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AI in the European manufacturing industry – a management guide

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Artificial intelligence will have significant influence upon the manufacturing industry. Rapid disruption of existing processes will lead to a clear distinction between those who were able to adapt quickly enough and those that fall behind. There are several challenges e.g. data availability and IT-security that come along with AI, that managers must address in advance to be prepared. The opportunities lie mainly in enhancing efficiency as well as fault detection and error recognition. Defining a framework and following certain success factors such as the definition of KPIs and developing a minimum viable product, increases the chances of success massively. **#Artificial intelligence #Manufacturing #Disruption #Management**

Contents

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1. Introduction

1.1. Context and relevance

In recent years the term artificial intelligence has become almost ubiquitous not only in scientific journals and research papers but also in common newspapers, in discussion panels or company presentations. Typically, one can find either very optimistic views on the influence of AI on our lives or very pessimistic ones: Sundar Pichai, CEO of Google, argues that AI will have more impact on humankind than the discovery of electricity. On the contrary, Elon Musk claims “AI is more dangerous than North Korea” (Clifford 2018). The pessimists argue that AI will either leave very little need for human labour or state AI will not reach a stage of crucial importance and therefore have a very limited influence on society (Agrawal, Gans, and Goldfarb 2018, 14). Although that does not sound very promising the predictions cannot both be correct but both be wrong (Mokyr 2017, 18–19). In fact, most experts predict that AI will be part of every day’s life and play a crucial role in shaping the future. But it is often overlooked that AI is already influencing life heavily, be it in the use of voice assistants, language translators, spam filters, plagiarism programs or ridesharing apps such as Uber, Bold and Grab.

PWC predicts the addition of up to $15.7 trillion to worldwide GDP by AI alone in 2030 (S.Rao and Verweij 2017). Predictions include rapid disruption of manufacturing activities through AI means especially in collaboration with technologies such as cloud computing, big data and the internet of things. The sense of urgency about AI and digitalisation in general has also reached governmental and supranational organisations. The United States published a new AI strategy a few years ago (The White House 2016). The EU Commission, France, China or Germany have developed their own strategies. As in many of these countries the manufacturing sector is still one of the most important contributors to GDP growth, job creation and wealth, a focal point is the development of smart manufacturing and taking advantage of AI in creating intelligent factories for the future. Vladimir Putin said in an interview two years ago that “whoever becomes the leader in this sphere [AI] will become the ruler of the world”

(CNBC 2017). Generally, AI is very auspicious to Europe that could add another €2.7 trillion to its combined GDP. In addition, forecasts predict that a low rate of unemployment alongside higher-skilled jobs can be maintained. By 2030, European economic activity could see a boost of almost 20% (McKinsey Global Institute 2018). Nonetheless the technology is still not mature and likewise diffusion is in many cases limited. The manufacturing sector, the backbone of many industries and oftentimes the biggest employer is about to face the next wave of disruption after the digitalisation with greater consequences. Although many companies are running pilots with regard to applications, implementation is usually limited to a few very specific processes at most (BCG 2018). Moreover, there is still scepticism and distrust towards AI in an industry that is considered to be conservative. And as AI is a topic that is highly complex, there is a need for managers to grasp the principles of AI but also promising use cases of its implementation. Managers need scientific research papers but also practical guidance to apply it. "Academics push technological frontiers, from artificial intelligence to deep learning, without considering how they will be applied" (Kusiak 2017, 24). The development of AI solutions is done by data scientists and computer engineers, but for firms it is crucial to have managers that are aware of the vast potential of AI to drive the development and to avoid common pitfalls.

1.2. Objectives of the thesis

Since AI has become a common phenomenon and is applied for real business situations, managers have an increasing need to not only understand what artificial intelligence is, but also what they can expect from it and where they can reap the greatest benefits. Therefore, the thesis aims at giving an overview of AI from a managerial point of view. Hence, an objective will be to develop a common ground in briefly explaining what AI is based on, how it works and what current challenges are. In addition, there will be an in-depth analysis of the opportunities and threats of AI as well as important strengths and weaknesses. The focus particularly lies on understanding the impact of AI in general and on the European manufacturing sector in particular. Furthermore, the thesis should help to develop a realistic view on AI that differs from overly optimistic and pessimistic statements oftentimes found in newspaper headlines. In that regard an objective is to demonstrate on which areas managers should focus when implementing AI in manufacturing. Hereby, it will be crucial to point out where the greatest advantages can be found but also to highlight pitfalls and challenges. Generally, an important objective is to give managers a sense of urgency by underlining the relevance of AI. In contrast to the objectives above some other issues are not included despite the need for further research. This includes specific strategies with regard to AI such as the attraction of data scientists or an in-depth guideline on the technical implementation of artificial intelligence into a company´s operating system which will not be discussed systematically. Also, there will be no extensive benchmarking with other sectors or territories although some examples of best practices will be given, wherever appropriate.

1.3. Methodology and structure

The present thesis is based on qualitative research. Firstly, a comprehensive overview of the state of artificial intelligence and its current and future industrial relevance is presented, as well as a brief overview about the current leaders in the development of AI, both on a company and a country level. Furthermore, future challenges of the manufacturing sector will be highlighted to understand the processes the industry will undergo. To complement this chapter, the current areas of AI application are discussed with emphasis on the European manufacturing industry, as well as persistent and yet unsolved challenges of AI that need further research. For the assessment of AI, a SWOT analysis was conducted. This analysis is based on a range of studies and forecasts from various sources that have been examined in order to determine7 the implications of the rise of AI for manufacturers. Hereby, not only research papers of AI experts but also forecasts of consulting companies and analyses from supranational institutions such as the European Commission are included. Moreover, the chapter will contain real-life cases of successful AI implementation, that provide an idea about the strategies other companies used, in order to create a competitive advantage and enhance, either the customer value or the efficiency of their own operations. In the last section the findings from the prior chapters are aggregated and utilised in order to answer the research question and find strategies to combat the challenges of using AI but simultaneously avoid the pitfall of neglecting the technology. Managers should be given an idea on where to start with AI implementation and which areas in a company should receive the highest attention, because they are either susceptible or promising. The last chapter will develop conclusions about dealing with AI which will shape the industry over the coming years.

2. Literature review

2.1. What is artificial intelligence and the current state of technology

Although the hype and excitement around artificial intelligence is a relatively recent phenomenon its roots date back to the mid-20th century. In 1955, John McCarthy and a group of researchers from the U.S. were the first using the term artificial intelligence and defining it as the ability of machines to perform tasks that usually require humans. They already identified a number of problems with regard to AI that persisted for decades such as the ability of machines to self-improve (McCarthy et al. 1955). But what is artificial intelligence? Even now there is no universal definition of what it means. For instance, confusion oftentimes arouses between the term's artificial intelligence, machine learning and deep learning. One can say that AI is an umbrella term for computational technologies that imitate, to some degree, the human brain as a framework of capabilities. For this master thesis the following definition will be used: "the extension of human intelligence through the use of computers, as in times past physical power was extended through the use of mechanical tools" (Kosters et al. 2009, 2). Machine learning, on the other hand, has become the latest trend, in which algorithms are able to independently improve their outcomes by making use of data input, hereby addressing the problem McCarthy raised many years before. It uses various techniques such as supervised and reinforcement learning (*See Appendix 1*). Therefore, it is a subbranch of artificial intelligence technologies (IBM 2018, 3). Deep learning rose to prominence in 2016 when Google developed Alpha Go, an AI program, that beat the world champion Lee Sedol in Go, an ancient complex strategy game. Alpha Go used a data set of past moves to predict the best option. Subsequently, Google developed another version, called Alpha Go

Zero that was only taught the game´s rules. By playing millions of games against itself it learned so quickly that it beat the former version within three days (The Telegraph 2017). Thus, deep learning is a subdiscipline of machine learning and the form of AI that functions closer to the human brain by relying on layers of artificial neural networks (Laserson 2011).

