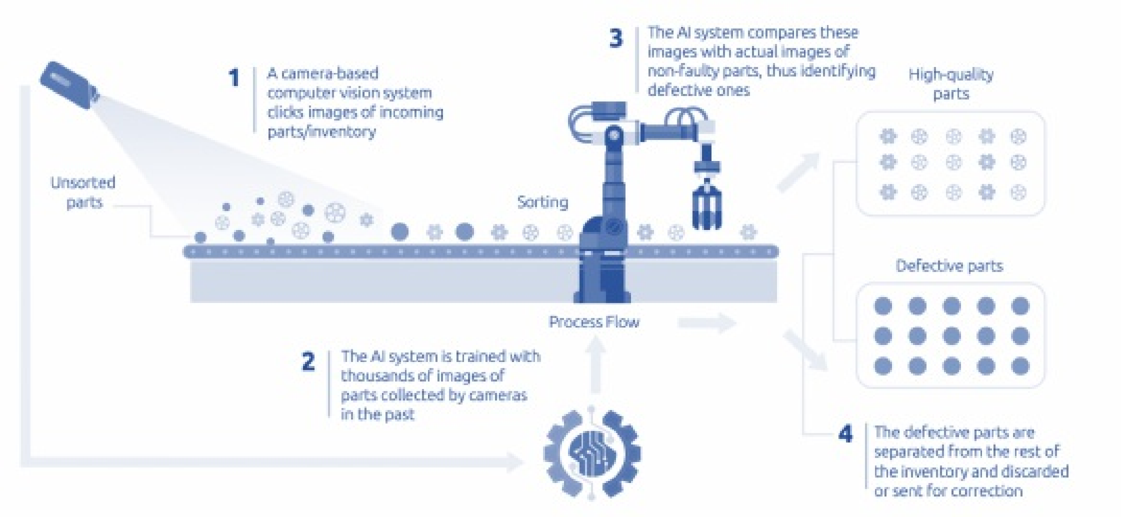

Figure 7: AI-based Quality Control explained (Source: Capgemini Research, 2019)

Inventory Management (IM). Another category of monitoring is the AI-based management of inventory (Charrington, 2017). A variety of AI-based software solutions enable flexibility and agility which manufacturers need to predict and respond to supply chain disruptions.

The second category includes applications related to optimization. Optimization refers to a step beyond monitoring where AI is applied to determine a plan for optimizing business metrics (Charrington, 2017).

Process Planning (PP). Many complex steps are involved in manufacturing scenarios and can significantly affect operational costs, speed, quality, materials input, equipment lifetime, and waste (Charrington, 2017). Computer Numeric Control machines are an excellent case to exemplify the complexity of process planning:

"A given part is made up of a sequence of operations such as cuts. Each cut is made using a specific tool, of which there are many, but only a few can be loaded on the machine at the same time. A variety of different optimization problems arise from this

scenario, including set-up planning, operation selection and sequencing, machine and tool selection, and tool path sequencing." (Charrington, 2017).

AI technologies have the capability to optimize the execution and planning of sequences to improve efficiency and productivity. Additionally, it also helps to schedule jobs and tasks efficiently. Here, AI technologies can help optimize the allocation of "*varying process times to machines with varying process power*" (Charrington, 2017).

Product Design. Many industries base their design on trial-and-error approaches and go through expensive and slow iteration cycles which involve idealization, design, high-performance simulations, experiments, modification and new iteration. AI-based software allows the industrial designer to skip these processes and generate optimized designs for mechanical components for a wide variety of production lines. Most prominently, the term generative design describes AI-based optimization in product design (Charrington, 2017). Here designers can specify a product's constraints and allow algorithms to produce designs based on pre-set optimization goals (e.g., heat efficiency, pressure resistance).

The third overall category includes applications related to control systems. Here AI technology is utilized in order to unleash the full potential of automation at the manufacturing facility (Charrington, 2017). Typical applications of AI in this context range from robotics to autonomous vehicles and energy management.

Robotics. In an industrial context, robots are widely used to pick-and-place items, work materials, sort or assembly products, and many more use cases. Typically, robots follow pre-programmed scripts with minimal sensory input and no reasoning. With AI technologies, robots can control their locomotion autonomously and learn from previous or programmed experience. For instance, computer vision provides robots with the ability to see and thus, avoids interference with the human workforce. In this context, autonomous vehicles can also be understood as mobile robots. Usually, they come into action for intra-logistics tasks such as pick-and-pack applications (Charrington, 2017). Generally, the combination of software-based AI and hardware-based robotics allows enterprises to build intelligent control systems that have massive savings potential and increase efficiency.

Energy management. Energy Management is of utmost importance for manufacturers to improve their performance (Lee, 2020). Usually, enterprises optimize their energy consumption by upgrading their equipment, reducing power-use of equipment or optimizing their control methods (Lee, 2020). Whether it is operational or auxiliary equipment, AI technologies enable manufacturers to optimize energy consumption, to improve energy efficiency, and save costs (Lee, 2020),

It becomes clear that the impact of AI on digitalization in manufacturing is massive and that manufacturers can choose from various use cases to integrate AI in their production workflows and beyond. However, as this revolution is unfolding, there is much to learn about this technology's potential challenges and limitations.

2.3.4. Challenges of AI in Manufacturing

Even though AI technology has proven an enormous value potential for manufacturers, integrating into existing systems remains cumbersome (Lee, 2020). According to Lee (2020), there are three overall challenges to AI in manufacturing: (1) reproducibility, (2) data and (3) security.

The first challenge refers to the reproducibility of machine learning algorithms. According to the literature, algorithms should be regarded as a hypothesis or theory rather than a systematic tool for logical reasoning (Lee, 2020). Furthermore, the lack of reproducibility of machine learning algorithms can also be derived because manufacturing use cases are often edgy and not replicable (Casado, M & Bornstein M, 2020). Hence, models have to be fed with new training data when the use case changes.

The second overall challenge is related to data. Typically, the creation of training data for the respective AI system depends heavily on human input (Lee, 2020). It involves manual cleaning and labeling of large datasets, a process known to be expensive and laborious (Casado, M & Bornstein M, 2020). Additionally, this data has to be maintained once the model is deployed. Without proper maintenance, meaning the continuous labeling and back-feeding of data, the AI system will lose accuracy and efficiency. Another issue related to data is the opacity of the technology. Many AI models do not explain how conclusions are made. For instance, a neural network input and output layers are visible but the computations between both layers are not comprehensible. The NN provides the outputs without breaking down the computational steps. For manufacturers, comprehensibility is essential to obtain single parameters of the object analyzed, e.g., a machine, and to be able to fragment the analysis process (Lee, 2020). Furthermore, explainability is also needed to gain trust in AI (Charrington, 2017).

Thirdly, the unreliability of AI algorithms can lead to safety issues. Here, Lee (2020) refers to computer vision algorithms that can be faulty when not trained enough. In 2018, this led to the fatal accident of an Uber autonomous vehicle killing a pedestrian due to the fact that the AI did not recognize it early enough (Lee, 2020).

These challenges give important insights into the adoption of AI and why some manufacturers are reluctant to use it extensively in order to automate their production processes. Furthermore, those challenges represent the difficulties of AI companies trying to commercialize their products or services in the manufacturing industry.

AI is introducing disruptive innovations for the manufacturing industry. This rapid development also changes how organizations create and deliver value. Therefore, this chapter will try to give an overview of business models in general and how AI companies apply new business models for their offerings.

3. Business Models: Theoretical Background and Literature Review

3.1. Definition

A business model can be defined as *"[...] the rationale of how an organization creates, delivers and captures value*" (Osterwalder et al., 2010). In another definition, a business model is defined as a narrative story of an organization's procedures combined with a viable concept for profitability (Magretta, 2002). In fact, a business model tries to answer how a business generates money and how it can deliver value to customers at the right price (Magretta, 2002). According to Gassmann (2014), a business model is further defined by the customers, the products, the offerings and the profit channel of an organization (Gassmann, 2014). The differences of busines model definitions mentioned above prove that there is not "one" definition per se. In summary, a business model can be considered a management tool that supports entrepreneurs and established businesses alike to create a structured and holistic picture of a business's fundamental mechanics (Magretta, 2002; Osterwalder, 2010; Gassmann, 2014).

The emergence of business models is dated back to the 1990s with internet-based companies' development (Zott et al., 2011). The rapid expansion of the Internet and its massive potential enabled organizations to deliver value in new unprecedented ways and caused a surge in interest for research to understand the underlying business ideas (Zott et al., 2011). Business model research also addresses the fields of innovation and technology management, especially with the idea to help companies commercialize innovative technologies through their business model (Zott et al., 2011). Literature shows evidence that technology does not have an intrinsic value and has to be embedded in appealing products or services combined with a business model that guarantees commercial potential (Zott et al., 2011).

3.2. Business Model Frameworks

3.2.1. Business Model Canvas

One of the most prominent frameworks applied to create and evaluate business models was published by Osterwalder et al. (2010) and is called the Business Model Canvas (BMC). Initially developed for startups, the BMC provides innovative companies with a framework to understand how they can achieve profits from their innovative ideas. For this, the BMC divides business models into nine building blocks which cover four primary areas of business: customers, offer, infrastructure and financial viability (Osterwalder et al., 2010).

