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Artificial intelligence in operations management and supply chain management: an exploratory case study

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ABSTRACT

With the development and evolution of information technology, competition has become more and more intensive on a global scale. Many companies have forecast that the future of operation and supply chain management (SCM) may change dramatically, from planning, scheduling, optimisation, to transportation, with the presence of artificial intelligence (AI). People will be more and more interested in machine learning, AI, and other intelligent technologies, in terms of SCM. Within this context, this particular research study provides an overview of the concept of AI and SCM. It then focuses on timely and critical analysis of AI-driven supply chain research and applications. In this exploratory research, the emerging AI-based business models of different case companies are analysed. Their relevant AI solutions and related values to companies are also evaluated. As a result, this research identifies several areas of value creation for the application of AI in the supply chain. It also proposes an approach to designing business models for AI supply chain applications.

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operations management;
supply chain management

1. Introduction

The concept of supply chain already existed a long time ago and is as old as the products themselves have been. The supply chain is a complex and integrative concept that covers the entire production and distribution channels from suppliers, manufacturers, distributors, and ultimately the end customer. Typically, the goals for the supply chain are to fulfil customer demand, improve responsiveness, and create a network among different stakeholders. Nowadays, the supply chain network is becoming more and more distributed, diverse, and transparent in terms of its business structure, business tasks, and stakeholders (Seyedghorban et al. 2020). The major problem for many organisations is that the visibility of entire supply chain and the degree of information available within company are not optimal (Seyedghorban et al. 2020). Therefore, the aim of Supply Chain Management (SCM) is to digitalise the business process, to integrate different stakeholders and assets to ensure that the products are in harmony with the customer's needs and to achieve goals related to total system competitive advantage (Tammela, Canen, and Helo 2008).

Many traditional IT systems are dedicated to supporting various business processes in logistics and supply chain, such as ERP (Enterprise Resource Planning), MES (Manufacturing Execution System), PPC (Production Planning & Control), SCADA (Supervisory Control and Data Acquisition), etc. (Haas 2020). Advanced technologies have digitalised almost every operational process to control manufacturing across entire supply chains (Schivone and Sprenger 2017). However,

these fragmented solutions are not 'intelligent' enough (i.e. not able to act rationally based on the environment), and not very suitable for current SCM, due to the dynamic nature of the supply chain, rapidly changing customer demand, unstructured decision problems, and the constantly changing status of business processes. To establish intelligent, rapid and effective business response systems, it is vital to operate with the highest efficiency in all major activities and business flows in the supply chain. Therefore, more advanced IT systems are required to deal with multi-level, highly variable problems of industrial operations in digitalisation (Seyedghorban et al. 2020).

Recently, the possibilities of applying Artificial Intelligence (AI) technology have gained increasing attention in many industries (Dubey et al. 2019). AI refers to the ability of machines to learn from experience and make decisions on series of performance as a human with intelligence (Duan, Edwards, and Dwivedi 2019). AI is an emerging field in computer science due to the latest developments in deep neural networks, convolutional neural networks, mathematical optimisation techniques used in operations research, constraint programming, and various numerical methods. These advances have made it possible for computers to conduct tasks that have previously been possible for humans only. According to Russell and Norvig (2016), the objective of an AI is 'to create rational agents who can perceive and act such that some objective function is optimised'. Examples of this kind of task are related to machine vision, natural

language processing, pattern recognition, problem-solving for decision support, and learning systems.

The definition of AI by AAAI (Association for the Advancement of Artificial Intelligence) is ‘advancing the scientific understanding of the mechanisms underlying thought and intelligent behaviour and their embodiment in machines’. This definition shows that AI is quite tolerant of different technologies, and one could say even agnostic. A widely-used textbook by Russell and Norvig (2016) states that AI is the intelligence of machines and software, a branch of computer science designed to create this intelligence. The purpose of AI is to try to understand intelligent entities (Soleimani 2018).