AI applications are in many ways still in a premature stage. The Gartner Cycle shows that many of the currently hyped solutions will undergo a period of disillusion before reaching a level of productivity (*See Appendix 2*). Nonetheless, there are plenty of use cases for instance, more than 60% of all commercial trades at wall street in New York, are nowadays executed by AI with almost now human interaction (Accenture 2018, 8). To determine the current stage of AI, researchers typically distinguish between narrow and general AI. Narrow AI describes a program that can fulfil a specific task or a set of tasks but is very limited to this. These programs, also called weak AI simulate thinking instead of reflecting about their actions. An example for this kind of AI are chatbots. They pretend to behave like humans but are very limited to this task and do not know why they are communicating to a person. Despite their misleading characterisation as weak, they are very useful in many situations. On the contrary, general AI is a concept that experts believe, will at least take a few decades to unleash its full potential. It describes a scenario in which artificial intelligence can carry out any task a human can. Thereby, a machine would prioritise, think in an abstract way and use creativity, which exceeds current abilities by far (Accenture 2018, 12–14). In fact, we are somewhere in between. That is why IBM defines an additional stage, called broad AI, which can be seen as an array of narrow AI systems that operate together and are able to make decisions (IBM 2018, 7–8). It is increasingly used in companies where it combines computational force with industry- and process specific knowledge. In practice, it can be used for banks where AI analyses a given customer portfolio and makes recommendations for cross-selling strategies. Reasons for the late advent of AI include the risen power of modern computers and processors. AI can only unleash its potential with vast amounts of data to learn from. Today, cloud solutions offer almost unlimited storage space for little investment. Thanks to IoT connectedness there are massive data sets that contain valuable information. But to get the information the data holds it is inevitable to analyse it closely. Here, classical programming that processes a predefined algorithm often reaches its limits. That is where AI techniques can show its potential (Barnard 2019).

2.2. Setting the pace – who is leading in Artificial intelligence?

For innovative technologies, it is oftentimes difficult to assess which companies are leading the way as research is undertaken behind closed doors and information is usually scarce. Therefore, a valuable indicator are patent applications because they show companies´ progress in a field, that they consider to be worth protecting. The World Intellectual Property Organisation registers and assesses whether applications should be protected. It reveals, that in 2019 the world´s leader in AI-related research has been IBM with almost 8300 patent applications followed by Microsoft with 5900 applications. Both firms´ research covers multiple disciplines of AI. In addition, there are several other multinational corporations that, in total, have a much lower number of patent applications but concentrate specifically on a single area of expertise. For instance, Baidu pays attention to deep learning, Facebook focuses on networks, Toyota and Bosch are investing in research for transportation and Siemens, Philips or Samsung strengthen efforts towards their core business in life and medical science (WIPO 2019, 15). But not only among companies it is worthwhile to look for the leaders in AI. Many are worried that Europe will miss the next big trend after the platform economy that is dominated by the United States and China. According to a McKinsey Global Institute study these concerns are legitimate. In terms of adoption and diffusion of AI technologies, Europe is already lagging behind China and the U.S. and investments are negligible - The EU commission announced €2.6 billion in AI whereas China invests almost the same sum in a single AI park in Beijing. Except for smart robotics, the diffusion of artificial intelligence technologies is more advanced in the U.S. (*See Appendix 3*). Although the report states that the prerequisites for successful AI development and use are well in Europe, the pace is currently set elsewhere in the world (McKinsey 2019b, 8–13).

2.3. Future challenges of manufacturing

Manufacturing is one of the most important sectors in many countries such as Germany or China that call it the backbone of their industry. Despite this, there are challenges that manufacturers have to overcome in order to retain their key position. The European Commission presented their vision of an innovative approach to manufacturing that "should address transformable, networked and learning factories" (Romero, Jardim-Goncalves, and Grilo 2017, 4–5). This vision is labelled factories of the future or Industry 4.0 (*See Appendix 4*). McKinsey claims that the real benefits of Industry 4.0 can only be reaped by manufacturers that invest in connectivity, intelligence and flexible automation through technologies such as IoT, AI, robotics and additive manufacturing (Goering, Kelly, and Mellors 2018). In contrary to previous industrial stages, focusing on optimisation will still be necessary but not enough anymore. Every single part of the factory of the future must be able to scan the environment, analyse it and make decisions based on these circumstances. The ability to react to an unknown situation and incorporate that knowledge is seen by many experts as the major game changer in the transition towards Industry 4.0 (Wang 2018, 723–26). However, PwC found out that only a fraction of all manufacturers has reached a scalable level for advanced digital operations. In most cases there are only a few dispersed prototypes that are not enough to overcome the imminent challenges (PwC 2019, 4). Moreover, as most sectors, manufacturers feel the pressure of an ageing population with a shrinking workforce, so that the necessity to find skilled employees will become even more crucial than nowadays. But not only internal challenges are awaiting the industry. Also, customers are becoming more demanding, eager to not only have quality products for affordable prices, but also a high degree of customisation. That goes against the trend to reduce inventories in order to shorten stock assets to free up cash (Zhong et al. 2017). In addition, interoperability will become an important challenge for manufacturing. Supply chains of the future will only partially be physical (*See Appendix 5*). Most of the processes and the value creation will happen in the cyber-physical space and the exchange between the two. Artificial systems and humans will thus need to collaborate on common problems and still be able to adhere to control processes, which is a further challenge. In general, managing not only the traditional physical supply chain but also the cyber variant and ensuring optimal connectedness between both, will be key for manufacturers in the future (Panetto et al. 2019). Hereby, focus will be needed on how to increase the resilience of such fragmented structures against internal and external influences.

2.4. Areas of AI application

Today, AI has grown from science fiction to real use cases. It is commonly used for language detection, processing and translation. Although this is mainly used by private individuals it also offers benefits to companies that either communicate with customers or facilitate machine-to-human communication. Furthermore, an area of application for AI technologies are robots. They are almost ubiquitous among manufacturers due to their capabilities, that free up manual labour and enable large productivity leaps. In addition to that, robotics is applied to transportation or industrial automation (Li et al. 2017). AI can already play an important role for manufacturers in monitoring and process control. Particularly, in fault diagnosis it consistently surpasses human performance. It can recognise mistakes, that are almost invisible to the human eye, in a fraction of the time needed even for skilled workers. Image recognition is a further field that has seen the advent of AI. It is used in manufacturing, for instance during the planning phase or when transforming physical models into digital twins or CAD models for additive manufacturing. At the overlap of image recognition and fault diagnosis there is a potential use case for the future. Diagnosis of medical dysfunctionalities or detecting early signs of severe diseases is a promising field, that can offer great benefits for manufacturers that develop and produce medical high-tech equipment (Wuest et al. 2016). In addition to these examples AI is also used for enhancing predictive analytics. Not only in manufacturing but in many industries, business success relies on the quality and reliability of forecasts. Be it in predicting demand patterns, the time key components would need to be replaced or the fluctuation of prices for input goods, predictive analytics becomes a lot more reliable with the support of AI. For many manufacturers especially the area of maintenance is already of high importance (Wang et al. 2018).