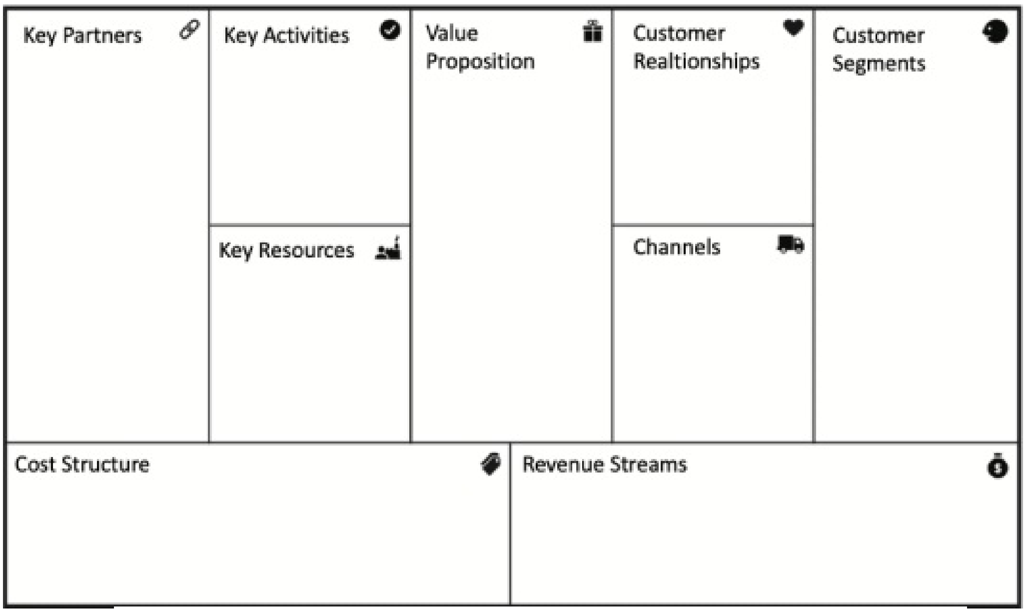

Figure 8: Business Model Canvas by Osterwalder et. al (2010) (Source: strategyzer.com)

As seen in Figure 5, the nine building blocks are (Osterwalder et al., 2010): key partners, key activities, key resources (infrastructure); value proposition (offer); customer relationships, customer segments, channels (customers); cost structure and revenue streams (monetization). In practice, each block of the BMC has to be filled out with the relevant content of the company's business idea and in an iterative process, will create a good understanding for a deployable business model. In the following the building blocks 1-9 will be described in short summary (Osterwalder et al., 2010):

Key Partners. This building block describes the various partners that support a working business model of an organization and enable risk reduction, economies of scale or the acquisition of particular resources and activities. It includes partners with whom a business forms strategic alliances, coopetition, joint ventures or buyer-supplier relationships.

Key Activities. This building block describes the value-creating activities of a business. In fact, the key activities represent the most important actions, such as production and problem-solving.

Key Resources. This building block describes the resources or assets needed by the organization to achieve its business goals. This can vary from physical assets such as machinery to human, intellectual or financial resources.

Value Proposition. This building block is central for the BMC. It describes the products and services offered by the business. An offering's value proposition can be manifold and depends on multiple factors (e.g. performance, design, price, newness, and many more).

Customer Relationships. This building block describes how an organization wants to establish relations towards its customers.

Customer Segments. This building block describes the target market of an organization's offerings. The different types of segments include categories such as mass-market, niche market, segmented market or multi-sided market.

Channels. This building block describes a business's communication with its customer segments and helps to provide a clear understanding of how those can be reached best.

Revenue Streams. This building block represents the profitability of a business model. It draws a clear picture on how an organization can generate money from its offerings.

Cost Structure. This building block describes the incurred costs of a business when it applies its business model. It helps to optimize costs and is tied to the revenue stream building block.

With the nine building blocks, the BMC is a handy tool for organizations that are keen to discover their business potential (Osterwalder et al., 2010). Concerning the digital nature of AI-based companies, it is also a suitable framework to apply (Lu, 2020). In a research paper about business innovation and artificial intelligence, Lu (2020) applied the above mentioned nine building blocks to AI technology and build the first bridge between business models and applied AI.

3.3. AI Software Vendors and Business Models

As part of commercializing AI technology, the business model is a supportive concept for drawing a holistic picture of a profitable AI organization. However, business models for the commercialization of AI software are not very well researched yet. In fact, the majority of AI studies portray the impact that AI has on business models of manufacturing incumbents, i.e., the buyers of such software (Burstörm et al., 2021) There is only a handful of literature available that allows drawing a picture about how AI suppliers commercialize their technology. So far, no established standard to classify business models exists (Bader et al., 2019). Due to this scarcity of available research, this thesis will try to give a short summary of what has been uncovered by literature and other sources published up to the date of writing of this thesis.

3.3.1. Types of Business Models of AI Vendors

In many ways, AI business models can be compared to the biopharma industry (Corea, 2017). Similarly, they are characterized by lengthy and costly R&D; long investment cycles and low-probability enormous returns (Corea, 2017). Additionally, Corea (2017) has created a classification of four AI business models according to a monetization-defensibility matrix (Corea, 2017):

1) *Academic spin-offs:* Spin-offs can be described as the most research-oriented AI companies in the ecosystem. Their business models are based on R&D and

can be characterized by an experienced researcher team that work on challenging computational problems to achieve major breakthroughs in the field.

2) *Data-as-a-service (DaaS):* DaaS can be described as a business that collects datasets or creates new datasets in order to connect uncorrelated data silos.

3) *Model-as-a-service (MaaS):* MaaS is the most common business model where AI vendors commoditize their generated models for recurring revenue streams. It comprises three subclasses such as *Narrow-AI, Value Extractor* and *Enablers*. *Narrow-AI* describes an AI company that solves one specific problem through innovative algorithms or better interfaces. Value Extractor is a company that provides AI models to extract value from existing data. It integrates into the existing technology stack of the customer or is available as stand-alone software. In the context of MaaS, *Enablers* are companies that allow the end-customer to increase workflow efficiency on their own.

4) *Robot-as-a-service (RaaS):* RaaS is categorized as a combination of physical and virtual agents that use AI technology to create business value. This can range from unmanned vehicles that transport components on the shop floor to whole robotic picking systems based on computer vision and deep learning algorithms.

Fig. 9 shows the monetization-defensibility matrix of the model mentioned above. The MaaS and DaaS models are the most financially viable models. They are also the most used AI vendors' models despite their low defensibility (Corea, 2017). In contrast, the RaaS and academic Spin-offs are characterized by low monetization potential but high commercial defensibility (Corea, 2017). Here, "as-a-Service" refers to a licensing model in which AI software is centrally hosted for customers to access via a browser. The advantages for AI vendors are that recurring revenue and decreasing costs make the business model more predictable and scalable. For customer, the barrier to procure an offering is much lower due to the decreased costs.

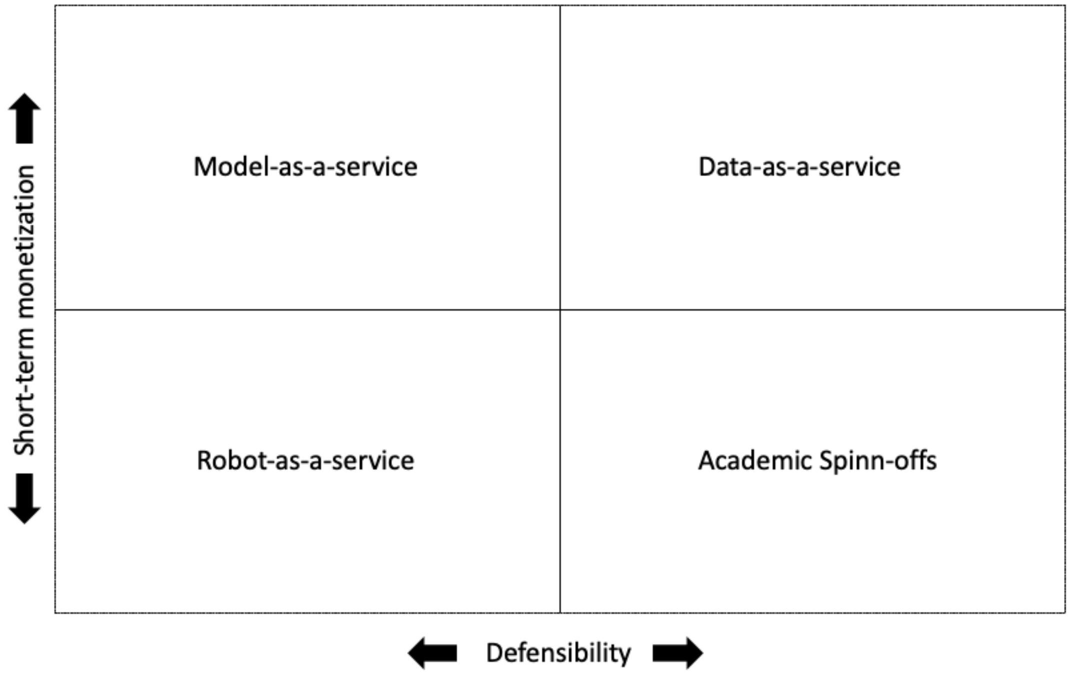

Figure 9: Categorization matrix of AI business models based on Corea (2017)

In another attempt to categorize AI business models, five type of vendors are described according to visible value creation and AI maturity (Fagella, 2020): AI SaaS Product vendor (product), AI productt vendor (product), AI Platform vendor (product), AI Tech and Management Consulting (service) and AI Management Consulting (service). AI maturity is defined as the AI vendor's potential to create a sustainable transformation at the customer (Fagella, 2020). The five types of vendors can be summarized by the following:

1) *AI SaaS Product Vendor:* Similar to the MaaS Narrow-AI model, the AI SaaS Product vendor is characterized by a commoditization of AI models tailored to a specific customer group. It comprises the narrowest customer base of all models (Fagella, 2020).

2) *AI Product Vendor:* Furthermore, the AI Product vendor is comparable with the MaaS Value Extractor due to the fact that it also integrates with client systems and use existing data to provide insights (Fagella, 2020).

3) *AI Platform Vendor:* The AI Platform Vendor offers a platform with a variety of applications offered to the customer. AI-Platforms are usually open-ended and enable customers to develop own applications on top of the platform.

4) *AI Tech and Management Consulting:* According to Fagella (2020), this business model offers project-oriented implementation of AI technologies combined with consulting work. This model is often applied by customers who aim for enterprise-wide adoption of the technology.

5) *AI Management Consulting:* This model is purely service-oriented and provides customer with strategic advice on AI rather than technical development or implementation.

In another classification of AI-based business models, Huu (2018) distinguishes between three different types of models that consider the degree of integration into existing IT systems of the customer. Firstly, the *AI on-top business model*, which is characterized by an AI solution that forms an additional layer on-top of an existing IT solution such as an enterprise resource planning system (Huu, 2018). Secondly, Huu (2018) mentions the *AI-enhanced process business model,* which is characterized by a deep integration of an AI product into the existing systems to improve a customer's workflows impactfully. Lastly, the *AI solution stand-alone business model* marks the third business model and is characterized by changing an entire workflow through AI (Huu, 2018).

All, Corea (2017), Huu (2018) and Fagella (2020) give initial hints about the variety of business models applied by AI software companies. For a more precise overview, Table 1 shows the previously mentioned business models, their category as well as their characterization. The category column distinguishes between product and service. At the same time, a product describes an AI solution as a stand-alone product that can be acquired in a subscription-based model or a one-off fee. The service category describes an AI solution that is developed in-house with the help of professional technology consultancies or service-oriented AI vendors.