From a technological point of view, the features of AI can enable the building of new kinds of functionality for information systems running operations and logistics. By studying previous research and cases, AI can be implemented in the following areas:

1. Learning systems that can adjust behaviour based on dynamically observed data (Baryannis, Dani, et al. 2019; Li and Liu 2019);
2. Situation-aware systems which can detect and understand the prevailing conditions, and adjust behaviour according to modes and situations (Min 2010; Singh et al. 2020);
3. Autonomous decision-making systems which can execute decisions in contrast with traditional Decision Support Systems (DSS) (Zijm and Klumpp 2016; Dwivedi et al. 2019);
4. The ability to process streaming images, video, audio and non-structured text type of data (Erhan et al. 2014; Brynjolfsson and McAfee 2017).

The AI research community has been connected to DSS and other approaches in the area of operation management, such as planning and scheduling since the 1960s (Nemati et al. 2002; Çaliş and Bulkan 2015). Currently, AI has a holistic impact on SCM. The technical reasons are that the development of machine learning and most intelligent technologies start in SCM. The business reason for implementing AI in SCM is that the adoption of AI can increase visibility and transparency in the supply chain, and can also improve consumer products/services and customer satisfaction.

Many big players in the technology field have put the effort in applying AI in SCM, such as Amazon, Walmart, Philips, eBay, etc. (Dwivedi et al. 2019; Mahroof 2019). Although a lot of emerging research exists, extensive studies on the role of AI in SCM remain relatively scarce due to a limited understanding of this phenomenon. Thus, in order to enhance knowledge of AI in SCM, this paper aims to study two research questions: what are the possible applications of AI in operations management and supply chain management, and what are the expected business impacts of such implementations? With these research questions, this paper investigates the concept of AI and its applications in SCM. It shows how to integrate different AI techniques and the future trends of advanced technologies in the operational

process, and how they together facilitate cost-effective supply chain solutions and provide greater visibility to decision-makers at a high level. This paper also explores how various forms of AI-powered SCM improve everything from process automation to process optimisation. We answer our research questions by analysing data collected from four leading companies and their solutions in real-life in how they leverage AI in their supply chains. The report also provides an evaluation of AI in SCM. The ultimate objective is to build up a comprehensive view of the development of AI technology linked to SCM.

The remainder of this paper is as follows: Section 2 presents the concept and methods of artificial intelligence, as well as insights into ways of developing and deploying AI in SCM. Section 3 is concerned with the methodology used in this study, and the exploratory research method is introduced. The case study in Section 4 illustrates four examples of AI implications and impacts, and in Section 5 we discuss implications and also summarise a framework for AI typology in the context of SCM. Finally, we present conclusions in Section 6.

2. Theoretical background

2.1. AI concept

Artificial Intelligence (AI) is a loosely defined term that can refer to several technologies. John McCarthy coined this concept at the time of the famous Turing Test in 1950. This field has had a long history since the Dartmouth workshop in 1956. However, it did not attract high interest at the beginning. From the early 2000s, AI made rapid progress and received new attention, and AI has been reconsidered in research areas and applications in recent years. AI combines the science and engineering of making intelligent machines. Therefore, the objectives of AI can be considered to be both scientific goals and engineering goals.

Scientifically, AI is the study and design of a branch of intelligent agents being developed to understand the environment rationally and take actions intelligently (Russell and Norvig 2016; Soleimani 2018). Many other fundamental disciplines, i.e. philosophy, mathematics, cognitive science, economics, neurosciences, and linguistics serve as roots in AI, and they overlap with each other (Solomonoff 1985). These root concepts build up an intelligent system that can mimic human behavioural patterns and solve real-world problems (Min 2010). For instance, philosophy contributes to the primary component of how a machine or a physical system can learn and operate based on a set of rules. Mathematics provides a formal representation of these rules designed based on algorithms and probability. Cognitive science includes studies of how humans think and act, and when applied in AI, it shows how computers think and learn different things. Linguistics focuses on how language and thinking are related. Neuroscience provides the study of brain functioning and how brains and computers are (dis)similar. The scientific side of AI attempts to explain real human intelligence.