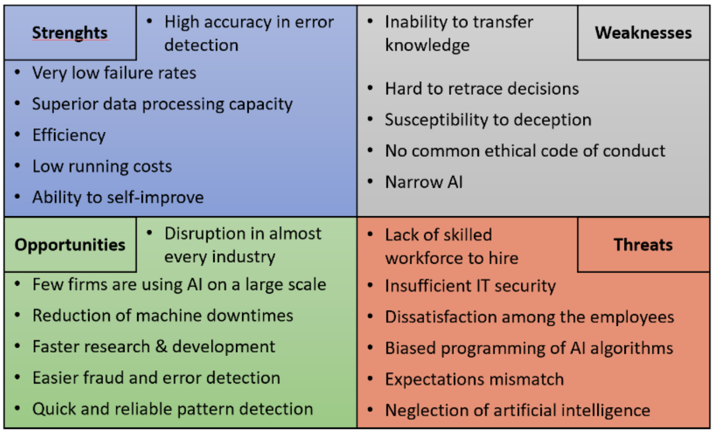
2.5. Unsolved challenges of AI

Despite the excitement and hype about AI, there are persistent challenges, that would increase the number of application fields when solved. Some of these, are problems that AI technologies are facing, whereas some others are related to the implementation and usage of AI in companies. The first issue is about explainability that arises due to the complexity of some AI technologies, namely deep learning methods. As it does not show which factors caused a decision or prediction, it is very problematic in cases in which discrimination can occur or certain societal question, that have major implications, such as in criminal justice applications. Moreover, AI systems are rarely capable of transferring knowledge. They might stand out in a certain task they were trained for, but struggle to transfer their knowledge to another, yet unknown problem. However, transfer learning is an area that receives attention and might see substantial progress in the near future (McKinsey Global Institute 2018). Another unsolved challenge is ethics. There are many ethics-related questions that come to mind, as machines with artificial intelligence, do not only determine the optimal product flow in a factory, but intervene in everybody´s day-to-day life. How to build an AI system that finds the "right" solution in each situation? This is further aggravated by the variety of ethical schools that contradict each other in many ways. Nonetheless, an essential challenge for the future will be to make algorithms compatible to common ethical standards. This can be applied to many situations such as hiring algorithms that need to take many factors into account without discriminating any applicant (Frankish and Ramsey 2014). But it must be acknowledged that this field has already seen progress. Many academic institutions are researching on the relation of AI and ethics. Further research is also needed on how to increase the robustness of AI systems to reduce incorrect reasoning.

3. Assessing AI in the European Manufacturing Industry

3.1. SWOT analysis

For the analysis of AI in manufacturing companies, the following section will be based on a SWOT analysis to structure different characteristics of AI in manufacturing. The dimensions of SWOT are composed of strengths and weaknesses that focus on the internal nature of a company and opportunities and threats which should highlight the external perspective. In this case, the internal sections will focus on AI itself and the strengths and weaknesses that are inherent. Based on this analysis, the following subchapters for opportunities and threats will deal with the question which opportunities the use of AI offers for the manufacturing sector and which threats can come along.



3.1.1. Strengths

Artificial intelligence technologies are complex and so are its areas of application. Still, there are strengths of AI in a manufacturing context they have in common and that can be transformed into competitive advantages. The reduction of not very complex, often boring routine jobs is one of them. It can involve quality inspections, as well as monitoring of sensor data or dealing with customer requests (Muro, Maxim, and Whiton 2019, 12–15). There are several other examples, but all of them have in common that they used to take time, were highly repetitive and had an inherent risk of potentially costly mistakes. An employee who does not recognise a tiny manufacturing defect in a million-dollar piece of equipment can cause a situation that costs a company a lot of money. AI-powered software can have high accuracy and low failure rates. That means firms cannot only redeploy their employees to more meaningful tasks, but also lower business risks by finding errors more reliably (Deloitte 2016, 1–3).

Moreover, a strength of AI is its data processing capacity that surpasses human capabilities by far. This becomes useful when it comes to pattern detection. AI software, that can use millions of data points as input, is able to determine significant patterns, on the ground of statistical and physical models, faster than any human can. As it is even capable of identifying outliers and special effects such as seasonal data, its contribution to many problem-solving processes and research projects can be extraordinary. (Chen, Kapoor, and Bhatia 2016, 176–81). Also, efficiency is a major advantage of AI usage. On top of the examples, a well-designed AI algorithm is a cost-efficient way of optimisation. Not only does it incur lower costs than human-led processes, in many cases it is impossible to have a human workforce that can replace algorithms, or at least achieve similar results. This strength is very valuable to Europe with often high labour costs. Outsourcing might eventually become obsolete in many cases when labour costs can be reduced by using AI-algorithms. Furthermore, the trend of machine learning and deep learning in particular, contains the ability to self-improve so that these programs eventually get better in what they do over time (Murphy 2018). In contrary to humans, machines don´t need weekends or maximum hours that must be considered and there is less need for retraining once the software is set up.

3.1.2. Weaknesses

Despite the manifold strengths of AI, there are also weaknesses. It is crucial to be aware of them, so that an application can be designed, that avoids these weaknesses and builds upon the strengths. Some of these problems can be solved by a company alone by carefully implementing AI solutions but others will persist until a general, widely accepted code of conduct for AI behaviour is developed (Helbing et al. 2019, 78–82). For European companies, this will likely be of higher relevance as data protection is construed more strictly than in China or the U.S. Depending on future developments, data protection laws and regulation can become a significant disadvantage for European companies, but could turn into an advantage if other countries follow a European approach. An important weakness of AI today is that it is not able to think as humans. As said before, researchers call the current form of AI narrow. This makes sense, comparing the ability of humans to transfer and apply knowledge to unknown tasks, to computers which are, although powerful, usually only able to fulfil a specific task or at most a set of tasks. Thus, a common weakness is the inability of AI software to be used for another than the originally intended purpose. Whereas humans can be retrained to work and excel in different jobs, given enough motivation and a certain intellectual capacity, machines are not yet able to do that. For rapidly changing tasks that demand adaptation, AI is therefore oftentimes still not applicable (Gupta et al. 2017).

Another issue that prevents the usage of AI is missing information. Why does the algorithm derive a particular result from a data input and what caused the rejection of another solution? Dario Gil, vice president of AI at IBM Research argues that insecurity about the foundation of AI decisions is key to understand the reluctance of top executives concerning AI (Ribeiro, Singh, and Guestrin 2016, 1135–44). "When people are making high-stakes decisions involving hefty investments, with safety as a key factor, black-box AI is a blind alley" (Yoshida 2018). Many manufacturing firms are producing sensitive components that must meet the highest safety standards and face a strong regulatory environment. The consequences in a safety-dependent environment e.g. aviation, of a sensor providing data and support to the pilots, based on AI, without anyone knowing what led to the result, would be drastic (Chalkiadakis 2018). It is obvious that whenever safety or money are at stake explainable AI becomes a major issue. A black-box approach might not be problematic for recommendations on the Amazon web shop but managers must know of how specific decisions are made (Holzinger et al. 2018, 1–8). This is particularly true for Europe that follows a different approach than the U.S. Whereas European regulatory authorities usually only permit the use of products, such as pharmaceuticals, after extensive testing, their American counterparts rely more on the research of the companies and impose drastic punishments in case of violations. Another example for persisting AI weaknesses is its susceptibility to be deceived. This does not mean the risk of cyber-attacks, that is inherent to all kind of software and not limited to AI, but its tendency to show incorrect results that are not easily comprehensible for a human. Plenty of examples have demonstrated how slight modifications to a picture caused a noticeable quality reduction in image recognition by AI-supported software. While this varies greatly depending on the type of utilisation, one has to be aware that AI can be fooled. For this, experts still call AI weak or narrow as it does regularly fail in transferring its capabilities to adjacent applications (Johnson 2019, 7–8). A further issue concerning AI that is widely discussed amongst the public and media as well is ethics. This wide array of issues is doubtlessly too complex to discuss it in-depth in this thesis, but nonetheless crucial to have in mind. Depending on the type of AI and the area of utilisation, there are certain ethical questions that are tough to answer. For instance, the development of autonomous cars involves the question of how an algorithm would react to situations in which people will be harmed as e.g. a crash. Prioritisation is a very difficult choice in this case, but it exemplifies the obstacles of decision-making processes that AI-algorithms need to go through (Goodall 2014, 60–64).

