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Artificial Intelligence in Supply Chains

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Abstract

Artificial Intelligence (AI) is set to drive a new wave of digital disruption that redefines industries and propels unprecedented levels of innovation. As one of the most data-rich environments within companies, supply chains create significant opportunities to harness the benefits of AI. This study follows a qualitative research approach that aims to explore the impacts and applications of AI within the supply chain. It was found that AI creates a broad spectrum of use cases that drive efficiency, automation and customer-centricity across all components of the end-to-end supply chain.

KEYWORDS

Artificial Intelligence, Supply Chain, Supply Chain Management

Table of Content

List of Figures

List of Tables

List of Abbreviations & Glossary

AI	Artificial Intelligence
AMR	Autonomous Mobile Robots
ANN	Artificial Neural Network
ASR	Automatic Speech Recognition
AV	Autonomous Vehicle
BOA	Back Office Automation
DL	Deep Learning
ML	Machine Learning
NLP	Natural Language Processing
NLU	Natural Language Understanding
RPA	Robotic Process Automation
SC	Supply Chain
SCM	Supply Chain Management

1. Introduction

"Artificial Intelligence is probably the most important thing humanity has ever worked on. It is more profound than electricity or fire." – Sundar Pichai (CEO of Google).

This quote emphasizes that we are facing another transformational time period. Analogous to the agricultural and industrial revolution, the digital revolution is having a profound impact on many facets of our society (Gesing et al. 2018). At the center of this revolution is Artificial Intelligence (AI), which has expanded beyond research labs to become omnipresent in our everyday lives. Already today, AI-driven applications such as speaking and perceiving devices, smart robots or self-driving cars are starting to deliver real-life business and consumer benefits.

In the context of the data-driven economy and the technology's disruptive impact, companies need to reevaluate all aspect of their organization. This includes what many consider as the backbone of every company: the supply chain (SC). According to McKinsey (2018a), it is one of the business functions, in which AI can create the most value. To harness this enormous potential, SC managers need to understand AI's possible use cases, including the benefits and risks that come along with it. The objective of this work is to facilitate this understanding by taking a practical approach, in which potential applications of AI within the SC context are presented and assessed.

The first part of this work aims to establish a fundamental understanding of AI by analyzing its general context. This includes the examination of AI's definition, key branches and accelerating factors. Subsequently, the analysis of use cases across various sectors and companies will help to illustrate the technology and its potentials. A comparison of AI's benefits and risks, as well as a future outlook, will conclude the first part. The second part will build upon these insights and examine the technology in the context of SCs. The definition of generic SC components will serve as the basis for the subsequent analysis of AI use cases within the field. Finally, the last part leverages qualitative expert interviews to assess the overall impact, benefits, risks and future implications of AI on the respective building blocks of the SC.

2. Research Methodology

This paper contributes to a joint research project of exploring how major digital technologies are affecting SCs by focusing on the impact that AI has on the field. Essentially, this study is guided by the subsequent research questions:

(1) What lies behind the term Artificial Intelligence and where does it apply?

(2) What are the impacts and applications of Artificial Intelligence within the supply chain?

(3) What are the major benefits and risks of Artificial Intelligence within the supply chain?

To develop a comprehensive answer to these questions a qualitative research methodology was chosen for this study. This is because the research questions are exploratory by nature and cannot be answered through quantitative methods (Stebbins 2001). Moreover, a qualitative approach should be preferred when examining a subject that does not aim to find one single "truth" but instead seeks to investigate potentials of an uncertain future (Sargeant and Sullivan 2011).

At first, secondary research is conducted to develop a fundamental understanding of the technology's general and SC context. In the next step, the findings will be complemented by primary research in the form of five expert interviews. This will help to gain various insider perspectives on the subject from experts that work at the intersection of AI and SCs (see appendix A). However, even though this approach is appropriate to gain an in-depth understanding of the subject, it is important to mention that the answers are based on a small-scale sample that is not statistically representative. Moreover, as the qualitative data relies on individual perspectives, it cannot be entirely objective. The expert interviews will follow a semi-structured approach, that uses a predefined set of open-ended questions as a reference but leaves room to extend the conversation beyond those if necessary (Patton 2002). The following topics will serve as guidance for the expert interview questions: a) how AI is changing SCs from an organizational perspective and the major trends at present; b) the current and future applications of AI in SCs; c) areas of SCs where AI will have the biggest and least impact on and where it will be more and less useful; d) the benefits and risks of applying AI in SCs; e) the hurdles of adopting AI in SCs and how to overcome them; f) the impact of AI on the workforce.

To conduct the proposed methodology, the study relies on primary and secondary data sources. While the primary data is collected through the expert interviews, the secondary data is based on published scientific papers such as journals or books as well as reports from major consultancy companies.

3. Understanding Artificial Intelligence

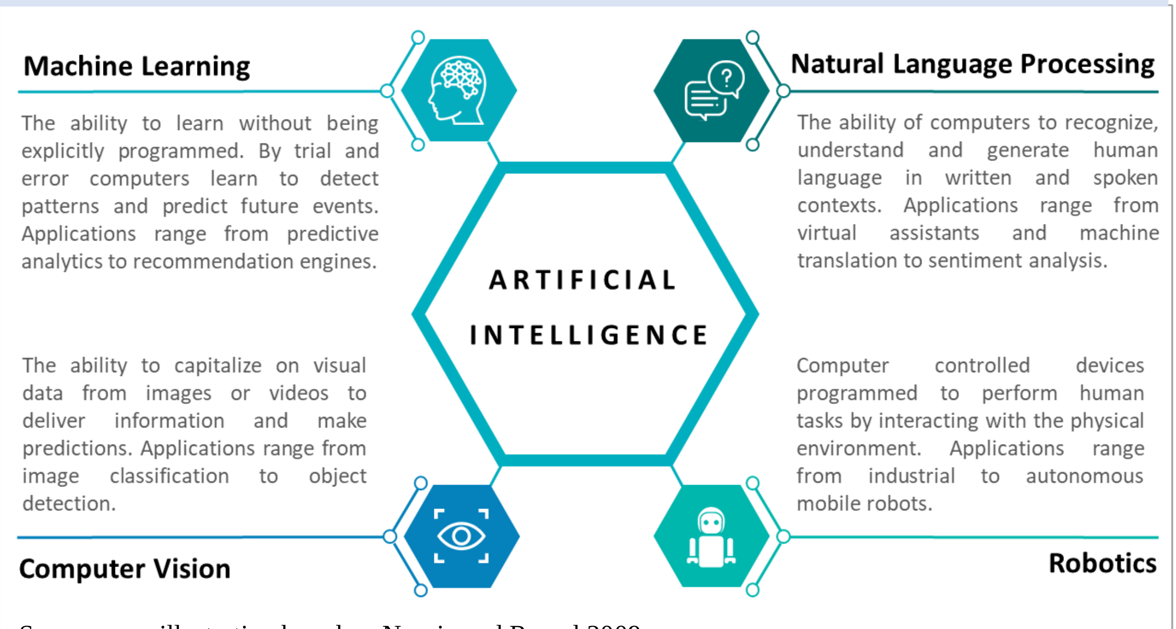
3.1. Defining Artificial Intelligence

Although the term AI is deeply embedded in today's academic and corporate environment, it still lacks a distinct and generally accepted definition. This is mainly due to the interdisciplinary and complex nature of the field. The term "Artificial Intelligence" was initially coined by the computer scientist John McCarthy who organized the first academic conference on the subject at Dartmouth College in 1956. The conference is recognized as the birthplace of AI as an academic discipline, in which McCarthy described it as the study of "machines simulating human intelligence" (McCarthy et al. 1955). For the purpose of this research, we will build upon this idea and define AI as an area of Computer Science that deals with the development of systems, able to carry out cognitive functions, which we typically identify with human minds. This involves fundamental abilities such as learning, understanding natural language, perception or reasoning (McKinsey 2018). The extent to which AI systems perform these abilities distinguishes Narrow (or "Weak") from General (or "Strong") AI. Narrow AI systems only use certain aspects of human cognition and focus on a particular problem they have been trained to solve, as opposed to General AI systems, which are capable of applying the full spectrum of cognitive functions (like humans) to solve any task they are confronted with. Since all current AI applications are designed around specific problems, and general AI has yet to be accomplished, the term "AI" will subsequently always refer to the narrow version of the technology. Moreover, AI should not be regarded as a single technology but as an umbrella term for a variety of technological branches, that are often interrelated and build on top of each other.