Table 1: Overview of AI Business Models in literature (Corea, 2017; Huu, 2018; Fagella, 2020)

Business Model	Category	Characterized by	Source
Model-as-a-Service	Product	Low Defensibility, High monetization	Corea (2017)
Data-as-a-Service	Product	High Defensibility, Low monetization	Corea (2017)
Academic Spin-Off	Product	High Defensibility, Low monetization	Corea (2017)
Robot-as-a-Service	Product	Low Defensibility, Low monetization	Corea (2017)
AI SaaS Vendor	Product	High Visible Value, Low AI Maturity	Fagella (2020)
AI Product Vendor	Product	Mid Visible Value, Low AI Maturity	Fagella (2020)
AI Platform Vendor	Product	Mid Visible Value, Mid AI Maturity	Fagella (2020)
AI Tech & Mgt Cons.	Service	Mid Visible Value, Mid AI Maturity	Fagella (2020)
AI Mgt Cons.	Service	Low Visible Value, Low AI Maturity	Fagella (2020)
AI on-top	Product	Mid Integration effort	Huu (2018)
AI-enhanced	Product	High Integration effort	Huu (2018)
AI stand-alone	Product	Low Integration effort	Huu (2018)

3.3.2. Challenges of AI Vendors

There is only little theoretical background about the commercial challenges that AI vendors face when selling their technology. In a study about the commercialization of AI software, Philips (1999) describes several problems that AI vendors experience. Besides, Casado & Bornstein (2020) identified significant challenges about AI software vendors, specifically on deployment, costs and defensibility.

One of the problems experienced by the companies of Philip's (1999) study was the underestimation of work needed to implement AI into the customer systems successfully: *"They thought they could sell their software as a product, and with a minimal amount of training, let the buyer's IT department install and set up the* *software"* (Philips, 1999; p. 19). This might to be true for more complex and horizontal AI software. Adding to this problem, Casado & Bornstein (2020) state that AI vendors have low gross margins due to the extensive costs of consulting work involved which can be assigned to the unexpected implementation effort (Casado & Bornstein, 2020). In fact, often, humans are plugged into AI systems to increase the accuracy of an operating AI model in real time. So far, companies have ignored the high consulting effort and only few have started to integrate this into their business models (Philips, 1999). Another reason for the high integration effort of AI is the lack of reproducibility (Lee, 2020). For instance, newly added datasets on edge use cases can result in lengthier deployment of a model and do simply not allow for a "plug-and-play" installation (Casado & Bornstein, 2020). This is often joined by the problem of technical incompatibility with customer systems due to different computational languages (Philips, 1999).

Another challenge of AI companies to commercialize their software is the non-customer-centric productization of their technology: *"A classic (in the sense that all high-technology firms struggle with this issue) problem that the Al firms each faced was that they were so excited about their technology, they forgot that their customers wanted solutions to their problems. "(*Philips, 1999; p. 21) Indeed buyers of AI software have a real problem and are looking for a natural solution which is often not easy when AI executives lack sales experience and at the same time have a solid academic background (Philips, 1999).

As already described in the previous section (Corea, 2017) some of the beforementioned AI business models lack defensibility. According to Casado & Bornstein (2020) this is due to the openness of AI development, where innovative models are created in open academic settings and can be accessed by all businesses (Casado & Bornstein, 2020). This would theoretically allow any company to develop their own AI solutions in-house. Naturally, the knowledge of experts is one of the key value propositions when buying AI software. With the ongoing democratization and digitalization of education this might also change in the future.

Table 2: Overview of AI vendor challenges (Phillips, 1999; Casado & Bornstein, 2020; Lee, 2020)

Problem	Consequence	Source
Underestimation of manual work	Low scalability, high deployment, low gross margins	Philips (1999), Casado & Bornstein (2020)
Model maintenance	Low scalability, low gross margins	Casado & Bornstein (2020)
Lack of model reproducibility	Low scalability, high deployment effort	Lee (2020), Casado & Bornstein (2020)
Technical incompatibility	Low Scalability, high deployment effort	Philips (1999)
Lack of customer-centricity	High deployment efforts, difficult sales	Philips (1999)
Defensibility	Competition, difficult sales	Philips (1999), Casado & Bornstein (2020)

3.4. AI Vendor Analysis Framework

3.4.1. The concept

As a conclusion of the literature review a conceptual analysis framework was created. This chapter describes the proposed analysis framework designed to analyze AI software vendors' that employ their products and services in the manufacturing industry. Consequently, one could call it the AI Vendor Analysis framework, or AIVA framework. It integrates the theoretical perspectives that have been presented in the previous sections and is in line with the theories on business models (Philips, 1999; Osterwalder et al., 2010; Corea, 2017; Fagella, 2020; Casado & Bornstein, 2020), application fields and technical aspects of AI (Bengio, 2015; LeCun, 2017; Charrington, 2017; Lee, 2020). The aim of this framework is to support answering the research questions in a systematic and facilitated way. Thus, the proposed framework attempts to construct theoretical relationships between the AI vendor and the utilized busines model. Additionally, a relationship between the business model and AI method used and application field served is built.

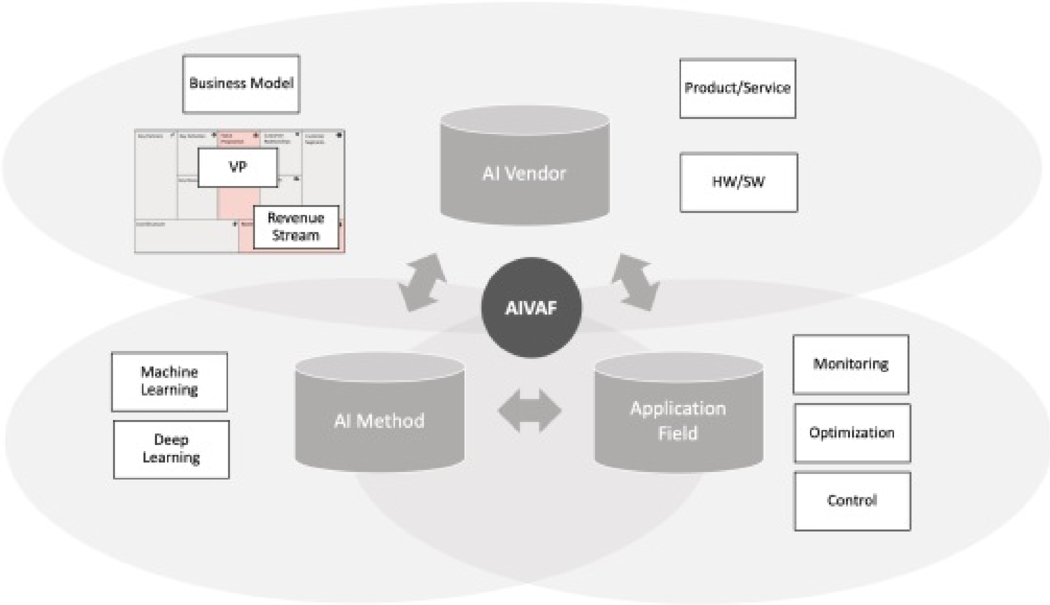

Figure 10: The conceptual framework for analysis "AIVA" (Own creation)

Figure 8 shows a visualization of the conceptual framework and its three major analysis dimensions:

1) AI Vendor dimension
2) AI Application Field dimension
3) AI Method dimension

The AI vendor dimension analyses the core assets and strategies of an AI software vendor in terms of business value and monetization. For this, the framework puts a focus on two building blocks from the Business Model Canvas: value proposition and revenue stream (Osterwalder et al., 2010). As described by Osterwalder et al. (2010) a business model can have several ways to generate revenue. The most important ones are one-off transaction and recurring revenues (Osterwalder et al., 2010). The value proposition describes the value that is delivered for a customer segment through a distinct combination of elements to that segment's needs. In the analysis process, the various elements provided to manufacturing companies will be uncovered and summarized. For analyzing the revenue stream, the framework integrates the AI-based business model categorization by Corea (2017) and revenue stream models proposed by Osterwalder et al. (2010). On a higher level, the vendors and their business models will be divided either into product- or service-centric businesses. Service-oriented can be businesses that, for instance, support manufacturers in the development of customized AI software solutions.

Furthermore, as there is evidence that platforms are an essential driver of economic growth in the artificial intelligence industry, the Platform-as-a-Service (PaaS) revenue stream was added to the analysis as well. In fact, there are many advantages in platform businesses including a higher scalability, the leverage of network effects and using various stakeholder to innovate and create value. In addition to that, the framework also analyzes whether the AI vendor is providing a hardware component (e.g., sensors for data collection) along the offered AI software.

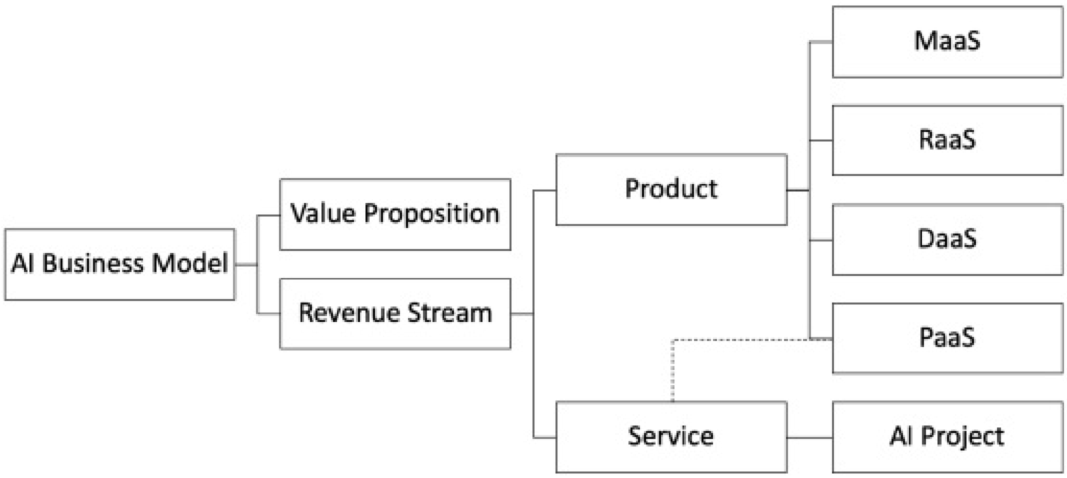

Figure 11: Analysis categories for BM analysis (Own creation)

The second analysis dimension of the proposed framework will identify the application fields in which an AI vendor offers its solutions. Here the overall categories analyzed are *monitoring, optimization* and *control* (Charrington, 2017).