3.1.3. Opportunities

Artificial intelligence foments hopes of impacting not only the revenue side but also helping in reducing costs and fostering innovation. An EY survey among more than 300 European enterprises reveals that 40% expect significant impact of AI in their industry within the next five years. Interestingly, these results diverge significantly by country. In Portuguese enterprises 64% foresee significant impact but only 9% do so in Finland. The expected impact in the business areas engaging customers, optimising operations, transforming products & services as well as empowering employees, differs substantially. Responses from the manufacturing sector indicate that almost all expect AI benefits in optimising their operations – more than in any other industry. Still, another 70% foresee improvements to product innovation and almost 60% hope to improve customer engagement and employee empowerment (Ernst & Young 2019, 48). Despite these expectations, it is surprising that only a fourth has already released AI applications within their company that are used in, at least, a few basic processes. Moreover, only as few as eleven firms report that "AI is actively contributing to many processes in the company and is enabling quite advanced tasks (Ernst & Young 2019, 32–41)." This reveals that although firms have clearly grasped the importance of AI, actual implementation is still in many ways in an early stage. Besides that, there is still a high number of top executives that believe AI is not crucial for business success as 21% in the PWC CEO survey state, AI is not a priority (Curran and Rao 2017).

Generally, the success of manufacturing companies mainly relies on their ability to achieve operational excellence. This means that manufacturers need to ensure their machines and conveyor belts are running without downtimes (Mulunjkar et al. 2019). Unexpected downtime of machines costs manufacturers approx. $50 billion per year (Wall Street Journal 2016). However, machine downtime is neither inevitable nor unpredictable. Big data and AI can already help to predict the likelihood of malfunctions, so that the responsible teams are able to react pre-emptively. Hence, an important goal for AI usage in manufacturing is to move from simply solving problems that cause downtimes etc. to avoiding them before they can occur (Lee et al. 2018, 20–23). Such a proactive approach is only achievable through a consistent and comprehensive use of different AI technologies. In contrary, "poor maintenance strategies can reduce a plant´s overall productive capacity by 5-10%" (Deloitte analytics). This shows the extraordinary impact maintenance can have on a company's performance. Nonetheless, almost all manufactures currently follow a reactive, planned or proactive approach at best (*See Appendix 6*). A proactive approach already makes use of some data analytics and statistical measurement. However, the original equipment effectiveness, an important KPI in manufacturing, can increase above 90% through the use of AI and advanced analytics (Saha, Syamsunder, and Chakraborty 2016). This state is called predictive maintenance and would make human intervention only necessary in rare cases, thus reducing maintenance costs. Replacement orders could be sent pre-emptively, and technicians would be called before the entire assembly line is stopped, because of a break-down of a single part. In order to reach this stage of virtually no downtimes, comprehensive data is needed. This is where AI comes into play because the data sets that will be generated by thousands of sensors are impossible to analyse by humans alone. Moreover, the true benefits can only be reaped if the data is analysed in real-time so manufacturers will need the effective intertwining of AI, advanced analytics, big data and the cloud (Ho 2018).

3.1.4. Threats

The implementation of AI into the operations of a manufacturer offers plenty of opportunities but carries certain risks as well. First, there is sometimes a mismatch between expectations and reality regarding the immediate effects of AI. Though potentially being very powerful, AI is not mature, which means that a lot of testing and research is necessary to find the ideal way of exploiting its strengths. Especially when manufacturers do not want to rely on standard applications but rather self-develop a state-of-the-art version, the time and financial investments that are needed to succeed, are oftentimes underestimated. Moreover, many firms simply do not employ enough data scientist and AI experts that can develop and implement an AI solution. For an average 10€bn company, Accenture predicts the need of 500-1500 data scientists and engineers which is tough for most enterprises without a clear strategy for talent attraction and internal training (Elser et al. 2019, 18). Capgemini shows that 70% of U.S. firms aim to tackle this problem, while only around 50% of the major European countries do. In comparison to China and the U.S., Europe is facing an even higher need for IT-experts (Analytics Insight 2019). Perhaps the most important risk is insufficient IT security. As all software, AI applications have a risk of being attacked. This includes copying and stealing sensitive information such as technology or customer data, to introducing malware or shutting down machines. Due to the diversity of IT-security risks and the little protection that traditional forces offer, companies are responsible to find alternatives and set up effective cybersecurity mechanisms. This entails high investments which not every firm is able or willing to undertake. The industrial landscape in Europe is mainly composed by small- and medium-sized enterprises. This is different in many other countries around the globe. However, their size and financial resources might deter them from undertaking the needed investments in IT-security. This breach is dangerous, and European politics should encourage IT-support for smaller companies.

In contrary to this, there are also internal risks that must be considered. For example, creativity and intuition might be lost if one relies on algorithms in situations where it is not necessarily the best option. There is plenty of literature discussing where to rely on human intuition and where a data-centric approach is preferable. Additionally, managers might need to take culture into account when introducing AI. Otherwise a software that makes decisions can cause dissatisfaction among employees that don´t feel valued anymore. A more general, yet practical, example for a threat would be the programming of an algorithm. Especially machine learning that learns from data input and refines its results can become biased by how the input looks like. Situations in which prejudices and social conventions lead to biases and unfair discrimination occur easily. Apple faces an investigation about whether their credit card discriminates women. A well-known software developer reported a twenty times higher credit limit than his wife, despite her having a better credit score (New York Times 2019). Here, the problem of black-box AI can be seen again. The same can happen to people with certain health characteristics (Yoshida 2018). The obvious answer to change that, is to create bias-free algorithms. However, this is difficult because biases are not specific to machines or AI but transferred from humans to machines. This can bring companies into morally questionable situations and customer repercussions. An infamous example of a failed AI experiment where incoming data caused undesirable results is Microsoft´s chatbot Tay. Targeting young adults in the U.S., the bot was intended to engage with people through casual conversation on Twitter. However, in less than a day, users managed to make Tay use racist language and express stereotypes about Jews and other minorities. Microsoft stopped the experiment and later apologised (Vincent 2016). This shows, that one needs to make a great effort so that algorithms have unbiased underlying data. By comprehending the functionality of an algorithm, managers can retrace every step of an AI process. However, the first step is ensuring maximum objectivity on data.

3.2. Best practices

3.2.1. Siemens AG – Case Studies

An overview of Siemens and its efforts in AI can be found in the appendix (*See Appendix 7*). In many ways the Siemens AG is a great example of a heritage manufacturer who understands, that its former focus on developing and manufacturing high-quality products might not be enough for the future and is therefore embracing the technological change. One of their flagship facilities is the factory in Amberg. It was built in 1989 and today, a product portfolio of more than 1200 different items is manufactured there. Jan Mrosik, COO of Siemens Digital Industries says, this inevitably forces the employees to adjust the configurations of the production assembly line approximately 350 times a day.

This takes time and reduces efficiency, so Siemens introduced a digitalisation initiative that transforms every product into a digital twin prior to the manufacturing process. Further, even the assembly line and the overall process receive a digital replica so managers can quickly model the repercussions of changes. Bottlenecks or quality insufficiencies can thus be identified much easier and faster (Forbes Insights 2018). The facility in Amberg produces so called PLCs, programmable logic controllers that supervise manufacturing processes in factories worldwide. More than 12m customised PLCs, an equivalent of almost 33.000 a day, are produced here with a very low rate of defect of about 0.001% (Nikolaus 2019). That can only be achieved through a complex system in which algorithms analyse incoming customer orders and optimise the production process (The American Society of Mechanical Engineers 2016). Nonetheless, some bottlenecks persist. For instance, Siemens uses X-Rays throughout the manufacturing process to ensure superior product quality. In this case, they were identified as a major bottleneck in the process due to the lengthy throughput time. However, purchasing and installing an additional X-Ray would cost 500.000€ (Siemens AG). For this purpose, Siemens developed an AI-algorithm that collects data from all stages of the process to decide whether a component had to go to the X-Ray station or not. Hereby, the bottleneck was oftentimes avoided. What Siemens calls a closed loop analytics approach, helped the company to make smarter decisions and to forgo the investment into an additional X-Ray, reducing CAPEX by 500.000€ (Siemens AG 2019) (*See Appendix 8*).