3.2. Branches of Artificial Intelligence

In this chapter, we will present some of the key technology branches of AI, that each apply particular cognitive abilities such as learning, understanding natural language or perception. It is important to mention that these branches are not exhaustive but instead have been the focus of AI research and business applications in recent years (Stanford 2016). These include Machine Learning (ML), Natural Language Processing (NLP), Computer Vision and Robotics (see Figure 1 for the respective definitions).

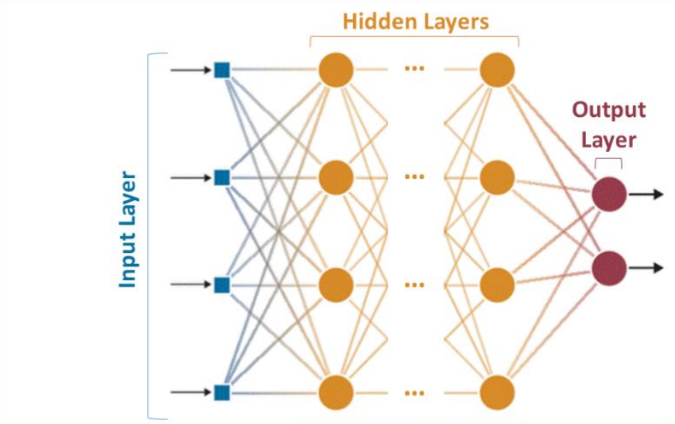
Figure 1: Key Branches of Artificial Intelligence



Source: own illustration based on Norvig and Russel 2009

Some branches focus on processing external information, such as NLP and Computer Vision; some use information to act upon it, such as Robotics; and others use information to learn from it, such as ML (McKinsey 2017). However, for many AI applications these branches often mutually reinforce and complement each other. For instance, ML models are the core technology for many advanced NLP, Computer Vision, and Robotics applications. Especially Deep Learning (DL), which is a subfield of ML, has significantly contributed to the advent of many AI applications in recent years. DL uses deep Artificial Neural Networks (ANN) to resemble the operation principle of the human brain (Deng and Dong 2014). Similar to how relations between neurons in the brain adjust and improve through experience, connections within the ANN are strengthened or weakened as new data inputs are received by the network (Gesing et al. 2018). By reinforcing connections that achieve good results and weakening the ones that lead to inferior results, the output quality gradually improves with every learning cycle. Figure 2 simplifies the structure and functionality of a deep ANN for two different problems types. ANNs consist of connected neurons, arranged in a series of layers. They are capable of processing all forms of input data such as pixel, audio or textual data (Hecker et al. 2017). In a popular case for computer vision, namely the recognition of faces, the input layers introduce the pixel data into the network. Hidden layers then break down the visual components to identify the distinctive features of a certain face. At the output layer, the ANN predicts whether the face belongs to Person X, Y or Z. As mentioned above, the prediction accuracy increases with every learning iteration. A deep ANN with numerous hidden layers can solve more complex problems as it can identify increasingly subtle features of the input data.

Figure 2: Functionality of a deep Neural Network



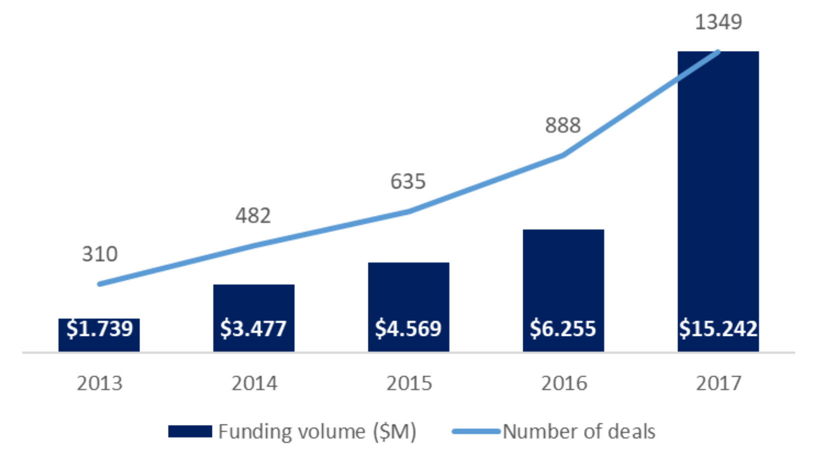
Problem Type	Inputs	Hidden Layers	Output
Face Recognition	Pictures	Person? Face? Gender? Age? Eye color?	Is it Person X? (%)
Online Ad Placement	Social Media browsing data	Demographics? Interests? Browsing history meta data	Will you click? (%)

Source: own illustration based on Gesing 2018

3.3. Factors accelerating Artificial Intelligence

Since the “birth” of AI in 1956, the field has gone through various cycles of excitement and hype, followed by so-called “AI winters” – periods characterized by declining interest, research, and funding (Norvig and Russel 2009). The two major AI winters in the 1970s and 1990s can be ascribed to AI not being able to live up to its hype, mainly due to the technological limitations during these periods (see appendix B.1.). Current AI activities suggest that we are again in an “AI spring”, with the technology being embedded in our everyday lives. This becomes obvious when looking at the increase in equity funding of AI startups in recent years (see Figure 3). The annual funding volume in 2017 ($15,25B) was nine times higher than in 2013 ($1,73B).

Figure 3: Equity Funding of AI Startups worldwide, 2013-17



Source: own illustration based on CB Insights 2018

Simultaneously, there has been a ninefold increase in the number of annually published AI research papers since 1996 (Scopus 2017). According to Gesing et al. (2018) and McKinsey (2018a), the current acceleration of AI can be ascribed to the convergence of three technological developments: increased computational power, access to big data and algorithmic advancements. As computer processing-intense technology, AI has benefited from the exponential growth in chip efficiency suggested by Moore’s law as well as the use of graphical (GPUs) instead of computer processing units (CPUs). GPUs allow for large parallel workloads, significantly reducing the time required to train AI algorithms (Gesing et al. 2018). Secondly, the proliferation of “big data” regarding volume, velocity, and variety is a crucial part of AI’s success. Traditional computing techniques were not able to process such large and often unstructured data inputs. However, advancements in DL algorithms and ANN (see chapter 3.2) have enabled AI systems to detect patterns and correlations in very complex datasets (McKinsey 2018).

3.4. Current Industry Applications of Artificial Intelligence

Although AI still has to live up to most of its promises, it has diffused into a variety of industries, making it difficult not to interact with the technology on a regular basis. Naturally, certain sectors apply emerging technologies quicker and to a greater extent than others. Table 1 shows that the same is true for AI by categorizing sectors based on their AI adoption score and presenting common uses cases at present. The score is a McKinsey (2017) developed measure that considers the AI assets, usage and labor of the respective sector.

Table 1: Artificial Intelligence Adoption and Use Cases by Sector

	Sector	AI spend next 3 years (% change)	Examples of current Use Cases
High AI Adoption*	High tech and telecom	11%	· Virtual assistants | · Personalized marketing
	Automotive and assembly	5%	· Autonomous vehicles | · Smart robotics
	Financial services	12%	· Robo advisors | · Fraud detection
	Resources and utilities	5%	· Smart grids | · Optimized energy efficiency
Medium AI Adoption*	Media and entertainment	4%	· Personalized content | · Automized editing
	Consumer packaged goods	4%	· Automated shelf mgmt. | · Inventory mgmt.
	Transportation and logistics	8%	· Predictive demand planning | · Route optimization
	Retail	5%	· Product recommendations | · PoS robots
Low AI Adoption*	Education	3%	· Intelligent tutoring systems | · Learning analytics
	Professional services	6%	· AI consultancy | · Automized document review
	Health care	6%	· Medical image diagnonsis | · Drug discovery
	Construction	1%	· Planning and design | · Risk mitigation
	Travel and tourism	7%	· Recommendation engines | · Virtual travel assistants

*Based on AI assets, AI usage and AI-enabled labor

Source: own table based on McKinsey 2017; Stanford 2016; PwC 2018

Tech companies such as Google and Amazon demonstrate the highest level of AI adoption, driven by investments in virtual assistants and personalized marketing. The sector is followed by automotive and assembly that already implemented smart robotic applications at scale and currently invests heavily in autonomous driving. Moreover, sectors with high AI adoption tend to increase their AI investment more within the next three years (McKinsey 2017). It becomes evident that the applications for AI or very broad and diverse. In the following, we will examine three company use cases from different industries (see table 2).