In a third dimension, the proposed framework will try to identify the vendor's AI method to give hints on the relationship between AI technology and the business model. Besides, the framework differentiates between proprietary and non-proprietary algorithms used. This could give hints on a relationship between short-term monetization and defensibility of a product or service (Corea, 2017).

3.4.2. Definitions

This study's focus is on entrepreneurial software companies selling AI products or services to companies in the manufacturing industry. The entrepreneurial AI vendor is defined as a software business that offers primary products or services utilizing machine learning, deep learning or other AI technologies described in the previous chapters and is not founded before 2010. The framework is not taking into considerations companies that are purely hardware-driven such as entrepreneurial semiconductor manufacturers. Consultancies and technology incumbents such as Amazon, IBM, and Google are excluded, too. For the AI vendor, the value proposition and revenue model are strategies and assets to commercialize their manufacturing industry products.

Since the framework focuses on the manufacturing industry, customers are defined as manufacturers who utilize the AI vendor's products or services to achieve their own strategic goals. No further definition of manufacturers is needed.

Furthermore, an application field is defined as a use case where an AI product is needed to solve the customer's problem (Charrington, 2017).

3.4.3. Limitation of the proposed framework

The AIVA framework builds the basis for the analysis of AI vendors in the manufacturing industry. However, there are certain limitations to the proposed framework. As the approach of this analysis is based on content analysis and therefore published information on the websites of the AI vendors the level of detail of information is limited. Especially, when it comes to the revenue stream, it has to be assumed that information cannot be collected most thoroughly. Furthermore, one can assume that components of the AI method as well as AI application field dimension might only be expressed in signals rather than details. In order to create a deeper analysis, one would have to conduct a detailed case study.

Lastly, the proposed has yet to be tested in a real-world situation despite the availability of data that points towards the applicability of the framework.

4. Research Process

In this chapter, the research process is broken down and the methodology is described. The research was done according to the following three significant steps:

1. A theoretical part including the review of literature
2. A qualitative part including an empirical study on business models of AI vendors in the European manufacturing industry
3. A discussion, visualization and systemization of results

The literature review was conducted to identify relevant theories and models about Artificial Intelligence and business models. The result of the literature review was a conceptualized framework that supported the empirical study and analysis of relevant AI vendors. The empirical study was conducted by applying the conceptual framework on the sampled data. The data for the empirical study was collected through a database called Dealroom as well as through semi-structured expert interviews. The systemization of results presents and discusses the findings of the empirical study.

It is worth mentioning that the focus of this study is set on Europe for two main reasons. Firstly, the European manufacturing industry is at the very beginning to make use of AI in manufacturing, while industries in the US and China are assumed to be already more saturated. Secondly, due to the rapid development of AI in the manufacturing industry, the number of AI vendors has been skyrocketing globally. Hence, analyzing all available AI companies on a global scale would go beyond the scope of this thesis.

4.1. Methodology of Study

4.1.1. Research Objective

The objective of this study is to provide a first understanding of business models used by AI software vendors in the European manufacturing industry. More specifically, the study tries to identify types of AI software vendors and discovers the ways in which they bring their offerings to the table. In order to do so, it is crucial to analyze the value proposition, the revenue model as well as the technology behind an AI vendor.
To recall, the research questions are:

Research Question 1: *What kind of entrepreneurial AI vendors operate in the European manufacturing industry, and is there a significant identifiable pattern that characterizes their business models?*

Research Question 2: *What factors influence an AI vendor's service- or product-orientation in the manufacturing industry?*

Research Question 3: *Which application fields and technologies are utilized by AI software vendors in the manufacturing industry?*

To answer each research question, this thesis conducted a qualitative study and semi-structured expert interviews.

4.1.2. Research Design

"Life can only be understood backwards; but it must be lived forwards" (Søren Kierkegaard)

The research part of this thesis is carried out by an empirical study as well as semi-structured expert interviews. For the study a qualitative research approach, in particular in the form of qualitative content analysis, was chosen. This research method, first introduced by Krippendorf (1980), is used to determine the presence of certain themes or concepts within qualitative data to quantify and analyze the meanings and relationships among this themes. Formally defined, content analysis *"[…]is a research technique making replicable and valid inferences from data to their context."* (Krippendorf, 1989). It is a method to classify written, verbal or visual materials into categories that are identified during a pre-defined analysis process. It is popular to analyzed documents of all kind, including "narrative responses, open-end survey questions, interviews, focus groups, observations, printed media such as articles, books, or manuals" (as cited by Elo & Kyngäs, 2008). In fact, content analysis has the purpose of providing knowledge, new insights, a representation of acts and a practical guide to action (Elo & Kyngäs, 2008). Furthermore, it is an unobtrusive method as researchers can collect data with or without direct contact with the subjects studied. In general, qualitative content analysis can be divided into deductive and inductive analysis. Deductive analysis means that one starts with a predefined set of codes that can be assigned to the sampled data. Inductive analysis refers to the creation of codes during the process of analysis. In the case of this study, a deductive analysis approach is chosen as the literature review provides the necessary theory to categorize business models, AI technologies and application fields. An alternative terminology for this kind of analysis is called testing categories, concepts or models (Marshall & Rossman, cited by Elo & Kyngäs, 2008). For a qualitative content analysis three main procedures are required: data preparation, data analysis and reporting of results.

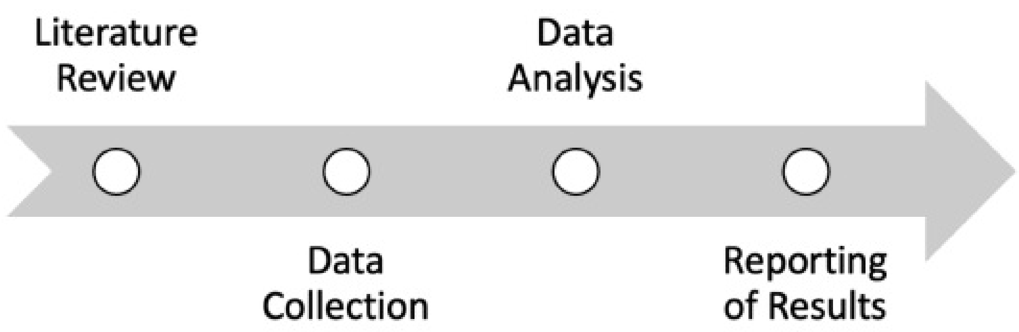

Figure 12: Research Process of Study (Own Creation)

There are also several limitations to qualitative content analysis. First of all, the validity of results depends highly on the quality of data. Secondly, the interpretation of data can be biased by the personal experience and knowledge of the researcher.

4.1.3. Sample Selection

The study utilized Dealroom as the tool for the sample selection. Dealroom is a widely used expert-validated database containing holistic information about 1,450,000 software and entrepreneurial companies worldwide. Another comparable source is the US-based database Crunchbase. Although often used in comparable studies, Dealroom was chosen over Crunchbase as it is based in Europe and has a stronger focus on European companies. Consequently, it is assumed that the quality of data is high. In addition to that, Dealroom has gained immense credibility in the European tech ecosystem by publishing a variety of reports on robotics, industrial technology and AI.

Dealroom organizes their data, among many other factors, around major technology groups, industries, geographies and founding date. In order to derive meaningful results from the study, the adequate selection of the qualitative data was of utmost importance and needed to be constrained. Consequently, the sample was pre-selected according to the following criteria:

- The company has “Artificial Intelligence” and “manufacturing” in its keywords.
- The company was founded between 2010 and 2020.
- The company is operational.
- The company is headquartered in Europe.
- The company has to be for-profit.
- The company has to be in the software business. Hardware-enabled software is also included.

Out of the sampled 1750 European AI companies meeting the criteria “Artificial Intelligence” and “Manufacturing” from the Dealroom database only 81 met all of the criteria mentioned above. The data was extracted by using the Dealroom export functionality and was stored for subsequent analysis and interpretation.

4.1.4. Data Analysis

The qualitative content that was analyzed for the study stems from the websites of the sampled AI vendors. As pointed out by Elo & Kyngäs (2008) any form of document is a legitimate source of data for qualitative content analysis. According to Byrman & Bell (2018), "websites and web pages are potential sources of data in their own right and can be regarded as potential fodder for both quantitative and qualitative content analysis "(Byrman & Bell, 2018; p.648). Using websites as a primary data source falls into the category of e-research where qualitative data is retrieved from web content. A difficulty of this method is the dynamic and fast-changing environment of the Internet (Byrman & Bell, 2018). Websites can be taken down, making it extremely hard for researchers to replicate the data collection (Byrman & Bell, 2018).

Furthermore, it can be challenging to find websites related to a research question. For this, the researcher has to rely on search engines such as Google that only show the iceberg's peak of what is available in the world wide web. However, websites in this study are bounded to companies and thus, exist on fundamentals that cannot change as quickly as another kind of websites. Furthermore, the ease of finding a website builds upon the fact that the majority of companies analyzed use their company name as their website URL. This made it easy to find a website in case it was missing from the retrieved sample. However, no such URL search was done as the sample include all website information.

Additionally, to add further meaning to the retrieved data as well as triangulate the findings of the study, expert interviews have been conducted. For this, a semi-structured interview method was selected to keep the flow of the conversation as natural as possible. Additionally, the semi-structured style is advantageous for exploring attitudes and beliefs that might vary or would not have been expressed in a closed-end interview style. Three interviews were requested via email of which only two interview participants responded and agreed to meet. The experts were chosen on the basis of their domain knowledge in AI, manufacturing and business models. The interviews were conducted through an online videoconferencing software called Zoom. While the interviews were not part of the qualitative content analysis conducted, they helped to shape the focus of this thesis and provided the analysis with additional guidance.

4.2. Findings of the Study

Based on the emerging patterns around value propositions and revenue models along the study, it was possible to identify three overall vendor clusters: AI service vendors, AI SaaS vendors and AI platform vendors. This section will describe each vendor type and the findings about it in more detail.

4.2.1. AI Service Vendor

Out of the 81 vendors analyzed, 43 (53% of the sample) companies were identified as AI service vendors. This marks the most common type of vendor providing AI products and services to European manufacturers. They can be characterized by an AI-based software offering which additionally demands a strong short- to mid-term service component. The services are provided in the form of consulting, maintenance or implementation. In some cases, the AI service vendor is purely service-oriented and provides highly customized AI products, similar to a technology consultancy. Therefore, one can differentiate between the 1) product-centric AI service vendor and the 2) pure AI service vendor.