The above-mentioned example of applying AI in an industrial context is of internal nature, mainly benefitting Siemens´ operational efficiency. Additionally, there is also large potential for value enhancing applications that are directly linked to the customer, highlighted in another real-life use case. For customers in the energy sector, the H-Class gas turbine is the flagship model and most efficient version in Siemens´ portfolio. Nonetheless, the chemical combustion process is still accountable for notable nitrous-oxide emissions. Despite being rarer than the carbon dioxide emission, they still account for 6% of all greenhouse gas emissions (U.S. Environmental Protection Agency 2018). Not only are these gases increasing the effects of the climate change, but also represent a significant cost burden for

European companies in the form of the European certificate trading system that allows companies only to emit a certain volume of emissions or to buy additional pollution rights (European Commission 2017). To decrease the negative consequences of operating gas turbines, Siemens engineers looked for solutions to lower nitrous-oxide emissions. However, regardless of the many solutions they tested, none was able to reduce the emissions significantly and maintain a similar efficiency after a certain threshold (Busch 2018). Consequently, they developed a multi-layer network of sensors, monitoring hundreds of different data points. With this information being fed to a neural network, a machine learning application was able to determine the best conditions for the chemical combustion process. Norbert Gaus, Head of Research says, “even after experts had done their best to optimize the turbine’s nitrous oxide emissions, our A.I. system was able to reduce emissions by an additional ten to fifteen percent”(Bradley 2018). What needs to be emphasised for both best practices, is the crucial role of big data. Mindsphere serves for Siemens as a smart cloud for industrial processes. It can record and analyse vast data amounts and draw recommendations on how to solve a specific problem and can thus be seen as the backbone of AI, that would be unable to work without the data input that Mindsphere generates. The success of applying AI is very closely connected with the use of big data and should always be accelerated together.

3.2.2. General Electric´s Predix & Exelon

For an overview of GE´s and Exelon´s operations and the challenge of wind energy please see *Appendix 9*Appendix 9. Exelon is operating various wind energy projects and has acquired significant expertise in managing them and generating profit. However, a major obstacle of wind energy is the unreliable power supply since wind is hardly predictable and does oftentimes not match the demand. To increase the precision of forecasts, Exelon concluded a cooperation with General Electric who manufactures wind turbines to develop a better solution. Hence, they used Predix, General Electric’s software platform, for gathering, analysing and evaluating industrial data. It combines data integration, the Industrial Internet of Things, machine learning, and predictive analytics (General Electric 2018a, 3). Based on that, the partners developed an innovative model that incorporates real-time and past data from sensors on Exelon´s wind turbines. The new model is substantially more accurate in forecasting wind behaviour (*Appendix 10*).

Predix can provide short term forecasts for the next hour but also for the next day and the next week. The latter is important for maintenance scheduling so that the lowest power intervals can be chosen and maintenance downtime is minimised (Gould 2017). Day-ahead forecasts improved by 9%, resulting in a reduction of under-forecasting and subsequently in a 1-3% higher annual energy production (Predix 2017, 6–11). What might not sound much cannot be underestimated. It must be highlighted that this gain has been purely realised by software optimisation. It nets Exelon an equivalent of 70 megawatts of additional capacity. This corresponds to the generation of four of the company's wind projects in Oregon, that usually go along with huge investments (Exelon Corporation Wind). In total, Exelon expects an additional revenue stream of $2 million annually, based on the better wind utilisation (General Electric 2018b, 15–16). The success of this project not only enhances the customer value tremendously but also has concrete benefits for General Electric. Exelon agreed to sign a long-term contract, therefore binding a major customer for the foreseeable future (Predix 2017, 10–11). More examples for AI usage in industry contexts are provided in the appendix (*Appendix 11*).

4. Managing AI in the European Manufacturing Industry

The fourth chapter will be an aggregation of the findings from the previous chapters, complemented by recommendations on some practical questions that managers frequently encounter when dealing with AI related topics such as implementation or set up of projects. This includes guidelines on what the managerial focus should be about AI. Moreover, some important success factors will be derived from the previous analysis that help companies to avoid pitfalls and costly failures to a large degree and profit from the vast opportunities that artificial intelligence offers.

After all, one can say that AI is a technology that should not be neglected. Despite this, the analysis in the literature review clearly showed that Europe threatens to fall behind in AI, in comparison to the

U.S. and China. This would be a significant locational disadvantage, taking into account the industrial landscape, that is mostly dominated by manufacturers across Europe, which can greatly profit from the diffusion of artificial intelligence technologies. The prerequisites are well in place in Europe, but the investments and efforts made, both on a company and a political level, need to rise tremendously. The fragmentation of Europe can be seen as a disadvantage for joint initiatives, but the European Union as a supranational institution and the different perspectives and focuses on AI in Europe can actually lead to a powerful competition for the best AI approaches and ideas.

However, many managers are still unsure where they should apply AI to achieve the greatest impact. In fact, implementing AI consistently across a company, requires significant investment in talent and thorough modifications to the technological structure. An analysis of 400 AI use cases across industries and business functions, proved that managers should focus on one main aspect: "Follow the money" (Harvard Business Review 2018). Whether it be a significant cost burden, or the major share of revenue, AI is usually most successful to create value where the financial impact is high. But even if managers know where to apply AI, they still face the challenge of how to do it or at least how to start. There is no universal strategy, but certain guidelines that can help finding a suitable approach. Firstly, AI implementation is unlike purchasing a new machine that gets set up and starts working as intended. Reaping the benefits of AI is more about providing the necessary prerequisites and the framework. Hence, what management needs to do before implementing AI solutions, is to develop an AI strategy and a clear business plan. As discussed before, a good start is usually to look at the biggest cost blocks and revenue contributors, but it might also be worthwhile to invest in driving efficiency or facilitating R&D, but it depends on the circumstances and challenges a company faces. Once this is identified, it is crucial to have the capabilities to implement and benefit from AI. Unfortunately, AI experts are in high demand and thus hard to find and very expensive. However, as a large corporation, being technologically ahead of competitors has always meant to invest in human resources and AI is no exception. Here, there are in fact two options for a company. It can either decide to outsource these activities to a specialised provider or build-up capabilities in-house. Outsourcing offers advantages such as lower initial costs due to the redundancy of hiring experts and setting up pilot projects, substantial expertise and the chance to focus on core activities. However, AI is expected to be an inevitable part of a manufacturers value chain sooner than later. Hence, developing knowledge and keeping this expertise in-house, might be a major advantage over competitors securing independency and a lower dependency on suppliers (Harvard Business Review 2019). These are all strategic decisions that entail significant consequences. This results in an additional success factor for AI implementation that is top-management sponsorship and promotion. Without it, AI often remains a niche test object, and the relevance of AI pilot projects means they need to have management support, that also helps in in budgeting decisions. The fulfilment of these prerequisites increases the chance of success. But even then, AI has not provided any value yet. That is why managers must undertake a difficult balancing act. It is inevitable to outline the disruptive potential of AI for the manufacturing industry and the urgency not to fall behind. But it is also important to keep expectations realistic. As stated in the literature review and the SWOT analysis, opportunities and examples of applications are manifold and impressive. But AI, as most technologies, will not instantly turn a company upside down. Therefore, an optimistic, yet realistic horizon of expectations must be established.

What does that mean in terms of applying AI to a business project? How can a project manager ignite enthusiasm and prevent early dissatisfaction? A key component for this is to start with a so-called MVP, a minimum viable product. Depending on the project, this is a product with very basic features just enough to get further feedback from testing and eventually customer interaction. In contrary to a fully developed solution it is less expensive and takes less time to build, so one can quickly determine feasibility and where improvements are needed. Starting with the biggest and most difficult projects rarely works, especially when using a technology that is new to a company (IBM 2018). Building an MVP also means developing KPIs, key performing indicators, to measure whether the goals have been met or not. As always, these KPIs optimally should be smart, meaning specific, measurable, achievable, realistic and time framed. It helps to reduce subjective intuition, but objectively determine if the project should be continued. Furthermore, it is crucial in building trust among the workforce when they see that AI has measurable impact. Once these conditions are fulfilled, managers should try to implement a fully developed version as soon as possible and scale it quickly. Scaling is necessary to take full advantage and in today´s world, a currently new product might be obsolete in a short period of time. These steps should help to have a solid idea of how to successfully implement artificial intelligence in a meaningful way and achieve impact. The analysis in the prior chapters and the literature review has shown that there are strategies that seem to be beneficial for AI implementation. Furthermore, managers can choose an approach that is suitable to the needs of the company. For instance, they can aim at establishing alliances with partners or even competitors. Daimler and BMW show how fierce rivals can establish a partnership to join forces in reducing the technological lead of other competitors (Financial Times 2019a). The example of Novartis and Microsoft (*Appendix 11*) even underlines that two companies from fundamentally different industries can benefit from a partnership. For firms that do not establish such ties, it could be worthwhile to develop the necessary know-how inhouse and found a centre of excellence where all initiatives and projects are bundled and supervised. Also, data can be aggregated, and AI strategies be orchestrated altogether. To be able to go this way, a company must hire or already have experts that can develop a CoE and execute projects.