Table 2: Artificial Intelligence Use Cases and Impact by Company

Company	AI Branch	Use Case	(Potential) Impact
Amazon	Deep Learning; Natural Language Processing;	Voice-based assistant Alexa	• Human-like comprehension ability • Able to perform >40k "skills"
Waymo	Deep Learning; Robotics; Computer Vision	Autonomous Vehicles	• Cost reduction • Fewer accidents • Lower emissions
Enlitic	Computer Vision; Deep Learning	Medical Imaging	• Increased diagnostic accuracy • Increased doctor productivity

Source: Author

Voice-based Assistants

One of the fastest growing real-life applications of AI are voice-based assistants, particularly in the form of smart home speakers. As the market leader in this segment, Amazon deploys the virtual assistant “Alexa” in its smart home speaker line “Echo”. Alexa uses a series of NLP models, namely, automatic speech recognition (ASR) and natural language understanding (NLU). ASR is used to detect the user’s spoken words and convert them into text, while NLU is used to interpret the intention behind them. Alexa then utilizes DL architecture to match the intent with one of its over 40,000 skills, which refer to the number of things Alexa is capable of doing (e.g. streaming music, sending messages, ordering products) (Kim et al. 2018). Moreover, Alexa learns the user’s voice and adjusts to its cadence over time (see Appendix 1 for the schematics of Alexa’s request and response flow). The training of voice-based assistants like Alexa with DL algorithms has significantly improved ASR performance, with the first devices reaching a lower word error rate than humans (Google Developers 2017).

Autonomous Vehicles

The acceleration of AI has enabled the technology to solve increasingly complex problems. One of them is the development of autonomous vehicles (AVs). To outperform human drivers, AVs need to perceive and predict changes in dynamic driving situations – something that is not achievable without DL technology (Gesing et al. 2018). Real-time environmental data generated by sensors, cameras and radars and historical driving data serve as input for the DL algorithm. The algorithm processes the data and enables AVs to detect objects, interpret road signs and maneuver through traffic (Gesing et al. 2018) (see Appendix 2 for the schematics of the learning-action cycle in AVs). Moreover, AVs are equipped with AI-based functions such as ASR, eye tracking, gesture controls and safety systems (Gadam 2018). Most of the AVs developed today are research projects of traditional car manufacturers or technology companies. However, the AV company Waymo, whose autonomous fleet has test-driven more than 10 million miles, is the first company to launch a commercial AV service in December 2018 in Phoenix, Arizona (Waymo 2018). The main rationales behind the development of AVs are convenience, cost efficiency, lower emissions, and increased safety.

Medical Diagnosis

As AI unfolds across industries, the technology will also impact public services. This becomes particularly evident in health care sector, as doctors spend the majority of their time crunching through patient data. Especially medical images, which account for 90% of today's medical data, are difficult and time-consuming to analyze (IBM 2016). A false diagnosis can have severe consequences, as every second to third cancer could be cured if detected early enough (WHO 2018). Enlitic is a start-up that leverages DL algorithms to improve the accuracy of medical diagnosis and doctor productivity. The learning process for medical imaging is similar to the face recognition example described earlier, as both classify as a computer vision problem. A set of medical images serves as basis for the DL algorithm to learn critical features related to a certain cancer type. Based on that learning the algorithm predicts the cancer likelihood of the patient. According to Enlitic, their DL algorithm can interpret a medical image up to 10,000 times faster and predict lung cancer 50 percent more accurately than human radiologists (Enlitic 2018). This enables doctors to interact with patients more frequently and focus on other complex medical decisions.

3.5. Benefits and Risks of Artificial Intelligence

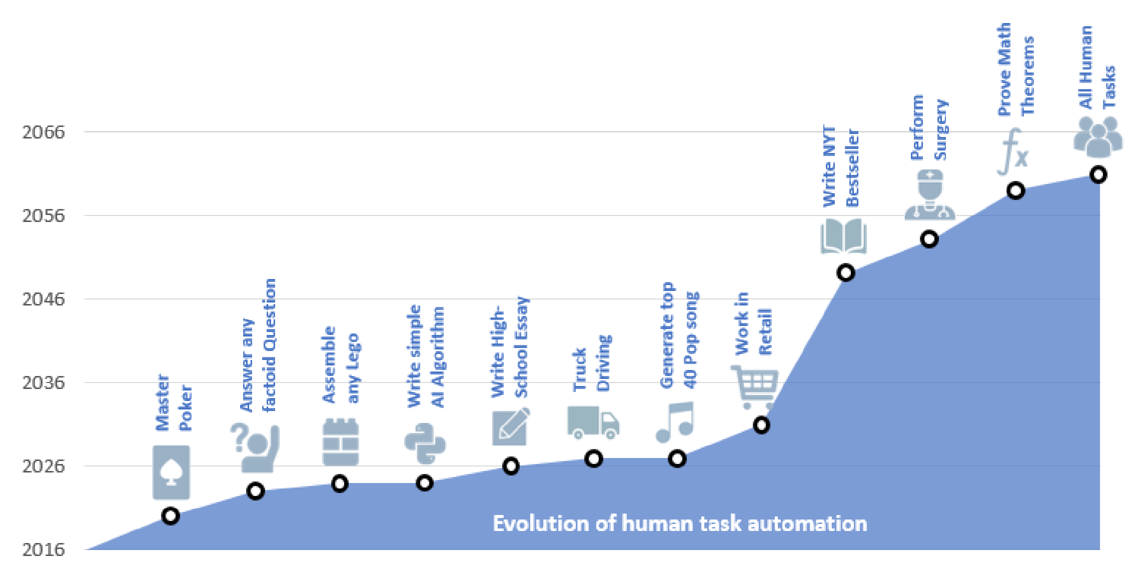
The significant progress of AI has brought up many controversial debates about the benefits and risks that come along with it. The economic gains driven by automation, amplification of the workforce and dissemination of innovation are regarded as the main benefits of the technology (European Commission 2017). It is estimated that by taking over mundane and complex business processes, while at the same time complementing and enhancing tasks of the existing workforce, AI can increase the productivity of labor in developed countries of up to 40 percent (Purdy and Daugherty 2018). Moreover, AI is fueling innovations and new business models, such as AVs and drones, which themselves will create new business opportunities. Consumers benefit from more personalized goods and services because AI enables companies to leverage data insights about customer preferences. Finally, the technology can help to solve some of the world's most serious problems. For instance, AI can be used to predict natural disasters more accurately and detect cancer cells in patients (see medical diagnosis use case).

On the other hand, the major risks are mass unemployment, the concentration of power, bias, ethics and safety of AI. Frey and Osborne (2013) estimated that roughly half of all American jobs are vulnerable to automation within the next two decades. Although the technology is also expected to create new jobs, it forces millions of lower-skilled workers to acquire new skill sets to stay relevant on the job market. This increases the discrepancy between the ones that have the technological know-how and the ones that do not. Currently, the most important AI resources, namely data and talent, are already highly concentrated among a few tech companies in China and the United States. It is estimated that 70 percent of all economic impact generated by AI and roughly 60 percent of the world's data will be distributed among these two countries until 2030 (PwC 2017; Economist 2018). This makes it difficult and costly for startups to achieve scale and compete with incumbents. Another major risk is the creation of biased AI systems. If algorithms are trained with faulty datasets, they are likely to make improper inferences. For example, an AI system with the goal to recruit new employees that is trained with data of companies where the majority of executives are male could wrongly infer that female candidates are not suitable for top management positions (Gryn and Rzeszucinski 2018). Regarding AI ethics and safety, concerns range from the technology being exploited for malicious purposes like cyberattacks to doomsday scenarios where a super intelligent AI that greatly outperforms humans in every cognitive function, becomes the predominant form of existence (Bostrom 2014).

3.6. Future of Artificial Intelligence

Although AI is already applied in a variety of industries, it is still in an early stage of its development. This becomes obvious when looking at the potential economic impact of AI. PwC (2017) forecasted that due to higher labor productivity and consumer demand AI could increase global GDP by 14 percent or nearly $16 trillion in 2030. However, the future impact of the technology cannot only be measured in economic terms. Since AI is defined as "machines exhibiting human intelligence", the evolution of the technology strongly depends on the variety and complexity of tasks it can perform better than humans. Grace et al. (2018) surveyed 352 AI Researchers from Oxford and Yale University about their predictions on when machines would outperform humans in various tasks (see Figure 4). According to the median estimates, AI will exceed human's ability in playing poker, assembling any Lego parts given the instructions and driving trucks in the next ten years (Grace et al. 2018). The tasks that machines can automate will be primarily mechanical at first and become more complex and creative over time. In 50 years AI could take on take on highly sophisticated tasks like writing a bestselling book, performing surgery or conducting research to prove mathematical theorems (Grace et al. 2018). Furthermore, the researchers assume a 50 percent chance of humans being outperformed by AI in all tasks by 2061 and of all jobs being automated by 2136. However, the study shows large deviations in the researchers' estimates and therefore lacks a clear consensus. This indicates that the future of AI is highly uncertain.