Application Fields: In general, the study shows that AI service vendors serve in all three overall application fields defined by Charrington (2017). The most commonly served application field is *Monitoring* followed by *Control* and *Optimization.* In relative comparison to other vendor types identified, the AI service vendor is primarily operating in the *Control* application field. In fact, 16 out of the 17 vendors that provide *Control* solutions are allocated to the AI service vendors. Here, the most offered solutions fall into the application field of *Robotics* and *Autonomous Vehicles*.

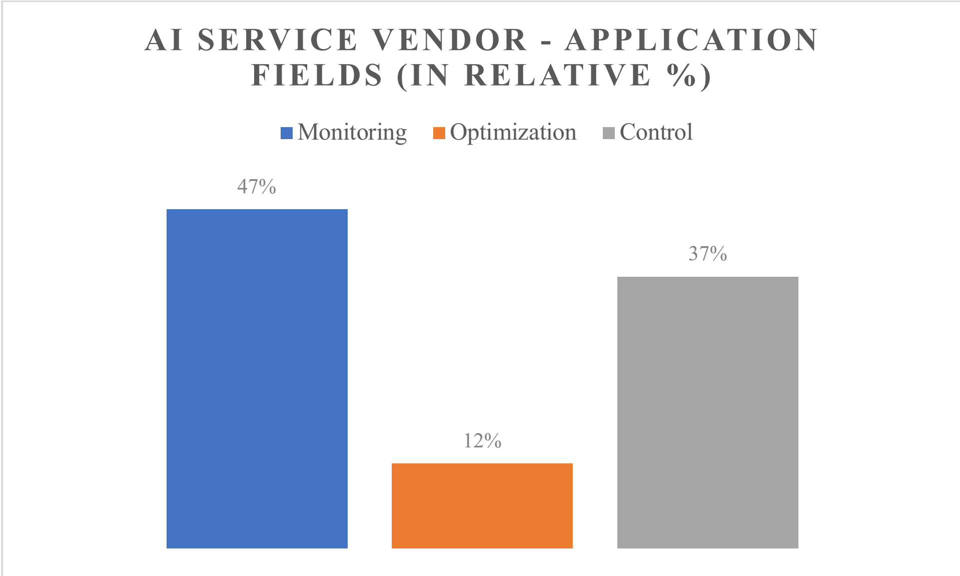

Figure 13: AI Service Vendor Application Fields (Own Creation)

AI Method: Furthermore, 17 out of 25 of vendor types that utilize Deep Learning algorithms, are AI service vendors. This might be derived from the fact that many of the AI service vendors provide *Robotics* and *Autonomous Vehicles* solutions. Both application fields rely on more complex computational methods such as CNNs. Furthermore, as part of the analysis it could be identified that AI service vendors also provide the majority of hardware-enabled software products. In fact, 18 out of the 43 AI service vendors offer proprietary hardware products that only work in combination with their proprietary algorithms.

1) *Product-based AI Service Vendor (35 out of 43)*

Value Proposition: The value proposition of the product-based AI service vendor lies in a dedicated implementation service of a subscription-based AI product. Instead of selling a "plug-and-play" software where the customer has to execute the deployment, the vendor offers a consulting and deployment service. The fundamental value proposition marketed towards the manufacturing companies were increased operations efficiency, high factory automation, autonomy, cost reduction, high flexibility and reduced downtime.

Revenue Stream: The AI service vendor's primary revenue stream is based on software licenses or hardware subscriptions. In addition, the AI service vendors complement their revenues with fees from implementation or maintenance services. Once the AI system has been implemented, the software is charged on a monthly or per-year basis. Instead of the manufacturer buying the robots, it leases the equipment and gets access to a cloud-based subscription service. Thus, ownership handling activities such as paying-off or maintaining equipment can be avoided and are shifted to the AI service vendor who factors in those components into his *Robot-as-a-service* model. Nevertheless, the AI service vendor is deploying the system as part of a service before transforming its services into a recurring revenue stream.

2) *Pure AI Service Vendor (8 out of 43)*

Value Proposition: The main value proposition of a pure AI service vendor is tailoring AI products to the specific needs of individual manufacturers. The concept of customer co-creation is prevalent for big tech companies but relatively uncommon for small AI vendors. For manufacturers, this business model allows them to cover complex edge-cases and utilize the AI vendor's technical domain knowledge to extract maximum value for its strategic goals. The fundamental value proposition marketed towards the manufacturing companies was better performance, increased efficiency, automation and reduced downtime.

Revenue Stream: The pure AI service vendor's primary revenue stream is based on consulting and development services. In comparison to the product-oriented AI service vendor, the revenue is generated through highly customized projects that are uniquely developed for the manufacturing companies.

4.2.2. AI Platform Vendor

Out of the 81 companies analyzed, 21 (26% of the sample) companies could be identified as AI Platform vendors. They can be characterized by a cloud-based platform approach that allows the user to manage a variety of applications and data services. In a broader sense, these are manufacturing-specific data science platforms with built-in Machine Learning capabilities, support for a range of ML algorithms and the ability to operationalize any models defined in the system.

Application Fields: According to the analysis the most common application field of the AI platform vendor is *Monitoring*. As seen in Figure …, it is followed by *Optimization* and *Control.* Compared to the AI service vendor and AI SaaS vendor, platforms have a high degree of productization in many use cases. Indeed, they often not only provide monitoring solutions but also applications for optimization and can be described as horizontal in their offerings. Out of the 21 platform vendors, 11 offer solutions for predictive maintenance and quality control.

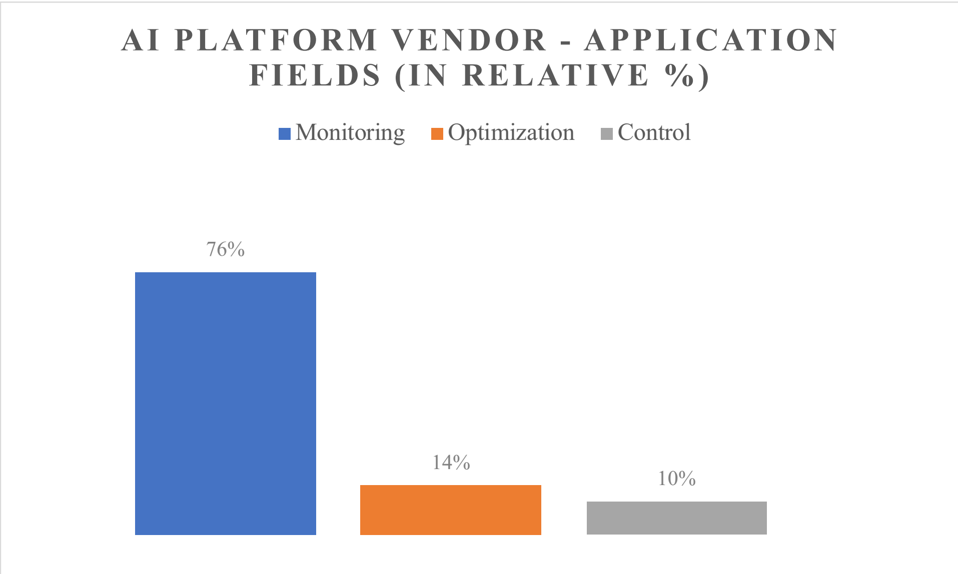

Figure 14: AI Platform Vendor Application Fields (Own Creation)

AI Method: 18 out of the 21 analyzed AI platform vendors use Machine Learning as their primary AI method for their offerings. The four other AI platform vendors utilize Deep Learning technologies. The platform vendors are purely software-driven and do not provide any hardware such as sensors to collect data from the manufacturer's equipment.

Value Proposition: The main value proposition of the platform approach is the enablement of the manufacturer to accumulate data into a centralized location from various production systems. Furthermore, the platform model allows production teams to access production data from any location. With flexible access to data, the manufactures have more visibility into production processes and thus, profit from an improved reaction procedure. Here, AI platform vendors not only provide the infrastructure of a centralized platform but on top deliver a set of tools and services that help the manufacturer to utilize the data to achieve its goals. The key value proposition marketed towards the manufacturing companies were increased performance, optimization, efficiency as well as improved quality and cost reduction.

Revenue Stream: The primary revenue stream of the AI Platform vendor is based on usage fees for their platform tools and services. Most of the AI platform vendors are charging on a *Platform-as-a-Service* revenue model, providing the customer with increased flexibility.

4.2.3. AI SaaS Vendor

Out of the 81 companies analyzed, 17 (21% of the sample) companies could be identified as AI SaaS vendors. The AI SaaS vendors can be characterized by an AI-based product that is available without or only a little service component on top. Thus, it offers the highest degree of productization on the market and can be utilized instantly without complex implementation procedures. Similar to a classic Software-as-a-Service model the vendor is running the AI application logic in the cloud and provides access through an appealing user interface.

Application Fields: According to the analysis the most common application field of the AI SaaS vendor is *Monitoring* followed by *Optimization* and *Control.* In comparison to the other vendor types, the SaaS vendor has a rather even distribution of use cases. It is worth pointing out that due to the high productization of its offerings it focusses mostly on vertical use cases. A vertical product serves one specific use case at the client's site. For instance, a vertical product can range from a predictive maintenance application for a certain machine type to an energy management solution for a certain group of manufacturers.

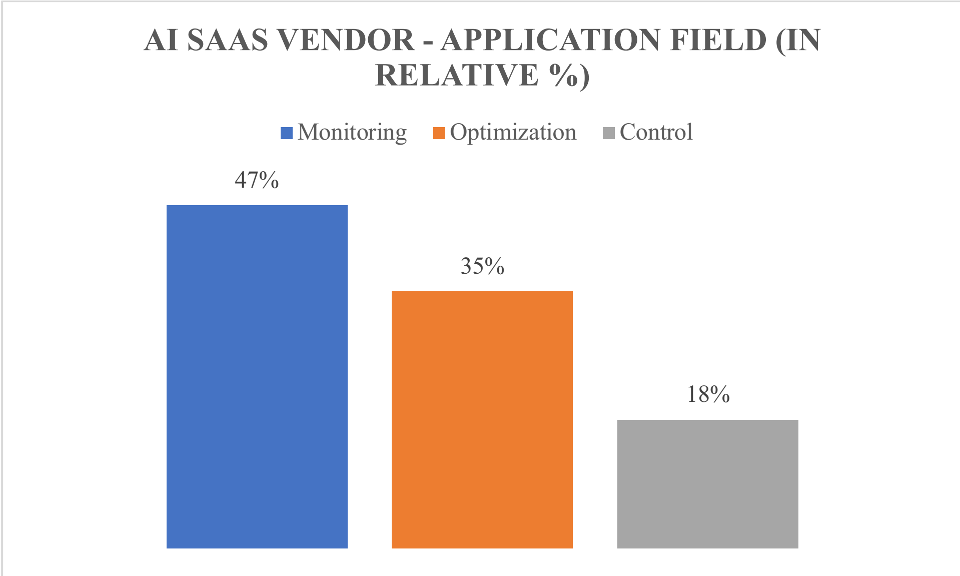

Figure 15: AI SaaS Vendor Application Fields (Own Creation)

AI Method: This type of vendor utilizes mostly Machine Learning algorithms to create value. In fact, 12 out of the 17 AI SaaS vendors identified utilize this learning method. Furthermore, 3 AI SaaS vendors also offer off-the shelf hardware solutions in combination with their software product. In all cases, the hardware is composed of sensor nodes that are easy to install and configure with the bundled software.