The analysis of the strengths and weaknesses of AI, as well as the future challenges of manufacturing in the literature review chapter, has further clarified that managers can expect significant support from AI in optimising their operations and driving efficiency, eventually leading to the smart factory in the future. Error detection in industrial components and fraud detection are other areas of application that will see greatly improved results with the diffusion of AI. Particularly for research-intensive manufacturers, AI can help in enhancing R&D. For managers, tasked with applying and developing AI, there are hurdles e.g. balancing the expectations, that are essential. Too much hype is disadvantageous since expectations quickly outgrow realistic goals, and dissatisfaction will follow soon after. However, it is needed to establish a sense of enthusiasm and necessity. Because neglecting AI is surely the worst mistake that can be done about it. The analysis has shown the outstanding potential and most likely, firms that fall too far behind will have a hard time catching up (McKinsey 2019a). Further it is recommendable to include the employees that might be sceptical about AI and to support a culture in which new technologies are treated as opportunities rather than threats. This can be done by involving people, transparently explaining the usage and implications, thus reducing concerns. Finally, managers have to make sure not only the people are ready but also the data. Large data sets are needed for AI applications and data that is labelled and not biased, since the implications of non-objective, discriminatory data have been thoroughly explained beforehand.

5. Conclusion

Based on the analysis in the prior chapters and the findings from the literature review there are several conclusions that can be drawn. AI is very likely to unfold significant influence upon the manufacturing sector. This will dramatically change the sector in the upcoming years and the time to act for manufacturers is now. Despite the given opportunities of AI, managers should address the challenges such as providing relevant, objective data in sufficiently large sets, dealing with ethical questions, hiring and training experts and improving IT security pre-emptively. For the implementation of AI, it is inevitable to ensure top-management support and to involve the employees, if needed even establishing a culture that embraces the change rather than repelling it. The greatest opportunities lie in error detection, pattern recognition and predictive maintenance. However, depending on the company there can be several other benefits that provide customer value or enhance profitability. To facilitate AI implementation managers should define KPIs, focus on building an MVP quickly and develop a roll-out plan to scale quickly. Under the assumption that these conditions are met, managers in European manufacturers have a good chance of not only implementing AI successfully but to drive technological progress and eventually build up new core competencies that can be the source of future competitive advantage.

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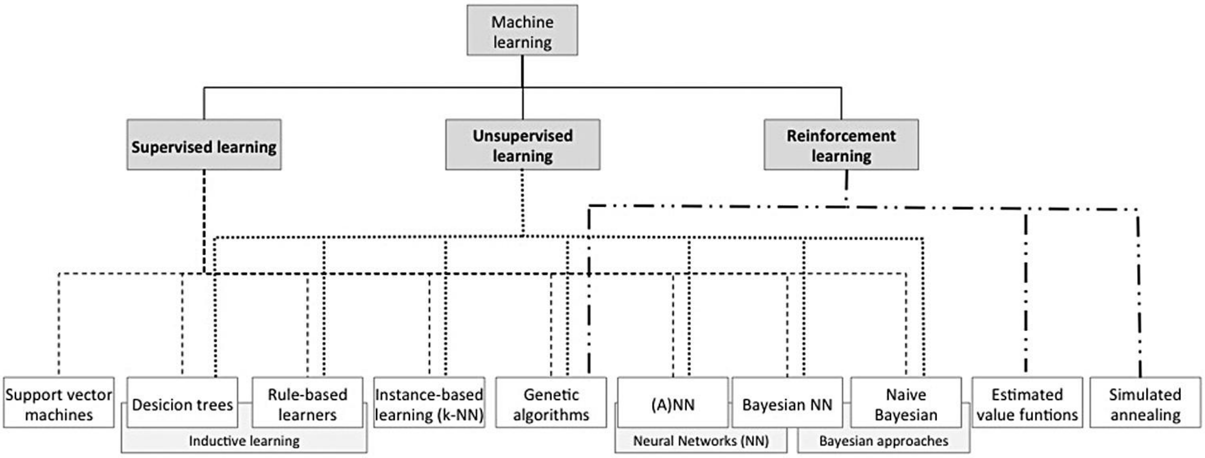
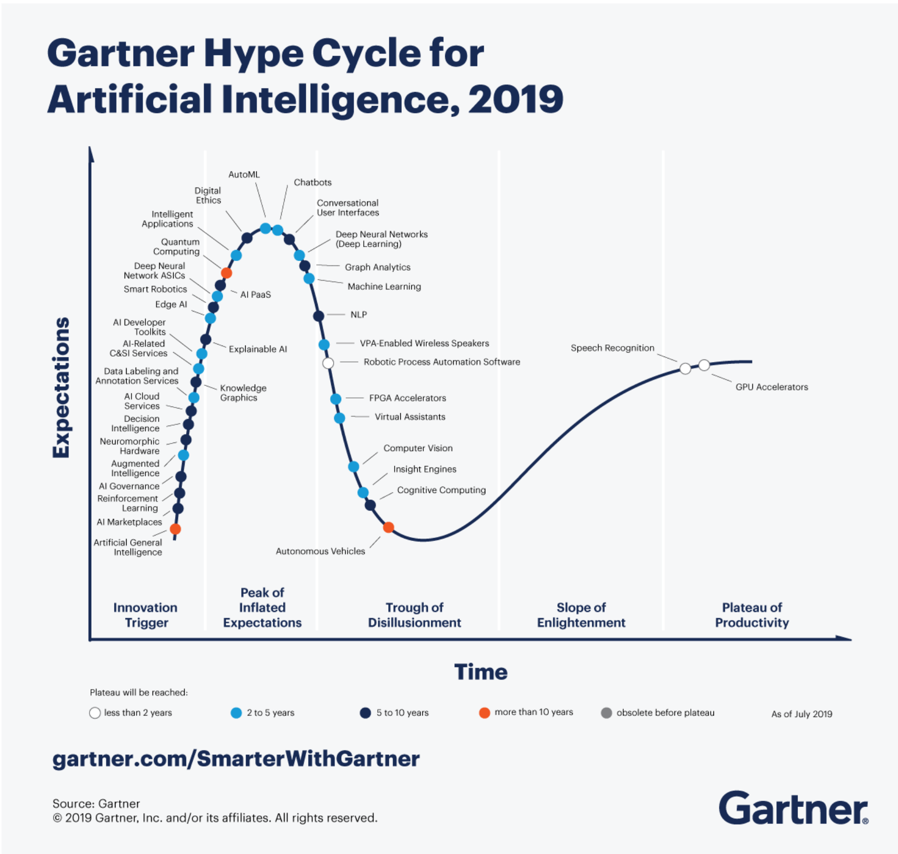
6. Appendix

Appendix 1: Overview of machine learning techniques



(Wuest et al. 2016)