Figure 4: Median Estimates of Artificial Intelligence exceeding Human Performance



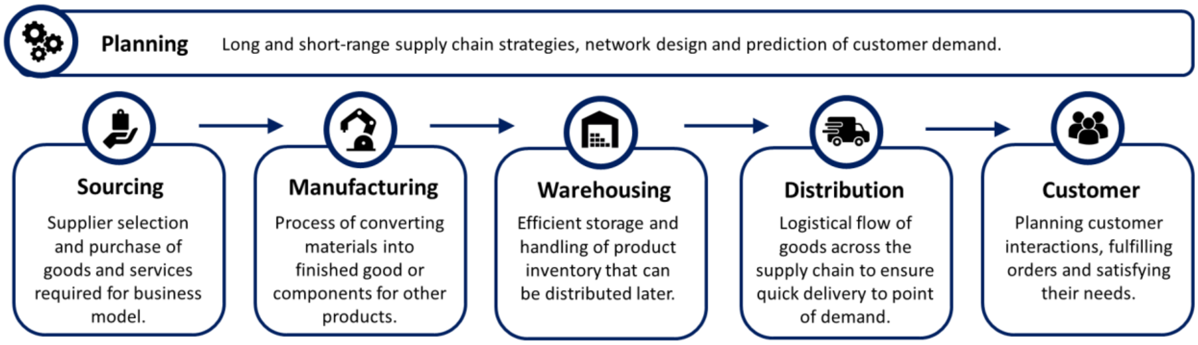
Source: Own illustration based on Grace et al. 2018 and CGF 2018

4. Artificial Intelligence in the Supply Chain Context

4.1. Defining Supply Chain Management

Before investigating the applications and impacts of AI within the SC, it is crucial to define Supply Chain Management (SCM). According to the CSCMP (2018), SCM comprises the management of the end to end flow of products, services and information from the point of origin to the point of consumption. Moreover, SCM takes on an integrative function, as it links key business areas and processes and facilitates the coordination between channel partners like suppliers, service providers and customers (CSCMP 2018). By assuring that key activities are performed timely and efficiently SCM is crucial to business success and fulfilling customers' needs. To be able to examine the impact of AI from a broad perspective, this study focuses on the six generic components of the end-to-end SC. These include the planning, sourcing, manufacturing, warehousing, distribution and the customer interface (see Figure 5).

Figure 5: Key Components of the end-to-end Supply Chain

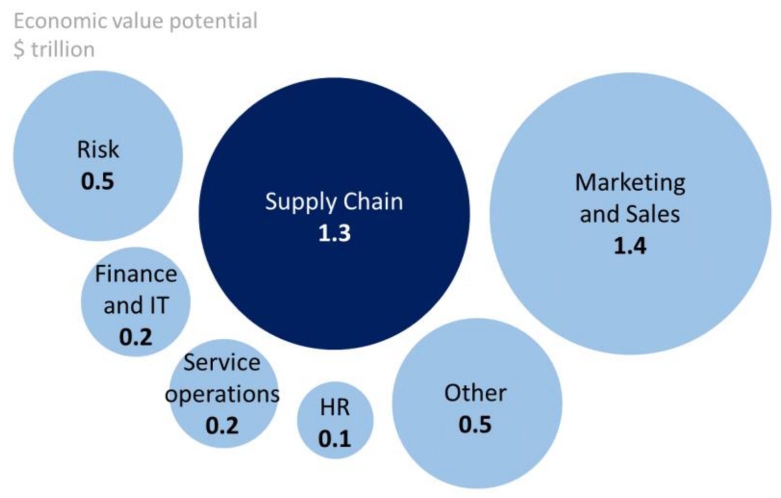


Source: Own illustration based on CSCMP 2018

4.2. Applicability of Artificial Intelligence within Supply Chains

To assess the applicability of AI within SC it is crucial to consider the conditions under which the technology proves beneficial. AI algorithms thrive by capitalizing on large datasets from a variety of sources, as they enable machines to derive unique insights and perform tasks better and more efficient than humans. The network-based architecture of modern SCs and the tremendous volumes of data they produce and derive from connected assets and devices across the SC seem to construct a natural framework for the scalability of AI (Gesing et al. 2018). In fact, the potential impact of AI on SCs is greater than on almost any other business area (see Figure 6). McKinsey (2018a) estimates that companies could extract between $1.3 and $2 trillion a year in economic value from utilizing AI in SCs. Much of

Figure 6: AI potential Value Creation in the next 20 Years



Source: Own illustration based on McKinsey 2018a that value is currently untapped because legacy SCM tools are overstrained by the mere volume, velocity and variety of data that characterizes modern SCs. Moreover, they often operate in functional silos, which leads to a lack of data access and visibility across the SC (Accenture 2017). At the same time, the ongoing globalization, increasing market volatility and rising consumer expectations add to the growing complexity of the economy. To cope with this complexity and ensure future competitiveness, SCs will need to leverage the available data for decision-making by embracing AI sooner or later (Accenture 2017).

4.3. Current Applications of Artificial Intelligence within Supply Chains

In chapter 4.3. we outlined that the diffusion of AI across industries and functions has led to a very broad field of application areas. Consequently, many companies have already or are planning to apply AI-based SC solutions. Table 3 lists the most widely discussed current and near future use cases of the technology considering the main components of the SC.

Table 3: Artificial Intelligence Use Cases in the end-to-end Supply Chain

Planning				
• Demand Forecasting	• Improved Risk Management	• Predictive Network Management		
Sourcing	**Manufacturing**	**Warehousing**	**Distribution**	**Customer**
• Intelligent Supplier Selection • Procurement Bots	• Predictive Maintenance • Collaborative Robots	• Vision-based Inventory Management • Intelligent Robotic Sorting	• Autonomous Fleet • Intelligent Route Optimization	• Virtual assistants • Product Recommen - dations
Back Office Operations				
• Streamlining support functions (e.g.: Finance, HR, IT) through intelligent RPA				

Source: Author

The use cases can be classified into four broad categories, namely those that capitalize on AI's ability to streamline back office operations (Back Office Automation), make predictions based on large and complex data sources (Predictive AI), power robots with conversational, visual and self-learning capabilities (Cognitive Robotics) and finally personalize customer and supplier touchpoints (Virtual Assistants).

4.3.1. Back Office Automation

The increasing complexity and competitiveness of global SCs put companies under pressure to operate in a cost-efficient manner. Simultaneously, back-office support functions such as accounting, finance, HR and IT are characterized by a large number of repetitive and meticulous tasks (Gesing et al. 2018). Here, back office automation (BOA) software can be used to improve cost efficiency, speed and precision. BOA is achieved by intelligent Robotic Process Automation (RPA), which refers to a form of RPA that is augmented by AI in the form of ML and NLP. While traditional RPA is used to automate rules-based transactional processes such as capturing or copying structured data, intelligent RPA enables systems to process unstructured data and self-improve over time (Gerbert et al. 2017).

A typical time-consuming and error-prone back-office process within SCs is the handling of invoices from a variety of suppliers. A company called Kryon Systems combines RPA software with computer vision and NLP to scan and verify (oftentimes unstructured) invoice data (Kryon 2018). Companies leveraging Kryon's technology can expect to save a significant amount of working time, pay suppliers faster, avoid late or false payment penalties and enable their workers to focus on more complex tasks like decision-making (see appendix B.3.)

4.3.2. Predictive AI

The influence of AI goes beyond the streamlining of back office processes. In fact, the technology's predictive power creates significant opportunities across the entire SC. The close matching of supply and demand through precise forecasting, reduced lead time and optimized inventory replenishment is crucial for high-performing SCs. However, multiple internal factors such as promotions, new product launches or distribution channels and external factors such as seasonality, politics or press coverage make it difficult for legacy systems to accurately predict consumer demand (McKinsey 2018). Here, predictive AI can make SCs work proactively instead of reactively towards disruptions in demand (Gesing et al. 2018). There are a variety of use cases such as demand forecasting, route optimization, network and inventory management that utilize the predictive power of AI to derive actionable insights and improve decision-making. Since it would exceed the scope of this work to present a company example for all of these applications, we will focus on use cases within predictive risk management and maintenance.