Value Proposition: The value proposition of the SaaS vendor stems from the ease of deployment as it does not require any additional implementation efforts. These off-the shelf solutions have a high degree of productization and are mostly tailored to a specific use case. For the manufacturer, it allows to create instant value without having to spend resources on huge implementation projects. Another value proposition is the ease of use. For the manufacturer, the AI SaaS product can substitute a team of data scientists as it usually does not require any previous data science know-how. The key value proposition marketed towards the manufacturing companies were ease of deployment, increased performance, efficiency, as well as reduced downtime and costs.

Revenue Stream: The primary revenue stream of the AI SaaS vendor is based on usage fees for their software. Most of the AI SaaS vendors are charging per month per seat. The nature of the AI SaaS vendor allows for software sales that generate immediate recurring revenue streams.

4.2.4. Summary of Findings

This section summarises the findings and contributions made. When comparing the three identified types of AI vendors in the European manufacturing industry, notable patterns can be identified. From the analysis, it becomes clear that the most dominant type of AI vendor is the AI service vendor. This result demonstrates that the commercialization of AI software in the manufacturing industry is strongly relying on services. In fact, as seen in Figure 14 the distribution of the sample shows that 53% of the sample companies are AI service vendors whereas only 26% of the companies are AI platform vendors and 21% of the companies are AI SaaS vendors.

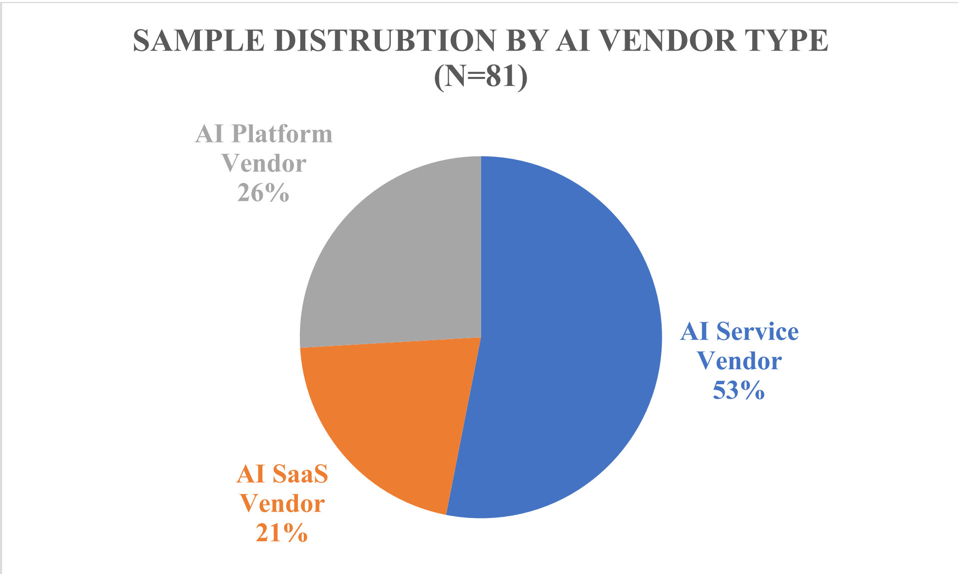

Figure 16: Sample Distribution by AI vendor type (Own Creation)

When looking at the application fields the study shows that certain vendor types are more prone to provide solutions for a category of use cases. This was also visualized in Figure 15. Furthermore, the study found evidence for AI service vendors being most present in the *Control* application field. It reveals that their value proposition of providing customized solutions is most demanded to deliver product in this field. Secondly, the analysis reveals that almost ¾ of the AI platform vendors serve the *Monitoring* use case. Thirdly, the AI SaaS Vendor is most dominant in the *Optimization* application field. This result highlights a pattern that each type of vendor with its different business model is most adequate for a specific application area.

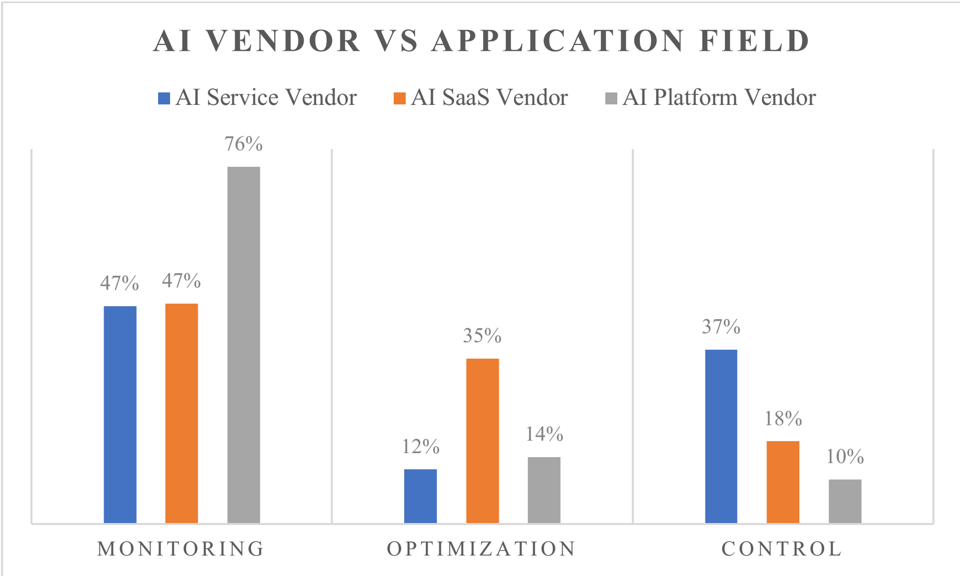

Figure 17: AI Vendor Applications Overview (Own Creation)

A more detailed typology of the overall application fields and the sub-categories identified is provided in Table 3. From all categories, irrespective of the vendor type, *Predictive Maintenance* is the most dominant application in the manufacturing industry. The study also shows that *Robotics* and *Control* are among the frequent AI software solutions offered by the vendors. Furthermore, the least served application use cases offered by AI vendors in the European manufacturing industry are *Job Scheduling* and *Energy Management.* The value propositions that are derived from the different use cases are very similar among each type of vendor. For instance, the findings show that the most common value propositions communicated by the vendor are: *increased efficiency, cost reduction* and *reduced downtime.*

Table 3: Overview of application fields and use cases (Own Creation)

Field	Application Use Case	AI Service Vendor	AI Platform Vendor	AI Saas Product Vendor	Σ
Monitoring	Predictive Maintenance	11	11	5	**27**
	Quality Control	5	3	1	**9**
	Inventory Management	2	2	2	**6**
Optimization	Process Planning	6	0	2	**8**
	Job Scheduling	1	0	0	**1**
	Product Design	1	3	2	**6**
Control	Robotics	7	2	3	**12**
	Autonomous Vehicles	6	0	0	**6**
	Energy Management	0	0	2	**2**

In addition, the study shows findings about the technology utilized. Summarizing the results, it becomes clear that each business model and vendor type is leveraging a specific AI method. A novel finding is that the AI service vendor is building its products on Deep Learning methods while AI platform and AI SaaS vendors are mostly leveraging Machine Learning methods. This result might demonstrate the superior scalability of traditional Machine Learning methods in comparison to Deep Learning.

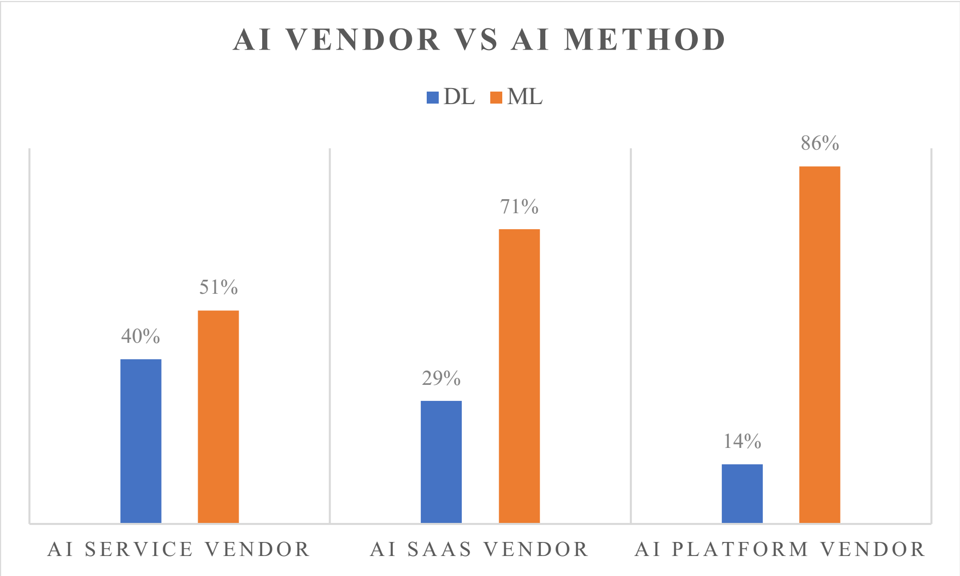

Figure 18: AI Vendor AI Methods (Own Creation)

While Machine Learning is leading as the overall AI method applied, Deep Learning finds only little utilization by AI platform vendors. In the next chapter, potential reasons for all of the above-mentioned findings will be discussed.

5. Discussion

This section enters the discussion of whether the findings of the study provide answers to the proposed research questions and whether there is any proof for the underlying hypothesis of this thesis. In order to interpret the results as systematically as possible, this section is subdivided by each research question.