Appendix 2: The Gartner Hype Cycle for artificial intelligence

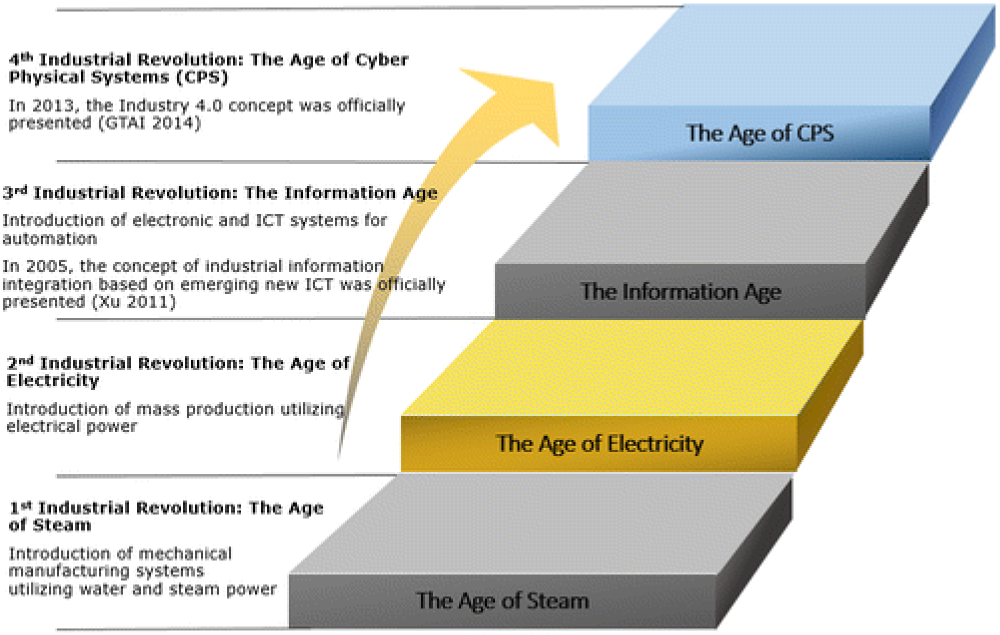


(Gartner Inc. 2019)

Appendix 3: The United States are technologically ahead in most AI applications

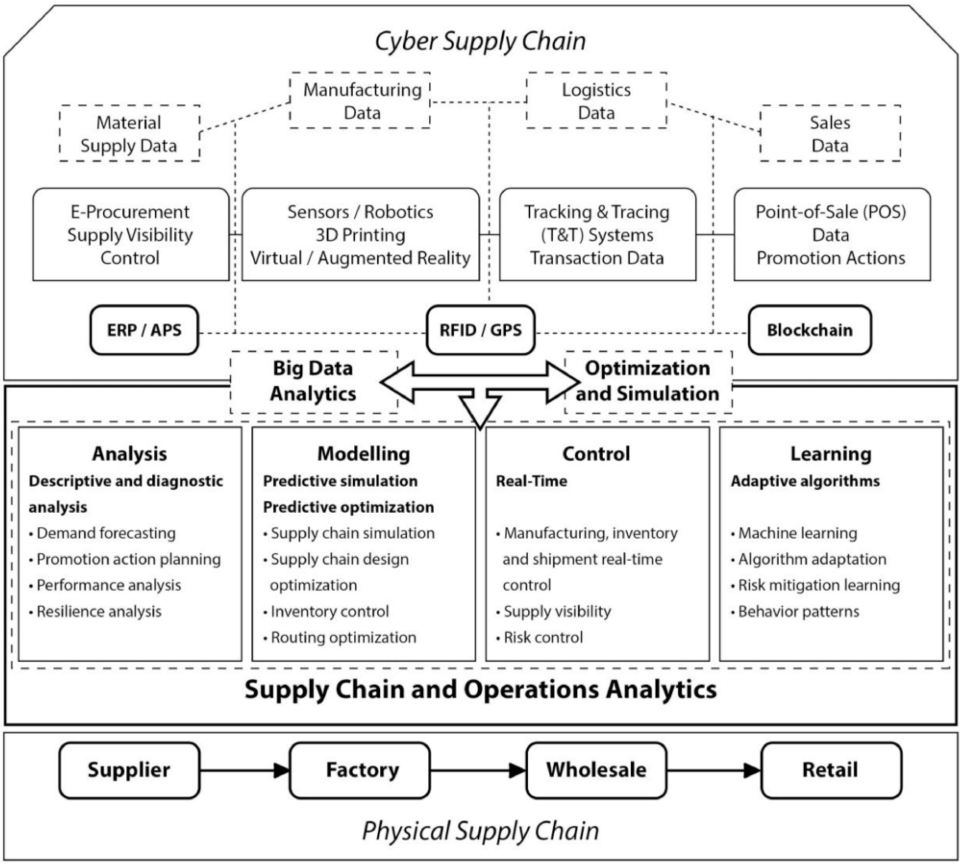
(McKinsey 2019b, 12)

Appendix 4: The 4th industrial revolution



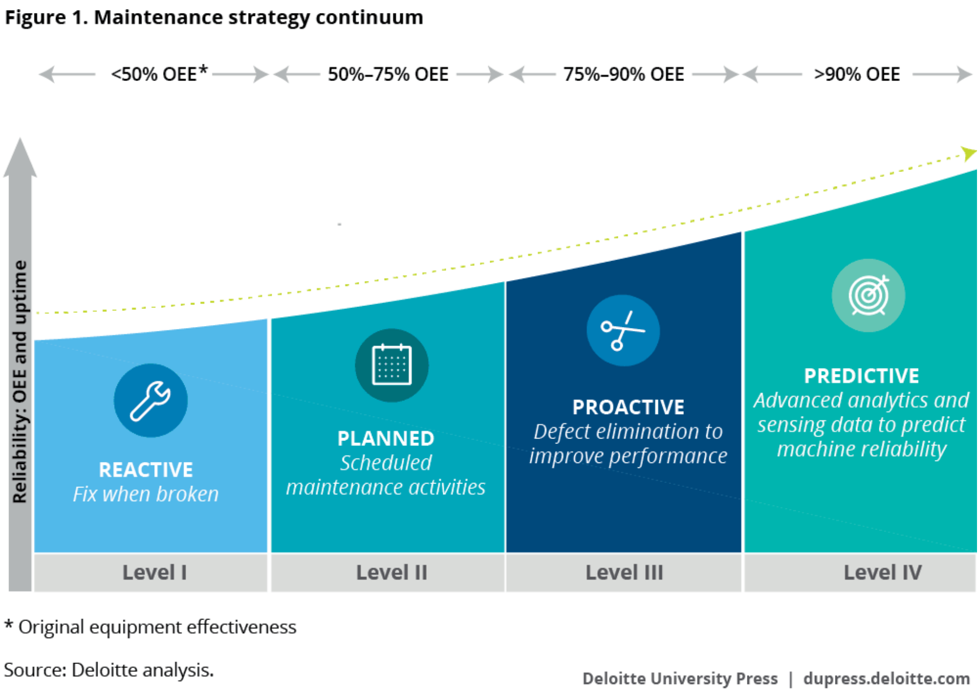
(Xu, Xu, and Li 2018)

Appendix 5: The supply chain of the future linking the physical and the cyber space



(Panetto et al. 2019)