External events such as strikes, natural disasters, terrorist attacks or regulatory issues and internal risks in the form of supplier failure or outsourced operations make SCs vulnerable to disruptions (Christopher 2011). Therefore, SC risk management is crucial to ensure business continuity. However, today's complex and global SCs make it extremely difficult to monitor and mitigate risk at scale. "Resilience360" is a solution developed by DHL that leverages AI to analyze various data sources for signs of probable SC disruptions (DHL 2018a). Advanced ML and NLP techniques allow for the daily monitoring of eight million online posts from more than 300,000 traditional and social media sites (DHL 2018a). By not only tracking the content but also understanding the context of these posts, the system can interpret the sentiment of risk-relevant discussions and events. Consequently, Resilience360 enables SC managers to identify and act upon potential disruptions in advance. While the platform is used for companies in a variety of industries, DHL utilizes Resilience360 to safeguard its own operations in more than 220 countries (DHL 2018b). An incident where the tool proved beneficial was during the Chile earthquake in 2014. It immediately delivered geospatial information on road damages, airport shutdowns, power failures and criminal outbreaks (DHL 2018b). This information enabled DHL to effectively reroute and protect customer goods and corporate assets. The company claims that compared to conventional methods, the tool enables five times faster access to comprehensive security information (DHL 2018b).

Another high-potential use case for predictive AI lies in fields of maintenance and quality inspection. While already being used in manufacturing to detect anomalies in products or machinery, predictive maintenance is increasingly being applied to other operational assets along the SC. Here, IBM Watson's visual recognition capabilities serve as a good example. The technology is fed with high-quality images from products or assets, to learn the difference between defect and functioning parts, classify the defect types and recommend appropriate maintenance measures (Clark and Sherk 2018). By processing more data, IBM Watson continuously improves its detection accuracy. Following this approach, the technology was able to identify wagon damages from live images of slowly passing cargo trains with an accuracy of over 90 percent (Clark and Sherk 2018; Gesing et al. 2018) (see appendix B.4.).

4.3.3. Cognitive Robotics

Similar to how advanced AI is revolutionizing software-based RPA, it enables physical robots to solve more cognitive tasks. Computer vision and self-learning capabilities have enabled them to better understand and adapt to changes in the environment (CGF 2018). Consequently, AI-driven (cognitive) robots are opening up many improvement opportunities across the SC. These range from robots that work collaboratively with humans, intelligently sort parcels, autonomously move goods or deliver them to customers (CGF 2018).

An emerging application field of cognitive robotics is the order fulfillment process in warehouses (Santagate 2018). Here, the robotics company GreyOrange can be considered as an excellent example as its solutions allow for the near end-to-end automation of this process. Its autonomous mobile robots (AMR) do not only automatically store and replenish inventory but also locate, carry and move orders to human operators at picking stations (GreyOrange 2018). AMRs work collaborative and use ML to gradually improve navigation efficiency and reduce fulfillment times. Moreover, the system learns from and adapts to changing inventories and seasonal demand volatilities. For instance, if the demand for a certain product increases, the AMRs rearrange the respective storage units so that the product is moved closer to the picking station, further reducing the order-cycle time (GreyOrange 2018). Amongst others, the company's solutions helped scale the operations of the biggest home improvement retailer in South America. The quicker and more efficient order fulfillment made the retailer double the number of orders he could handle previously, while greatly lowering operating cost. GreyOrange's most recent innovation shows that it continues to leverage AI to automate ever more steps of the fulfillment process. It has developed an autonomous picking system, that uses computer vision to identify and pick more than 100,000 different products with a near 100 percent accuracy (GreyOrange 2018).

4.3.4. Virtual Assistants

In the age of the digital consumer, a seamless and personalized experience is key for customer satisfaction. SCs play a vital role in shaping customer experience by ensuring a quick, smooth and transparent product delivery. Here, AI can be leveraged to create a more personalized customer experience, particularly through the application of recommendation engines or virtual assistants. The latter are defined as software-based agents that support humans with the execution of cognitive tasks and communicate via voice or text (Hoy 2018). The example of a voice-based assistant has been given in chapter 3.4 in the form of Amazon's Alexa. To enhance the experience of their customers the logistics company DHL has added a skill to Alexa that enables customers to query the smart speaker on the status of their shipment (DHL 2017).

The startup Package.ai expands this concept with its chatbot "Jenny" by interacting with customers at every touchpoint of the order process, while optimizing last-mile delivery. Similar to Alexa and other virtual assistants, Jenny's conversational and context-understanding abilities are driven by a combination of NLP and ML models. More precisely, Jenny is able to coordinate delivery windows, shipping information or last-minute changes between customers and logistics providers (Package.ai 2018). As she talks to both parties, Jenny designs the optimal route that maximizes successful delivers and driver productivity. To be able to do that Jenny's considers customer time windows, traffic conditions as well as the logistics provider's schedule and capacity constraints (Package.ai 2018). Additionally, the chatbot's ML algorithm leverages historical delivery and consumer data to continuously improve its decision-making. Jenny creates an autonomous customer support channel that can increase customer satisfaction and reduce labor cost. Moreover, Package.ai (2018) claims that the reduction of failed deliveries and optimized routing has helped companies to improve operational efficiency by up to 30 percent.

5. Assessing the Impact of Artificial Intelligence on Supply Chains

To further assess the impact, the technology has on SCs, various experts that work at the intersection of SCM and AI have been interviewed. A list of the interview questions as well as brief descriptions of the experts' background can be found in Appendix A. The expert answers in combination with the reviewed literature and use cases, serve as the basis for the qualitative assessment. "Impact" refers to the degree to which AI will affect, augment or replace conventional methods and processes. Table 4 illustrates the impact of the four main AI application categories (predictive AI, cognitive robotics, virtual assistants and back office automation) on each component of the SC. Subsequently, the impacts on each component of the SC will be summarized.

Table 4: Qualitative Study: Impact Assessment of AI on Supply Chains

	Predictive AI	Cognitive Robotics	Virtual Assistants	Back Office Automation
Planning	Demand Forecasting	—	—	Automation of support functions across the entire SC Intelligent RPA
Sourcing	Supplier Selection	—	Procurement Bots	
Manufacturing	Predictive Maintenance	Collaborative Robots	Virtual Assembly Assistants	
Warehousing	Optimized Inventory Mgmt.	Automatic Order Fulfillment	—	
Distribution	Route Optimization	Autonomous Fleet	—	
Customer	Product recommendations	PoS Robots	Voice-based Assistants	
Average	**High Impact**	**Moderate Impact**	**Minor Impact**	**High Impact**

Source: Own table based on expert interviews

5.1. Impact on Planning

Most experts agree that SC Planning is the component where predictive AI will prove most beneficial. This is because the planning process is data-driven and analytical by nature. However, due to the multitude of influencing factors, conventional methods struggle to make accurate predictions about customer demand and replenishment cycles. As illustrated by the SC risk management use case, AI enables SC planners to scan through massive amounts of historical and near real-time data, to account for a variety of factors (e.g.: natural disasters, online sentiment) that could potentially disrupt the demand or flow of goods. Moreover, the expert on SC strategy emphasizes that AI can break down data silos between departments or factories by optimizing the planning process holistically and providing end-to-end visibility across the SC. Overall, AI-based planning approaches enable faster and more accurate demand predictions. McKinsey (2018b) estimates that such approaches could reduce forecasting errors by up to 50 percent.

5.2. Impact on Sourcing

Predictive AI is will help buyers to select and negotiate with suppliers more intelligently by drawing insights from historical purchase records and external market information. Moreover, similar to how consumers become used to requesting information and ordering products through Amazon's Alexa, sourcing buyers might delegate supplier communication and order processing to virtual assistants (Zagorin 2018). Procurement chatbots are already being used for the automation of these processes. However, the expert on AI research states that the impact is likely to be minor as the human element remains crucial in building and maintaining supplier relationships.

5.3. Impact on Manufacturing

Predictive AI and cognitive robotics are likely to have a high impact on manufacturing. The first proves beneficial by leveraging machine, sensor and visual data to anticipate and detect machine failure (see IBM Watson use case). This could reduce annual downtime by up to 20 percent and overall annual maintenance cost by up to 10 percent (McKinsey 2018b). Moreover, human-robot collaboration is expected to significantly alter manufacturing processes. The manufacturing expert attributes this to ML, computer vision and NLP techniques, that enable robots to become more context-aware and safely work alongside human. For instance, robots can replicate human movements by observing them. Overall, AI is expected to add value to many aspects of manufacturing by increasing efficiency, safety and product quality.