First of all, it is worth mentioning that the conducted study is limited by some constraints due to the research method applied. The key assumption here was that the websites of the companies can be a source of information for the business model analysis including value propositions, revenue streams, AI method applied and application fields. However, in some cases information was missing, for instance, on the particular method used by the companies. Another strong limitation was the proposed analysis after Corea's (2017) business model matrix. There was barely any information or indication that the analyzed companies use either a MaaS, DaaS or academic spin-off business model in accordance with Corea (2017). In fact, solely companies which state that they offer *Robot-as-a-Service* on their websites were discovered. On another note, the websites provided the study with interesting insights into the value proposition and revenue streams according to Osterwalder et al. (2010) Business Model Canvas. Furthermore, the vendor classification by Fagella (2018) served as a great construct to identify more specific types of vendors according to the proposed AIVA framework. In the course of the study, several vendor types could be classified, and their underlying business models elaborated.

Research Question 1: *What kind of entrepreneurial AI vendors operate in the European manufacturing industry, and is there a significant pattern identifiable that characterizes their business models?*

As described in chapter four, the study identified three overall types of AI vendors that operate in the European manufacturing industry. The findings show that each vendor type differentiates in their value proposition and revenue stream according to the building blocks of the Business Model Canvas by Osterwalder et al. (2010). First, the study looked at the revenue stream building block as part of the monetization strategy of the identified vendor. It is notable that the most common type of revenue stream stems from services. Here the AI service vendor type attributes to 53 percent of the companies analyzed. Instead of offering commoditized software products, this vendor is focusing on the provision of highly customized software products that deeply integrate into the manufacturer's tech stack. This might also be indicative as a strategy to overcome the thorny edge cases and thus, the complexity that is encountered when providing their software to the manufacturing industry. Hence, the finding is in accordance with the results reported by Casado & Bornstein (2020) who say that entrepreneurial AI vendors are embracing service revenues on their path to find a product-market fit. In fact, Casado & Bornstein (2020) argue that entrepreneurial AI vendors often underestimate the involvement of human labor and other manual activities in relation to providing AI solutions to the market. One could argue that the service revenue model is compensating the work effort that occurs due to manual activities. Furthermore, it is worth mentioning that many of the service vendors identified operate in the *autonomous vehicle* and *robotics* space. Companies in this category are building, developing, and implementing autonomous vehicles and robotics systems together with AI-based software products that enable a wide range of manufacturing applications. In fact, the study found evidence that AI service vendors tackling the *control* application field utilize complex Deep Learning techniques more often than any other vendor cluster. This may explain that the AI method ultimately has an influence on the type of business model chosen. In fact, one could argue the more complex the technology set, the higher the service component of the vendor. Furthermore, the high number of service vendors could also give indications for the demand site perspective. In fact, many manufacturers might prefer some guidance along their digital transformation. Furthermore, the co-creation between AI vendors and manufacturers might be relevant to incorporate important domain knowledge to capture the full potential of artificial intelligence software. Ultimately, one could conclude that a service-centric AI software with a high degree of customization might offer a higher transformation potential. This finding is also in accordance with what has been stated by the interviewees about service vendors. Furthermore, it has been said that the service-centricity of AI vendors in the manufacturing industry also stems from the high integration efforts for which a vendor has to build specific domain knowledge based on the client's needs. Integrating an AI system is not only about the computational method or prediction, but also about latency, the ability to be integrated into any existing production systems and the general infrastructure. Hence, AI vendors are often ignored by AI vendors who want to provide their software in the form of a standardized product.

The second type of vendor identified is the AI SaaS vendor. Its business model is characterized by a high degree of productization. In contrast to the service vendor, this type offers artificial intelligence software as a product with only little or no service component. It is notable that the AI SaaS vendor builds the smallest cluster of companies analyzed. Only 17 out of the 81 analyzed companies are falling into this group. This finding leads to the conclusion that software vendors are rather the exception than the norm. It shows evidence in accordance with the studies of Philipp (1999) who proposed that AI applications often involve massive deployment effort and are rarely sold off-the-shelf. Due to a general underestimation of manual work involved (Phillips, 1999; Casado & Bornstein, 2020) it could be assumed that the AI service model has a higher financial return for the vendor than the product-centric AI SaaS vendor. However, this interpretation has to be viewed with caution as the study did not factor-in the business success of each vendor type.

The third type of vendor identified is the AI platform vendor. The business model, similar to the SaaS vendor, is based on a cloud-based platform product. AI platform vendors put pre-trained machine learning models to work and create industry-specific content to support transforming production data into actionable insights. The majority of the companies analyzed offer a platform with a broad range of applications ranging from PM to QC. The findings show that AI platform vendors add a service component to their software products. The service is of educational nature to help manufacturers understand how the data can be leveraged with the libraries of pre-trained ML models. The study gives evidence that the main value proposition of the AI Platform vendor is composed of three operational metrics: reliability, productivity, and safety. Both, the *AI platform vendor* and *AI SaaS vendor*, generate recurring revenue streams without or only a little service component. In addition, both types utilize non-proprietary machine learning techniques, strengthening the argument that AI method complexity and revenue model are closely connected.

As a conclusion of the first research question, one can say that the study successfully yielded a typology of companies. In fact, the companies were clustered into three vendor types based on their revenue model and value proposition. When looking at the technology and use-case dimensions of an AI vendor, one could conclude that service-centricity overrules product-centricity. However, this finding has to be cautiously interpreted as the study did not analyze the success of each vendor type in executing their revenue model or delivering their offerings. As a result of the lack of information about revenue streams, it was also not possible to allocate the various business models into the classification matrix of Corea (2017).

Research Question 2: *What factors influence an AI vendor's service- or product-orientation in the manufacturing industry?*

The results of the qualitative study provide evidence that there are at least two factors that can influence whether an AI vendor operates service- or product-centric. Firstly, the study indicates that the AI method used and the application field served ultimately impact an AI vendor's productization degree. In fact, the study suggests that the higher the complexity of the AI method utilized by the vendor, the higher the service centricity and vice versa. As stated earlier in this thesis, many service vendors operate in the *control* space. The study found that due to the higher complexity of problems in this field, AI vendors are utilizing more advanced computational methods such as *Deep Learning*. This alone does not indicate for a higher service level. However, *Deep Learning* models have to be trained on particular use cases. For instance, when training a computer vision algorithm to detect flaws in a specific manufactured product. In order to train the model for specific and customized use cases, the manufacturing domain knowledge has to be incorporated in the development of the system. Thus, these kind of offerings require the vendor's manual involvement to adapt the model to the manufacturer's need. On the other side, the product vendors, meaning the SaaS and platform vendors, operate primarily in the *monitoring* and *optimization* domain.

The study shows that the most applied use case is *predictive maintenance.* From the findings, it appears that vendors that provide offerings for this use case are rather product-centric. Hence, a closer look is required for the discussion. The companies that provide vertical predictive maintenance solutions, do their data science mostly behind closed doors and do not involve any co-creation with the manufacturing customer. One argument could be the lower complexity of the AI method that allows a high reproducibility. *Predictive maintenance* vendors utilize simple Machine Learning models to, for instance, monitor production equipment and predict downtime. Thus, once the data for a certain use case has been acquired, the model's training and engineering can be prepared and directly applied by the manufacturers. This allows the product-centric vendors to provide subscription-based software in the form of SaaS or PaaS without the cost-intensive manual service. However, the study does not provide any further casual arguments that could underline this assumption.

A second factor that may impact the product- and service centricity is the strategic focus of the manufacturing client itself. The service vendor provides customized AI solutions for their manufacturing clients, whereas the product vendor provides standardized AI solutions. Hence, the service vendor allows manufacturers to cover thorny edge cases or other more complex specific AI products to their needs. In addition, the study showed that manufacturers profit from the dedicated service and technical knowledge that accumulates during the deployment period of an AI solution. On the other side, the product vendor offers a high degree of flexibility for the manufacturer by providing a plug-and-play solution for a specific but common use case. This leads to the conclusion that the manufacturer's strategic focus has an impact on the business model formation of an AI vendor. It is essential that this finding purely relies on the strategic value proposition delivered to the manufacturer. One could argue that the vendor's cost structure is also a strong driver for or against product centricity. However, due to the missing information about prices and costs it is not possible to make any factual argument.

Research Question 3: *Which application fields and technologies are utilized by AI software vendors in the manufacturing industry?*

As already presented in chapter four, several patterns around application fields and technologies emerged during the course of analysis. First and foremost, it is notable that each application field in accordance with Charrington (2017) was discovered at least once in the sample set. This is indicative for the broad range of application fields already served by entrepreneurial AI software vendors in the European manufacturing industry. Another interesting finding is the number of application fields served by each vendor type. For instance, the study suggests that AI platform vendors are mostly offering solutions for multiple application fields in the *monitoring* and *optimization* domain. In fact, 12 out of the 21 AI platform vendors serve at least two different fields. This finding is also in accordance with Fagella (2018) who states that AI platform vendors offer a broad range of use cases and do not focus on individual solutions.

In contrast, AI SaaS and AI service vendors focus on individual solutions and only serve one specific use case. Again, the study differentiates both by the level of service-centricity and ultimately their business model. Furthermore, the study shows findings about the difference in technology utilized by each vendor type. A novel finding is that the AI service vendor is building its products on *Deep Learning* methods while AI platform and AI SaaS vendors are primarily leveraging *Machine Learning* methods. One could conclude that this result might demonstrate the superior scalability of traditional *Machine Learning* methods in comparison to *Deep Learning* methods.

To conclude research question three, one could say that each vendor type is explicitly focusing on a specific application category and AI method. While service vendors focus more on *control* applications, AI SaaS and platform vendors are more active in *monitoring* and *optimization.* Similarly, *Deep Learning* methods are primarily utilized in the *control* use cases while *Machine Learning* methods are standard in the remaining application field categories.

6. Conclusion

The discussed study provides a typology of AI vendors that operate in the European manufacturing industry and has suggested patterns in the business models of the identified AI vendor types with a weight on value proposition and revenue stream.

Furthermore, the study showed that there are two streams of business models in the market: the service-centric models and the product-centric models. In addition, the study presented evidence for H2) as most of the sampled AI companies were employing a service-centric business model.

This thesis was created to provide readers an overview of AI technologies as well as present the various application potentials in the manufacturing industry. Furthermore, this thesis aimed to understand the business models and types of AI vendors and gather insights on their operations and value creation processes. This thesis contributed to the general understanding of the AI ecosystem in the manufacturing industry by connecting the two streams of research with theoretical viewpoints and qualitative data analysis. On the contrary, this study only represents an initial approach to contribute to a whole new field of research that tries to close the gap between traditional business modeling and the commercial value of artificial intelligence solutions in the manufacturing industry.