Appendix 6: The impact of predictive maintenance strategies

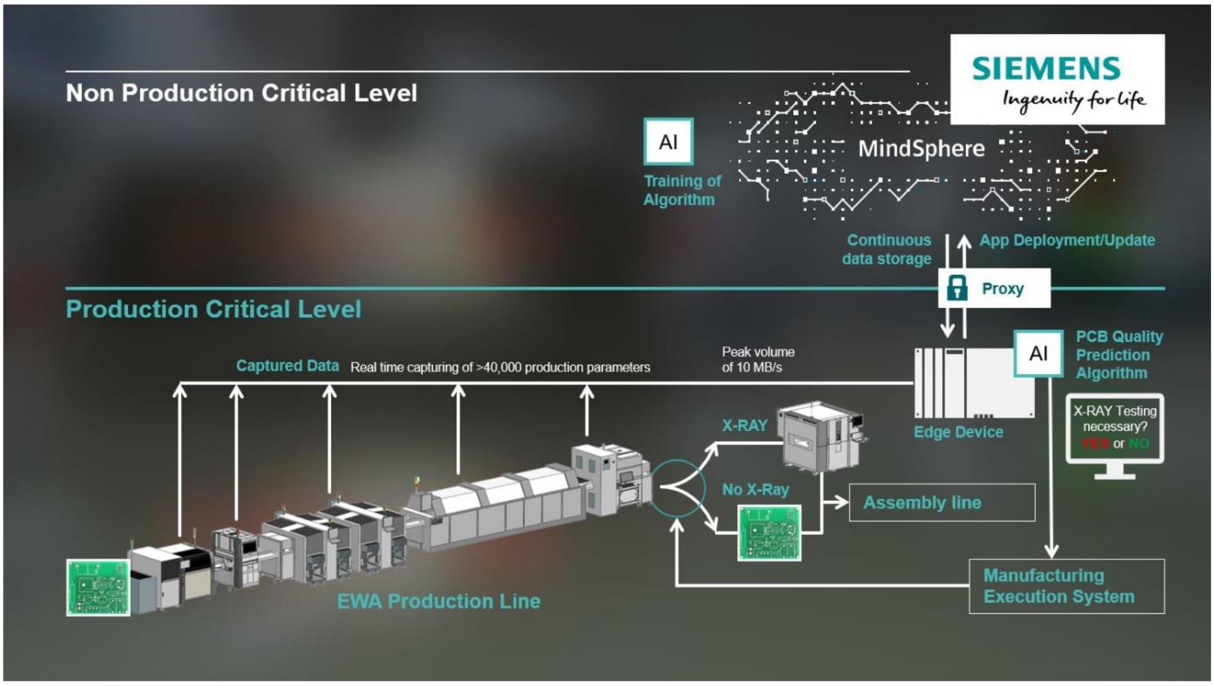


(Deloitte analytics)

Appendix 7: Further information about the Siemens AG and its initiatives regarding AI and digitalisation

The Siemens AG is the largest industrial manufacturing conglomerate in Europe and one of the most famous German companies with approximately 385.000 employees and €83bn in revenue. It was founded in 1847 and has since then managed to maintain its heritage as an inventor that was the first to present many new and unconventional innovations. This explains the tremendous importance the company sees in artificial intelligence when CEO Joe Kaeser says: "This seamless integration of the virtual and the physical worlds in so-called cyber-physical systems eclipses everything that has happened in industry so far" (Kaeser 2018). In that sense, it is not surprising that there are currently more than 450 individual AI-related projects at Siemens (Barnard 2019). It ranks number 11 worldwide on AI patent applications with more than 3500 according to the WIPO (WIPO 2019, 60). Furthermore, Siemens invests heavily in software companies to change from industrial giant to a modern technology leader. From 2007-2017 more than $10bn of investments were undertaken in acquisitions in the U.S. to drive digital transformation. The latest acquisition was Oregon based Mentor graphics that offers electronic design automation products and services for electrical engineering and electronics for $4.5bn dollars (Martini and Sachse 2017). But what is the impact that advanced technologies in general and artificial intelligence in particular have on their daily operations? (See chapter 173.2.1)

Appendix 8: Introduction of AI into Siemens assembly line operations

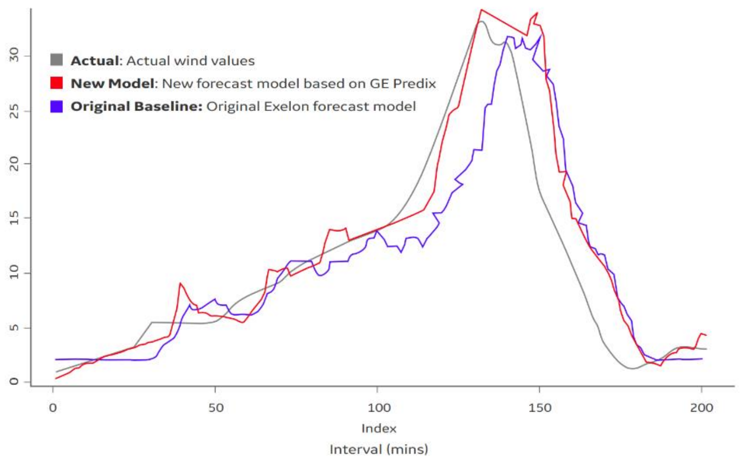


(Siemens AG 2019)

Appendix 9: Overview of General Electrics and Exelons business activities

General Electric belongs to the most successful manufacturers worldwide. The U.S. company operates in almost all countries and is a major rival in many projects of Siemens, that was discussed in the previous subchapter. Not only Siemens, but also GE recognises the importance of staying ahead of the competition in terms of innovation and the usage of modern technologies. Exemplary for their efforts to incorporate data analytics and artificial intelligence into their operations and portfolio of products and services is the following case study with Exelon, a wind energy producer. It is a Fortune 100 company and the largest energy provider in the United States. In 2018, they reported revenues of $35.9 billion with an employee base of around 33,400 (Exelon Corporation 2019). Their wind energy business unit is still significantly smaller than conventional and nuclear energy production. Nonetheless, Exelon operates 40 wind projects that generate 1500 megawatts (Exelon Corporation Wind). One megawatt is generally enough to power around 650 houses so that the wind business unit is capable of providing 975.000 houses with energy (Hagadone 2015). Nonetheless, Exelon faces major challenges in forecasting their power supply accurately. This information is necessary for the providers to match with the demand. Only if Exelon manages to determine the wind energy, they can generate meticulously in advance they receive the full revenues. Additional energy that could have been provided but has not been predicted early enough too often cannot be used anymore and thus does not yield any profit. To see how Exelon sought to overcome this challenge in cooperation with General Electric please see 3.2.2.

Appendix 10: Comparison of wind forecasting models at Exelon with and without AI support



GE model forecast compared with actual generation and original baseline forecast

(General Electric 2018b)

Appendix 11: Other cross-industry examples for best practices for AI usage

Novartis & Microsoft AI partnership

The development of new drugs is one of the most lengthy and costly processes in business. It takes an average of 14 years and $2.5bn from the initial research phase until the drug is allowed for application to humans. Clearly, there is a lot of potential not only to save costs for pharma companies that suffer from high risks that sunk costs cannot be recovered if the drug turns out to be ineffective but also to reduce lead times significantly. Therefore, the Swiss pharma giant Novartis joins forces with Microsoft, a leader in artificial intelligence, to realise benefits for its operations. A five-year partnership has been signed and Novartis CEO Vasant Narasimhan says tangible results should be seen within a period of three years. The goals include the introduction and application of AI to all areas of Novartis, research and development as well as finance and manufacturing. Particular importance rests on the use of deep learning for the development of new treatments in order to improve speed and facilitate the accuracy of medicine for certain persona. One of the major obstacles in healthcare is the different reaction of humans to specific treatments. Personalising the development could thus lead to a much higher rate in which the patient reacts positively to the medication and decrease costs for Novartis that in turn would even allow production of drugs for smaller subgroups that have formerly been unprofitable to serve (Financial Times 2019b).

Siemens & Órbita bike sharing in Lisbon

In Lisbon Siemens and Órbita have been established a partnership for bike sharing. They already introduced over 1400 bikes of which two thirds are electrically powered. For this purpose, Siemens developed a special application called Operide. Its goal is to improve the eBike fleet performance with an operator support system based on artificial intelligence. It constantly collects real-time data and connects it to external information such as data about important events taking place in Lisbon, traffic and public transporation data as well as weather forecasts. The difficulty of managing such a network is to balance demand and make sure that there are always enough bikes available wherever the customers need it. Simultaneously, not only enough bikes but also a sufficient number of free docks have to be ensured so that the customers can lock the bike again. A particularly challenging task that becomes almost impossible without the appropriate use of data and analytics. Siemens and Órbita therefore jointly developed an AI-driven operating system that can predict the status of bikes and stations taking into account the aforementioned factors among several others. It further helps the operator on where bikes shortages can potentially occur so that the network can be balanced for an optimal degree of efficiency and customer satisfaction (Waltinger 2018, 43–50).