5.4. Impact on Warehousing

Within warehousing, predictive AI has a significant impact on decision-making. This is because warehousing processes and inventory levels are highly influenced by demand forecasts. The data scientist and forecasting expert emphasized that AI-based inventory management has enabled some of her clients to reduce stock holdings in their warehouses by up to 30 percent. Moreover, the expert on AI research argues that due to its structured environment and task similarity, warehouses can be considered an ideal ground for AI-driven automation. How cognitive robots are capable of taking over large parts of the order fulfillment process has been illustrated through the GreyOrange use case.

5.5. Impact on Distribution

The global rise of e-commerce has fueled the desire for instant product delivery among customers. According to the SC planning expert, AI can be used to close the gap between rising customer demands and conventional delivery methods, firstly through optimizing delivery routes and secondly by powering new means of transport. Intelligent route optimization is based on predictive AI, which is able to consider several inputs such as historical driving and live traffic data to recommend most efficient delivery routes. Additionally, the logistical flow of goods across the SC and to the point of demand will be significantly impacted by the usage of

AI-powered autonomous delivery trucks and drones. All in all, AI is likely to accelerate SC delivery times, while simultaneously driving down delivery cost.

5.6. Impact on Customer Interface

According to the expert on SC strategy, AI has the greatest impact on customer-facing tasks and customer experience as a whole. He believes that here the predictive capabilities of AI prove particularly beneficial due to the enormous amount of consumer data and the closed problem to be solved, like predicting what one customer might buy next. This is in contrast to for example manufacturing, where there is lot of complex processes and equipment involved that makes automated decisions more difficult. Moreover, next to tailored product recommendations, the customer experience is becoming more personalized through virtual assistants that significantly alter the way consumers interact with companies (see Alexa and package.ai use case).

5.7. Benefits and Risks of Artificial Intelligence within Supply Chains

Table 5: Benefits and Risks of implementing AI within the Supply Chain

BENEFITS	RISKS
• **Predictive planning capabilities** ○ More accurate demand forecasts ○ Better asset utilization ○ Optimized replenishment cycles • **Decreasing operating cost** ○ Task automation ○ Reduced asset downtime ○ Reduced inventory levels • **Augmentation of the workforce** ○ Focus on high-value tasks ○ AI tools improve decision-making • **Optimized warehouse and logistics operations** ○ Reduced lead-time ○ Quicker, safer and greener product delivery • **Enhanced customer experience** ○ Tailored products and pricing ○ Anticipation of customer needs ○ Personalized customer touch points	• **Poor AI execution** ○ Inaccurate, incomplete or biased input data ○ Overfitting AI model • **High implementation cost** ○ Training AI engine resource and time intensive ○ No SaaS solution but holistic integration in IT infrastructure • **Job displacement due to automation** ○ Short-term: Repetitive tasks ○ Long-term: More complex tasks • **Security** ○ Wrong decisions within critical infrastructure (e.g.: machinery) ○ Data theft and privacy ○ Hacking of autonomous system (e.g.: self-driving trucks) • **Ethics of AI** ○ How to teach moral judgement to AI

Source: Own table based on expert interviews

Table 5 summarizes the benefits and risks of implementing AI within the SC. While the benefits have been widely discussed throughout the use cases and impact assessment, it is important to contrast the major risks of implementing the technology. Especially notable is the risk of poor AI execution due to inaccurate, incomplete or biased input data. The data science expert attributes this to the fact that data within the respective components of the SC is oftentimes siloed and therefore hard to access comprehensively. The expert on SC strategy claims that AI is not a stand-alone plug-and-play solution, but rather needs to be integrated into the existing IT infrastructure and linked to business processes to deliver value. This integration comes with the risk of being costly and time-intensive. The risk of job displacements, which has already been discussed in the general section of this paper, also holds true in the SC context. However, while the experts agree on the fact that AI will render many skills obsolete, they have different opinions on whether the technology will create more jobs than it destroys. Finally, the integration creates risks related to the security and ethics of AI. The expert on manufacturing emphasizes that a major security risks stems from the fact that AI does not always make the right decisions. This is particularly critical in environments like manufacturing or transportation, where false decisions can have severe consequences on health or safety. At the same time this raises the question of how AI should react in life-or-death situations, for instance when an AV is involved in an unavoidable accident. Such cases show that the ethical aspects of AI-based decision making remain one of the most difficult challenges to overcome and cannot be neglected.

5.8. Future Outlook of Artificial Intelligence within Supply Chains

The use cases and impact assessment gave a broad overview of how AI will alter the way SCs operate. At present, only a few early adopters have implemented and are reaping the benefits of an AI-driven SC. The SC planning expert underlines that due to the ongoing digitalization and increasing number of IoT devices within SCs, data volumes and therefore the value AI can deliver will accelerate in the near future. This would facilitate widespread adoption of the technology since AI will become a prerequisite for SC competitiveness. Under the premise that AI algorithms become better at understanding new problems they have not been previously trained on, the SC strategy expert believes that no process or function within SCs is excluded from being at least partially automated. The experts repeatedly characterized the future SC as “self-learning”, “self-healing” and “self-adapting”. In the long-term future, they commonly foresee a fully automated SC with minimum human interaction. In this scenario AI would be capable of selecting vendors, placing orders, scheduling production as well as autonomously storing, handling and transporting goods. Moreover, the connectedness and constant sharing of data across the network would provide SC planners with end-to-end and real-time visibility of the SC (McKinsey 2016). According to the SC planning expert, their focus would shift to monitoring performance, handling exceptions, building relationships and setting strategic directions across the SC (see appendix B.5. for an abstraction of a possible future SC structure).

6. Conclusion

Within the context of this paper, comprehensive answers to the two initial research questions have been developed. The first research question was concerned with understanding what lies behind the term AI and where to apply it. We have seen that AI has to be regarded as an umbrella term for a variety of interrelated technologies with the common goal to carry out cognitive functions by simulating human intelligence. Through further narrowing down the term, the fields of ML, NLP, computer vision and robotics emerge as the key branches of AI in the academic and business context. Regarding the applicability of the technology, we have seen that although AI adoption levels vary between sectors, use cases can be found in nearly all of them. Among the prominent use cases are voice-controlled assistants, AVs and medical diagnosis.

The second research question dealt with the impacts and applications of AI within the SC context. It has been shown that the network-based and data-rich environments of SCs create a broad spectrum of AI use cases that touch upon every component of the end-to-end SC. The qualitative study has indicated that the most significant impact on SC is likely to come from use cases that fall into the application categories of BOA and predictive AI. This is because both of them overcome major shortcomings that characterize SCs at present. While BOA frees SC support functions from a high number of repetitive and time-consuming tasks, predictive AI enables companies to finally capitalize on the vast amounts of SC data and shift from a reactive to a proactive SCM approach. Cognitive robotics has been shown to moderately impact SCs by enabling efficient human-robot collaborating and taking over entire SC processes such as the order fulfillment within warehouses. Lastly, a minor impact has been ascribed to virtual assistants, which primarily affect the customer interface of SCs by altering the way consumers query information and interact with companies.

The third research question was concerned with understanding the major benefits and risks of integrating AI into the SC. It has been shown that AI improves customer-centricity, amplifies the workforce and enhances operational efficiency and visibility across all components of the end-to-end SC. However, we have seen that the integration of AI comes with the major risks of being poorly executed, resource-intensive, security-threatening and labor-displacing. Since AI will also boost economic growth and therefore create new jobs, the net-effect of the latter risk factor remains uncertain.

The broad approach of this study provides SC managers with a comprehensive understanding of the technology and lays the foundation for further in-depth research on the subject. However, due to the emphasis on generic SC components, the study's validity on an industry level remains limited. Since SCs and AI use cases vary from industry to industry, future studies should focus on an industry-specific examination of the technology.

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Appendices

Appendix A – Expert Interviews

Appendix A.1. – Interview Questions

Question 1: How do you think AI is changing supply chains from an organizational perspective? What are the major trends at present?

Question 2: Where do you see the current major applications areas of AI within supply chains?

Question 3: What are the future applications of AI within supply chains that you foresee? How will they shape the supply chain of the future?

Question 4: Considering the generic supply chain components (Planning, Sourcing, Manufacturing, Warehousing, Distribution, Customer Interface), in which of these the areas will AI have the biggest and least impact or where is it more or less useful?

Question 5: Where do you see the major benefits of applying AI within supply chains?

Question 6: Where do you see the major risks of applying AI within supply chains?

Question 7: What do you think are the hurdles of adopting AI in supply chains? How can companies overcome then?

Question 8: What do you think will be the impact of AI on the supply chain workforce?