6.1. Significance

Due to the fact that European manufacturers are in the midst of a digital transformation, familiarity with newly emerging products and concepts, such as AI is of utmost importance. Furthermore, the field of AI and business modeling is on the verge to help entrepreneurs better understand the commercial roadmap ahead when building an AI solution for the manufacturing industry. For both, this study makes a vital contribution and thus, addresses three stakeholder groups: researchers, manufacturing managers and entrepreneurs.

For researchers, this thesis creates a reliable information base that helps to explain the typology of entrepreneurial AI software companies in the European manufacturing industry. The study and its valuable findings towards AI companies' business models could serve as a first foundation for further elaborative studies.

For manufacturing managers, this thesis creates a firm basis to comprehend the various possibilities they have to procure AI software. Furthermore, the study gives insights into several advantages and disadvantages that come along when implementing AI software with an entrepreneurial AI vendor. Managers who want their businesses to utilize AI software in their production can use this thesis as an initial handbook to grasp the revenue models and value propositions behind the software vendors. In addition to that manufacturing managers could use this thesis to understand the number of application possibilities of AI as well as get a comprehensible explanation of artificial intelligence technologies in general.

For entrepreneurs, this thesis provides great insights into the strategies and key assets of AI software vendors in the European manufacturing industry. Furthermore, the study equips entrepreneurs with a reflected set of data which business model suits best for their AI solution.

6.2. Limitations

The presented study has several limitations. First of all, the main assumption of this study was that content can be retrieved from the websites of the sampled companies. This was only partially possible as some of the relevant keywords were sometimes missing and further assumptions have to be made. Furthermore, the data gave no insights into profitability or other success indicators that might have helped to characterize the vendor types further. Secondly, the sample itself was retrieved by a crowdsourced database and although expert-validated, it is not entirely reliable in terms of the actuality of data. One major drawback of the thesis is the absence of reliable scientific work about AI business models. Even though research has been carried out on the commercial value of AI for manufacturers, only a few studies have empirically described the business models of the vendors who provide the AI software to the industry. The study could have been more convincing with a firm foundation of business literature on artificial intelligence.

6.3. Outlook

Further research should be done to investigate the findings of this thesis with more empirical evidence. The study presented can be extended in various ways. First and foremost, the study's sample size can be extended or even retrieved on a global scale. The initial assumption that the number of AI vendors in the European manufacturing industry exceeds the scope of this thesis was neglected when only 81 companies were identified. Although enough to provide interesting insights into the business dynamic of those vendors, a bigger sample size is advised to validate the findings of this study and add insightful nuances. Furthermore, it would be of huge value to investigate the success factors of each vendor type as well as the acceptance of each type by the manufacturing industry. One could argue that due to the high number of AI service vendors, the business model is more successful than its counterpart. However, this assumption has yet to be validated in a follow-up study that investigates the pricing, revenue numbers and cost structure of each vendor type analyzed.

Another valuable part of this thesis is the proposed AIVA framework. The framework assumes that it helps vendors understand their value proposition and revenue stream in relation to the AI solutions and methods provided. It can be utilized as a complementary tool when assessing a business following the traditional BMC by Osterwalder et al. (2010). Future researchers and entrepreneurs should add the emerging theoretical foundations around the topic to the framework that could gradually improve the quality of any analysis undertaken.

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Appendix A: Analyzed companies

Source: Dealroom (URL: www.dealroom.co)

No	NAME	WEBSITE URL	HQ REGION	HQ COUNTRY	Vendor Type
1	Neural Concept	https://neuralconcept.com/	Europe	Switzerland	AI SaaS
2	Mindtrace.ai	http://mindtrace.ai/	Europe	United Kingdom	AI Service
3	CorrosionRADAR	http://www.corrosionradar.com/	Europe	United Kingdom	AI Service
4	Cognite	http://cognite.com	Europe	Norway	AI Platform
5	Mov.AI	http://mov.ai/	Europe	Portugal	AI SaaS
6	Cloud NC	https://cloudnc.com/	Europe	United Kingdom	AI Service
7	Exotec	https://www.exotec.com/	Europe	France	AI Service
8	Magazino	https://www.magazino.eu/	Europe	Germany	AI Service
9	NavVis	https://www.navvis.com/	Europe	Germany	AI Service
10	Thingtrax	http://thingtrax.com	Europe	United Kingdom	AI Platform
11	SLAMcore	https://www.slamcore.com	Europe	United Kingdom	AI SaaS
12	Wandelbots	http://www.wandelbots.com	Europe	Germany	AI Platform
13	Keelvar	https://www.keelvar.com/	Europe	Ireland	AI SaaS
14	Wizata	https://www.wizata.com/	Europe	Luxembourg	AI Platform
15	Arculus	http://www.arculus.de	Europe	Germany	AI Platform
16	Datapred	http://www.datapred.com/	Europe	Switzerland	AI SaaS
17	Agile Robots	http://www.agile-robots.com/	Europe	Germany	AI Service
18	EyePick	https://eyepick.co/	Europe	France	AI Service
19	Celus	https://www.celus.io/	Europe	Germany	AI Service
20	Nomagic	http://nomagic.ai/	Europe	Poland	AI Service
21	Fizyr	https://fizyr.com/	Europe	Netherlands	AI Service
22	GenLots	http://genlots.com	Europe	Switzerland	AI Service
23	Witrac	http://witrac.es	Europe	Spain	AI SaaS
24	Rovenso	http://www.rovenso.com	Europe	Switzerland	AI Service
25	Smart Steel Technologies	https://smart-steel-technologies.com/	Europe	Germany	AI Platform
26	AiSight	https://aisight.de	Europe	Germany	AI SaaS
27	Scallog	http://scallog.com	Europe	France	AI Service
28	Gideon Brothers	https://www.gideonbros.ai	Europe	Croatia	AI Service
29	TiHive	https://www.tihive.com/www_site/	Europe	France	AI Service
30	Intelecy	https://www.intelecy.com/	Europe	Norway	AI SaaS
31	Senseye	http://senseye.io	Europe	United Kingdom	AI Platform
32	Flowlity	http://www.flowlity.com	Europe	France	AI SaaS
33	Reliability Solutions	http://reliasol.pl/en/	Europe	Poland	AI Platform
34	Wakeo	http://wakeo.co	Europe	France	AI Platform
35	Neuron SW	http://neuronsw.com	Europe	Czech Republic	AI Platform

36	PerfectPattern GmbH	http://www.perfectpattern.de	Europe	Germany	AI Platform
37	Metron	https://www.metronlab.com/	Europe	France	AI SaaS
38	Industrial Analytics GmbH	https://industrial-analytics.io	Europe	Germany	AI Service
39	INTRANAV	https://intranav.com	Europe	Germany	AI Platform
40	Crosser	https://www.crosser.io/	Europe	Sweden	AI Platform
41	The MoonVision GmbH	http://moonvision.io	Europe	Austria	AI Service
42	Conundrum	https://conundrum.ai/	Europe	United Kingdom	AI Service
43	SIRFULL	https://www.sirfull.com	Europe	France	AI Service
44	IFollow	https://www.ifollow.fr/	Europe	France	AI Service
45	Diota	https://diota.com/en/home	Europe	France	AI Service
46	Flexciton	http://flexciton.com	Europe	United Kingdom	AI Service
47	BOX ID Systems GmbH	http://www.box-id.com	Europe	Germany	AI Service
48	Photoneo	http://photoneo.com	Europe	Slovakia	AI Service
49	micropsi industries	http://micropsi-industries.com	Europe	Germany	AI Service
50	Braincube	https://braincube.com/	Europe	France	AI Service
51	Darktrace	http://www.darktrace.com/	Europe	United Kingdom	AI Service
52	Cosmo Tech	https://cosmotech.com	Europe	France	AI Service
53	Metis Labs	http://metislabs.tech/	Europe	United Kingdom	AI Service
54	QiO Technologies	http://qio.io	Europe	United Kingdom	AI Platform
55	Rhebo	http://rhebo.com/en/	Europe	Germany	AI Service Vendor
56	DCbrain	https://dcbrain.com/	Europe	France	AI SaaS
57	Scortex	http://scortex.io	Europe	France	AI Platform
58	Eiratech Robotics	http://www.eiratech.com	Europe	Ireland	AI Service
59	Sensewaves	http://www.sensewaves.io	Europe	France	AI Platform
60	Stanley Robotics	http://www.stanley-robotics.com/	Europe	France	AI Service
61	Riskmethods	http://www.riskmethods.net/	Europe	Germany	AI Platform Vendor
62	Elmodis	http://elmodis.com/	Europe	Poland	AI Service
63	Unibap	https://unibap.com/	Europe	Sweden	AI Service
64	Waylay.io	http://waylay.io/	Europe	Belgium	AI Platform
65	Cevotec	https://www.cevotec.com/	Europe	Germany	AI Service
66	ArtiMinds Robotics	https://www.artiminds.com	Europe	Germany	AI Service
67	Intelligent Robots	http://i-r.io/	Europe	United Kingdom	AI Service
68	GESTALT Robotics GmbH	http://www.gestalt-robotics.com	Europe	Germany	AI Service
69	Aica	http://aica.tech	Europe	Switzerland	AI SaaS
70	Octonion	https://octonion.com/	Europe	Switzerland	AI SaaS
71	Robominds	https://www.robominds.de	Europe	Germany	AI SaaS
72	Renumics	https://renumics.com/	Europe	Germany	AI Platform
73	Orobix	https://orobix.com/index.html	Europe	Italy	AI Service
74	DeepEyes	https://www.deepeyes.co	Europe	Germany	AI Service

75	Asystom	https://www.asystom.com/	Europe	France	AI Service
76	TOffeeAM	https://www.toffeeam.co.uk	Europe	United Kingdom	AI SaaS
77	SimScale	https://www.simscale.com	Europe	Germany	AI Platform
78	Elise	https://www.elise.de	Europe	Germany	AI Platform
79	syncron	https://www.syncron.com	Europe	Sweden	AI SaaS
80	deevio	https://www.deevio.ai	Europe	Germany	AI Service
81	enlyze	https://www.enlyze.com	Europe	Germany	AI SaaS

Appendix B: Interview Partner

Company Name	Position	Company Focus	Duration
Applied AI	AI Strategist	AI Strategy Research	30 min
Rapidminer	Head of Data Services	Data Science Platform	45 min