In terms of engineering, AI is an umbrella term for any intelligent system. It is a cross-disciplinary research area of both computer science and data science. As distinguished

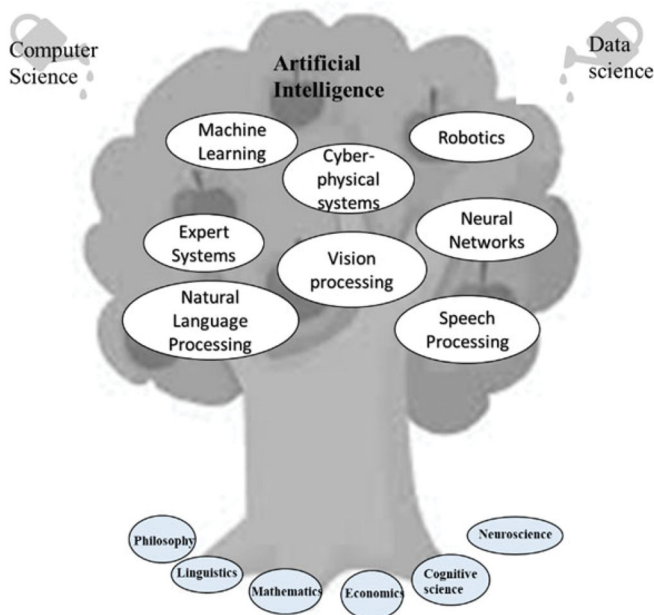


Figure 1. Artificial Intelligence as an umbrella term.

from the classical computing system, in which a computer is told what to do precisely, in AI, a computer should have the ability to learn from a massive amount of given historical data (experience) and find a pattern on their own, then make decisions and find solutions accordingly (Min 2010). AI is concerned with how to process data, how to give computers the sophistication to perceive the surrounding environment, and also how to act intelligently with algorithms and synthesis (Russell and Norvig 2016; Nilsson 1980). Technically, AI requires vast amounts of data, immense data processing, and (for the most part) cutting-edge statistical methods (Davenport 2018). AI consists of many sub-fields that use a variety of techniques such as machine learning (ML), cyber-physical systems (CPS), expert systems, natural language processing (NLP), vision processing, speech processing, neural networks, robotics, etc. (Duan, Edwards, and Dwivedi 2019). These techniques enable the system to achieve 'intelligence' from different aspects. They both support and interact with each other. Typically, several methods are used in one AI application. These techniques will be discussed in the following section. Figure 1 shows AI-related concepts and terminologies and the techniques supporting AI.

AI is thriving and has become more and more popular in recent years because of various organisational and environmental factors, such as dynamic customer expectations, intense global competition, overall digitalisation in companies, and a rapidly changing technological landscape (Dubey et al. 2019). The three main technological driven forces can be summarised as increasing computing power, increasing quantities of data, and increasingly advanced algorithms:

- Cloud infrastructure is becoming more and more mature. It is the mainstream computing resource in today's technical infrastructures. Many companies, such as Google, Amazon, Microsoft and Salesforce, are making robust computing infrastructure available via the Cloud

(Brynjolfsson and McAfee 2017). With this infrastructure, AI can be bought or rented as needed.

- The growing amount of data is collected from sensor feeds, business transactions, and operations (Lee et al. 2019). These data are valuable assets for business but also present a big challenge in terms of extracting the desired knowledge. Big Data-heuristic algorithms are the solution to this challenge. They can be utilised to gain critical insights into operations and supply chain, and also provide correct information based on an intelligent, selective search of the whole set of massive data (Lamba and Singh 2017; Kolinski et al. 2020).
- Algorithms (model) are more advanced and superior in many applications that were once done best by humans (Brynjolfsson and McAfee 2017). This force is also an outcome of the combination of the two forces above (cloud infrastructure and data amount). The classic algorithms are memory-based filtering algorithms. They have been replaced by more efficient and robust systems based on machine learning (Brynjolfsson and McAfee 2017).