Appendix A.2. – Expert Profiles

<u>Expert #1 – Data Scientist and Forecaster</u>

Expert #1 is a data scientist and senior consultant in Camelot's AI team. Camelot is a globally leading consultancy, specialized on SCM. She holds a Master's degree in Quantitative Economics and has focused her work on developing forecasting models in various industries such as logistics, retail and commodities.

Expert #2 – Supply Chain Strategy Consultant

Expert #2 is a strategy consultant in Accenture's Supply Chain & Operations team. He holds a Master degree in Chemistry, Doctor in Philosophy as well as a M.B.A. in Management and Operations. During his work at Accenture he identified and co-developed digitalization opportunities across the SCs of clients from various industries such as high-tech, chemicals and pharma.

Expert #3 – Artificial Intelligence Researcher and Technology Consultant Director

Expert #3 is director at BearingPoint, a global management and technology consultancy. He is responsible for the SC digitalization of clients from various industries such as chemicals, pharma, logistics and manufacturing. Moreover, he focuses on researching AI applications that contribute to the efficiency of SCs.

Expert #4 – Manufacturing & Artificial Intelligence Consultant

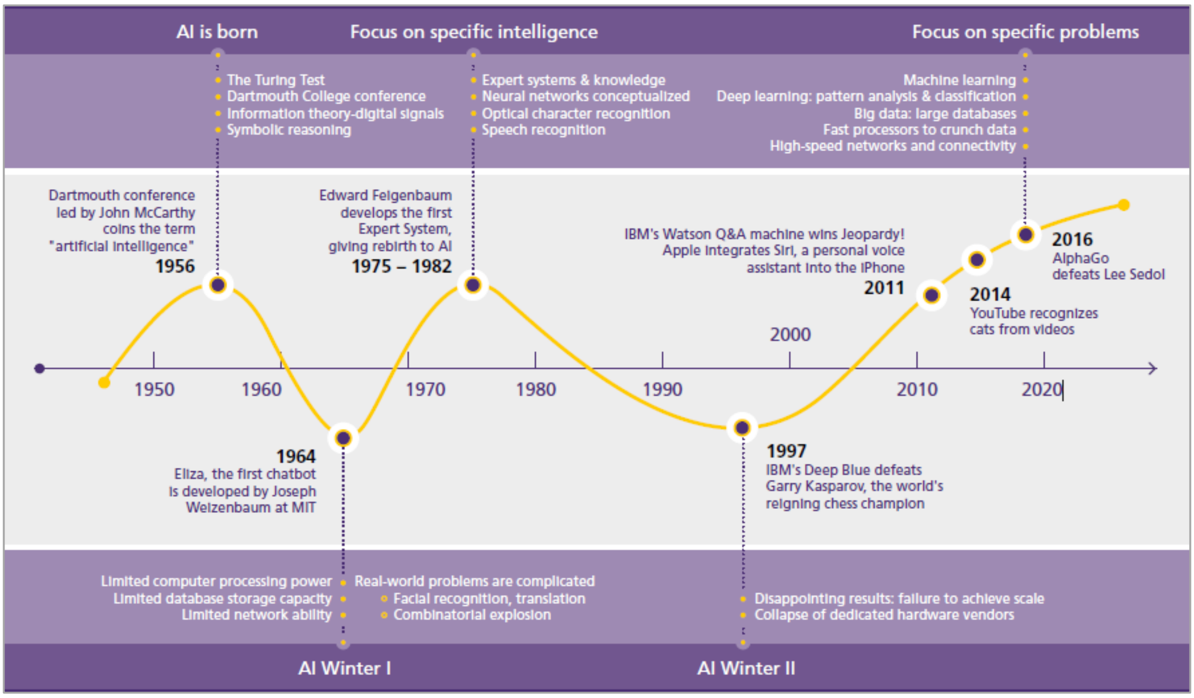
Expert #4 is an AI consultant at Deloitte. He holds a Bachelor degree in Mechanical Engineering and has been working in FMCG manufacturing as well as Oil & Gas engineering roles. Currently, he helps consulting clients to introduce AI solutions into their SC operations, while focusing on the manufacturing component.

Expert #5 – Supply Chain Planning Manager

Expert #5 is senior supply chain manager at bluecrux. The company helps clients with the digitalization of end-to-end SC processes. He holds a Master degree in Logistics and Supply Chain Management as well as Industrial Engineering. He has 10+ years of experience in SCM and worked, amongst others, as SC planner and researcher for Procter&Gamble and Bridgestone Europe.

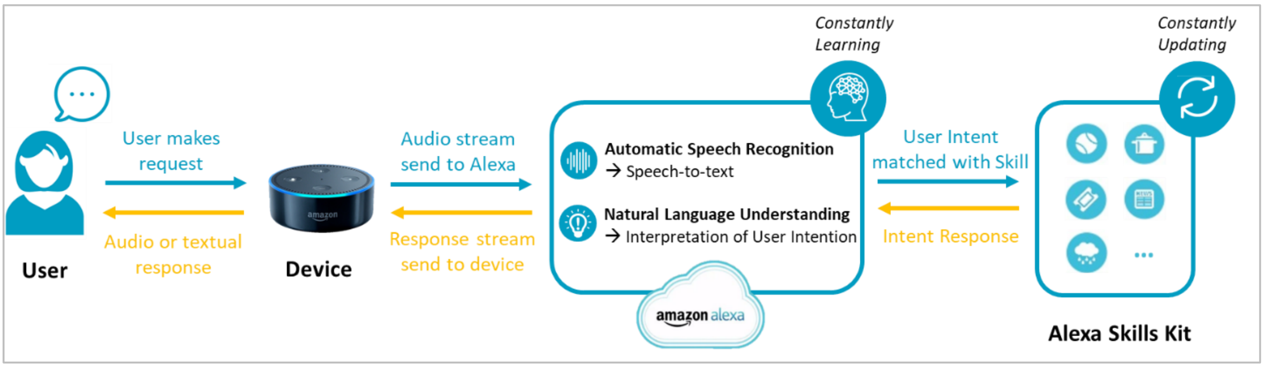
Appendix B – Figures

Appendix B.1.: Timeline of Artificial Intelligence



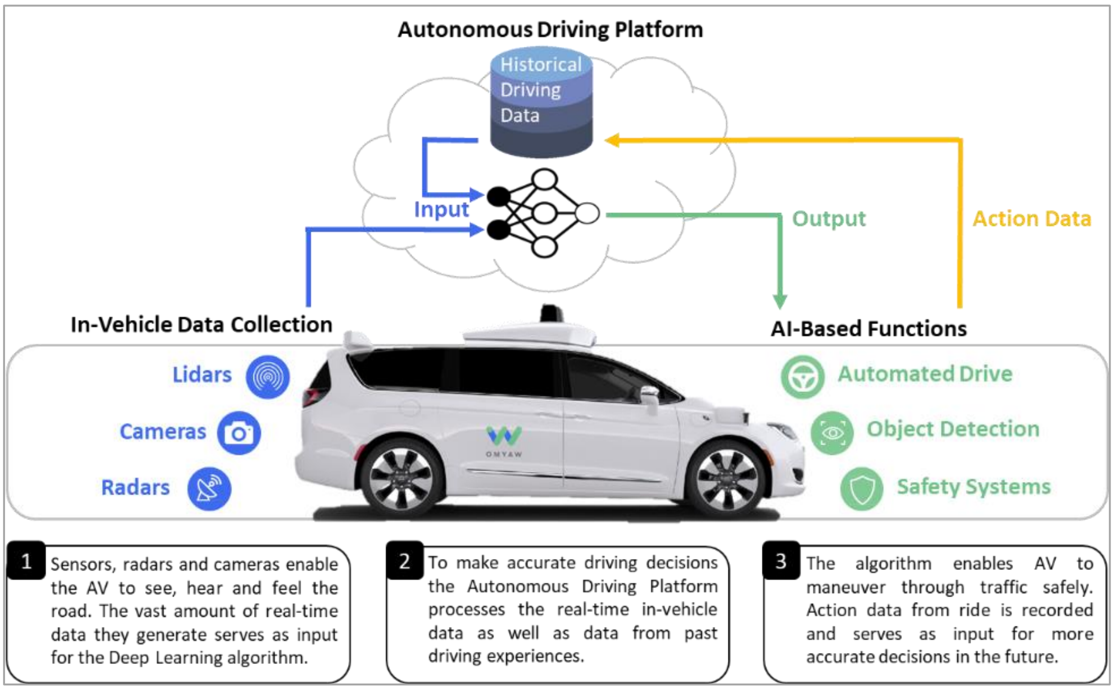
Source: Gesing et al. 2018

Appendix B.1.: Amazon Alexa Request and Response Flow



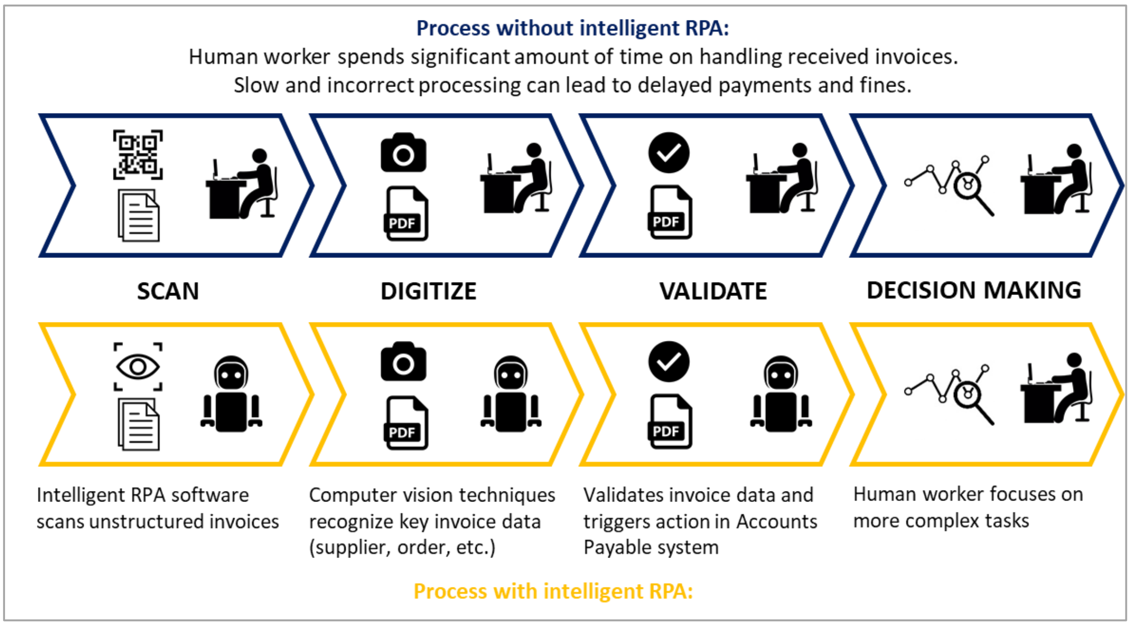
Source: Author

Appendix B.2.: Learning-Action Cycle in Autonomous Vehicles



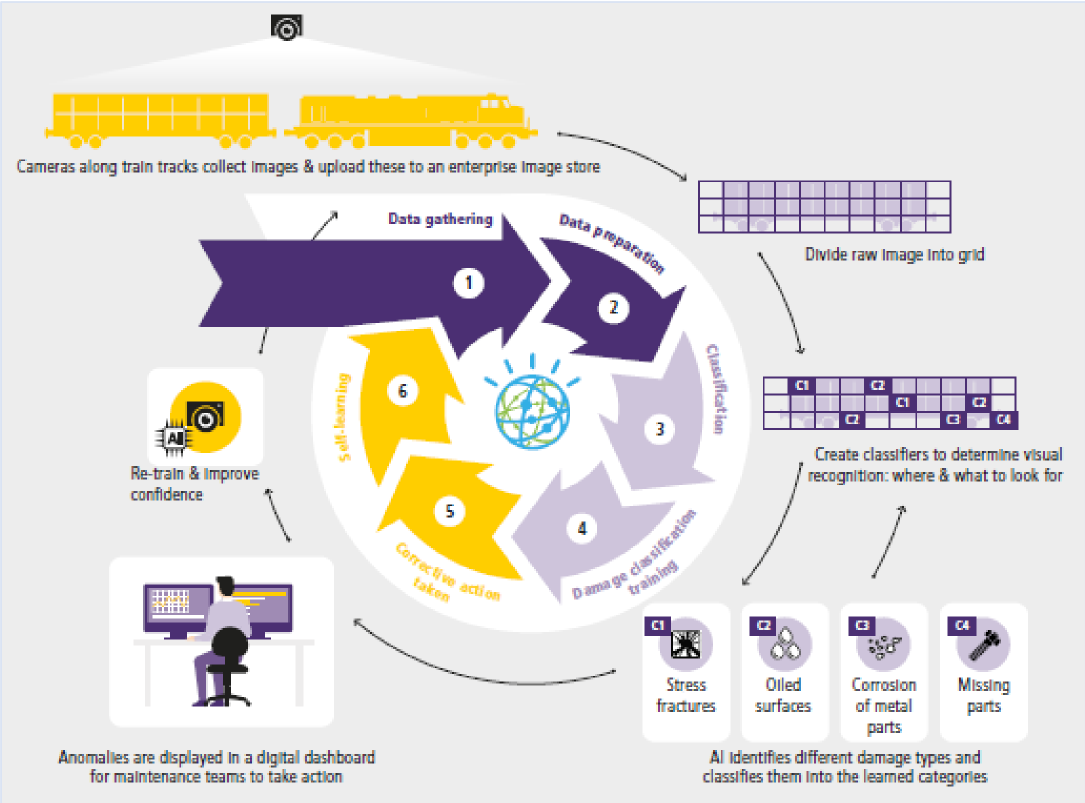
Source: own illustration based on Gadam (2018)

Appendix B.3.: Back Office Automation Use Case: Processing of Supplier Invoices



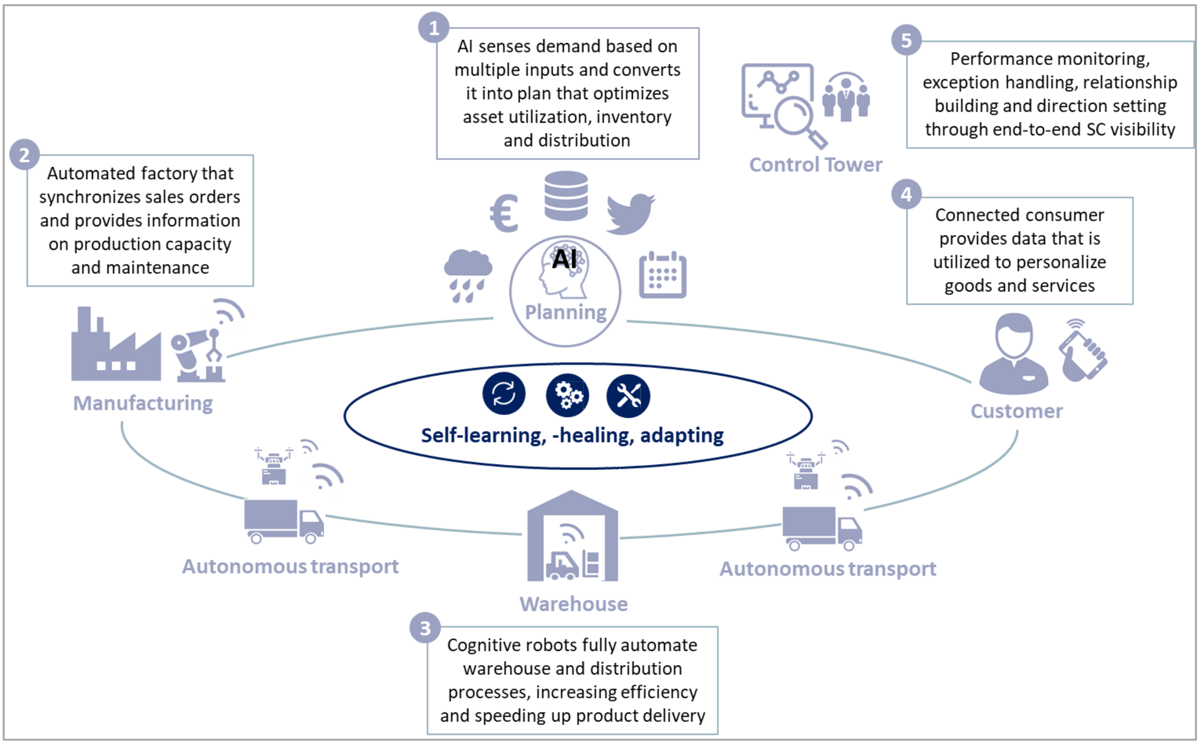
Source: own illustration based on Ernst & Young 2016; Kryon 2017

Appendix B.4.: IBM Visual Inspection Use Case



Source: Gesing et al. 2018 and Clark and Sherk 2018

Appendix B.5.: Abstraction of a potential Future Supply Chain



Source: own illustration based on expert interviews; CGF 2018; McKinsey 2016