Several previous research studies have analysed not only the business benefits of AI but also the barriers to AI adoption (Davenport and Ronanki 2018; Ransbotham et al. 2018; Chui and Malhotra 2018). The commonly recognised obstacles and challenges of AI are as follows:

- Without top management and a clear AI strategy in the organisation, there will be a failure of AI. It is critical to have a specific goal and correct direction in moving towards AI.
- It is challenging to implement AI throughout the entire organisation with existing processes and systems if the company lacks robust technological infrastructure and collected data.
- Other most often reported inhibitors of AI in the current situation are expensive AI related-technologies and the high expense of talented expertise with appropriate skillsets in AI.

There are several excellent examples of AI and state-of-the-art applications, including IBM Watson's AI app development platform, DeepMind's AlphaGo to play chess, Google Translate, autonomous vehicles, style imitation in picture processing, recommendation system, Email filter, handwriting recognition, face detection/recognition, and so on (Schoemaker and Tetlock 2017; Dwivedi et al. 2019). In this paper, the most commonly used methods of AI are selected and listed as follows:

- Machine learning (ML): This is the most crucial technology of AI, which enables machines not only to process data but also to process unstructured knowledge. ML-based systems can learn from data, identify patterns from large numbers of examples, make decisions based on structured feedback, and then perform tasks on their own. Ultimately, these systems can keep improving their

performance and problem-solving skills with minimal human intervention (Brynjolfsson and McAfee 2017).

- Artificial neural networks (ANN): theory was inspired by the biological nervous system. It uses an interconnected network of computer memories to achieve the learning from precedent examples and experience, and to distinguish features, recognise patterns, cluster objects, and process ambiguous or abstract information (Min 2010; Singh and Challa 2016). ANN is an advanced generation of ML algorithms. It works on large data sets and requires more computing power and specialised computer architectures (Brynjolfsson and McAfee 2017).
- Machine Vision (MV): MV refers to the technology and methods used to recognise objects, interpret content and extract information from an image or a video on an automated basis. It is different from image processing, where the output is another image (Brynjolfsson and McAfee 2017). MV technology is widely used in object recognition and image understanding.
- Expert System (ES): ES is a computer program that solves problems or gives advice based on well-deliberated calculations and unmanageable amounts of data: these tools produce analyses and help to evaluate alternative decision options (Jarrahi 2018). The sub-files of ES include rule-based systems that generally require human experts and knowledge engineers to construct a series of rules in a particular knowledge domain (Davenport 2018), and decision support systems which assist the decision-maker in addressing uncertain demand (Baryannis Validi, et al. 2019).
- Natural Language Processing (NLP): NLP-powered systems can be used to extract information or meaning (i.e. entities, locations, topics, sentiment, etc.) from previous patterns in speech or text. This is achieved by statistical analysis of words or phrases (that is, statistical NLP), or based on semantic analysis and ontologies (decomposition and relationships among words and phrases: that is, semantic NLP) (Davenport 2018).
- Speech Processing (SP): SP refers to the using of digital signal processing techniques to transmit speech into speech digital signals (Fu and Sun 2017). Speech recognition technology and other data capture technologies are used to implement the voice-directed system. This system provides audio prompts directing instructions to users. Users can also respond by speaking and verbally confirming the completion of tasks back to the system (Fu and Sun 2017; Levy 2018).
- Robotics: Robotics is an interdisciplinary branch of engineering and science that includes mechanical engineering, electronics engineering, information engineering, computer science, and others. It includes two parts: the first is the 'presentation layer' concerning the design, construction, operation, and use of robots; and the second part is the 'technical layer' with focus on computer systems in terms of their rule engines, control, sensory feedback, and information processing, workflow and orchestration tools (Davenport 2018).

- Evolutionary Computation (EC): EC includes different algorithms to solve the optimisation problem. The techniques of EC mostly include genetic algorithm, ant colony optimisation, swarm intelligence, and neuro-evolution. These algorithms mainly reflect the process of natural selection, where the fittest individuals are selected for reproduction to produce offspring of the next generation.

Many researchers adapt known algorithms to their needs and propose a new name, so that numerous different AI approaches are introduced (Hengstler, Enkel, and Duelli 2016). However, most of the AI methods are statistical in nature (Davenport 2018). Before embarking on an AI initiative, it is crucial to understand which technologies perform what types of tasks and best address specific needs (Davenport and Ronanki 2018). The techniques of AI share the same fundamental hypotheses: computation is a useful way to model intelligent behaviour in machines. They all have their strengths and limitations. However, they usually reinforce and overlap with each other.

2.2. Artificial intelligence and supply chain management

Supply Chain Management (SCM) is a complex concept. There are various definitions of SCM. From the business process perspective, a supply chain (SC) often spans the entire globe and involves production, trade, and logistics organisation around the world (Zijm and Klumpp 2016). From the business function perspective, SC concerns the management and synchronising of three flows, namely the product flow from suppliers to final customers, the financial flow of money from customers to suppliers, and also the information flow connecting suppliers and customers (Kochak and Sharma 2015; Li and Liu 2019). From the business entity perspective, SC represents not only the products but also the entire system of organisations, people, resources, and even services (Stefanovic and Stefanovic 2009). To achieve such a high level of sophistication, SCM solutions are typically designed to facilitate all the major flows among different functions, both within and between enterprise organisations.

Based on the predictions of Gartner, at least 50% of global companies will adapt their IT infrastructure with AI-related technologies and transform their supply chain operations by 2023 (Panetta 2018). Organisations can integrate their SCM solutions with intelligent technologies to improve business in terms of process automation. Organisations can make smarter planning decisions, increase the agility of their digital supply network, reduce costs, and gain more profound and broader insights into their supply chains, with greater visibility into static and real-time data. However, the potential for the application of AI has not yet been fully explored in the SCM area.

Baryannis, Validi, et al. (2019) have revealed that a SCM approach is considered as AI if it satisfies both of the following characteristics: that it can autonomously decide on a course of action that leads to success in SCM-related objectives and can do so under a partially unknown supply chain environment. Put simply, AI-based SCM can make decisions based on self-

learning in any scenario. Soleimani (2018) points out that AI techniques can be implemented in four identified attributes in SC: optimisation, prediction, modelling and simulation, and decision support. Choi et al. (2018) summarise six areas in which big data and various machine learning methods are applied in the operation management field: forecasting, inventory management, revenue management and marketing, transportation, supply chain management, and risk analysis. These areas are also related to AI.

There are several key ways in which these transformational technologies empower SCM businesses. It would be interesting to explore AI use cases across different sectors.

Walmart, as one of the largest retailer, is leveraging its AI capability to process considerable volume of data. 'Social Genome' is a Big Data analytics solution designed by Walmart to provide customers better services through analysing customers' activities on different social media. By creating insight of customer's preferences and behaviours, Walmart is able to inform the direct target customer about one product's information (Roden et al. 2017).

ABB is collaborating with IBM Watson to build an AI platform for its ABB Ability. This combination aims to obtain real-time cognitive insights for companies in utilities, industry and transport. For instance, ABB and IBM will leverage Watson's artificial intelligence to help in finding the defects of an asset from both real-time production images captured through an ABB system, and also historical data from IoT on the factory floor. The manufacturer will get real-time alert messages about its critical faults by using this solution.

Another interesting example of using AI solutions to improve its business is Infinera, a manufacturer of telecom equipment. It optimises a predictive solution for its SCM by using Intrigo Systems, in combination with the AI-powered OLPP platform from the company of Splice Machine. Infinera uses machine learning to make better predictions about delivery dates by analysing past variability in production lead times and logistics provider performance (Korolov 2018). This makes Infinera able to survive and stay in business when the depression economic environment.

In order to improve its inspection work and product quality simultaneously, the Japanese company NEC has developed a warehouse product inspection system by making use of image recognition technology in logistics operations. The system can make an instantaneous judgement on whether or not products to be shipped match the products on the shipment schedule list. Differently from others, it does not use an attached barcode or other ID information, but uses a unique image recognition technology (Umeda et al. 2017).

Despite the relatively short history of AI in SCM as a distinct research field, several articles have been published that review related literature. Table 1 summarises the current implementation and applications of AI in SCM in existing research. Most are real-world applications, and some of them are still proof of concept studies. They are classified by different business partners, business purposes, and AI methods.

Of course, those methods interplay with each other and are used together to implement an application, and each application can be used in different business processes.

Based on analysis of the current implementation of AI in SCM, it can be seen that AI can address SCM problems from two main aspects: advanced automatic infrastructure and optimised business processes.

- **Advanced automatic infrastructure:** it can be recognised that AI has gradually improved the decision-making process with supply chains by utilising knowledge and data in the automated systems (Baryannis, Validi, et al. 2019). AI improves SCM both internally (within a given enterprise) as well as between supply chain members (e.g. customer-supplier chains). However, it is critical that AI systems can leverage and optimise the efforts of a combination of artificial and human intelligence in addition to fully automated decision making.
- **Optimised business processes:** AI can optimise business processes in three main steps: (1) monitoring: companies can monitor goods and operations in real-time by connecting equipment, products and vehicles with IoT sensors; (2) analysing: the collected data can also be used in advanced analytics, and actionable insights generated to help companies to better understand the business; (3) acting: companies can improve their business and efficiency based on the valuable insights obtained and taking reasonable actions.

2.3. Developing and deploying AI models in SCM

As summarised in previous sections, the core of AI, different to traditional 'rule-based software programming', rather ensures that machines have the capability of defining and training models, engineering features or variables, of tweaking parameters, rebuilding models, and retraining and updating models (Davenport 2018). AI techniques have been widely used to extract useful information from data. The techniques infuse intelligence into the systems to automatically learn and adapt to the changing environment using historical experience through training (Lee et al. 2019). It is essential to realise that AI has the ability of repetitive training in analysing data, learning from data, and storing knowledge (Singh and Challa 2016). However, in order to implement AI and deploy the training, a considerable amount of high-quality data is required. Moreover, it is vital to use the right data sources to train the model. Otherwise, it is not able to get good results/right decisions.

2.3.1. AI training

Many recent studies on training machine learning and neural network models to achieve business forecasting purposes have demonstrated that AI that can perform a variety of intelligent business tasks. For instance, various forecasting methods are introduced for different tasks, such as detecting credit risk (Zhu et al. 2019), reducing the bullwhip effect (Singh and Challa 2016), inventory level (Paul, Azeem, and Ghosh 2015), and for customer demand (Kochak and Sharma 2015). Cavalcante et al. (2019) focussed on the application of supplier selection by defining risk profiles of suppliers. On

Table 1. Links between AI Methods and Applications in SCM.

Business partner	Business purpose	Applications in SCM	AI method	Reference
Supplier	Supplier selection	Supplier selection/Partner selection	Machine Learning; Expert System; Artificial Neural Network	Cavalcante et al. 2019; Soleimani 2018; Wu and Barnes 2014
		Minimizing supplier risk/Forecasting SMEs' credit risk in supply chain finance	Machine Learning	Zhu et al. 2019; Soleimani 2018
Manufacturer	Order intake	Order-picking system	Expert System	Manzini, Gamberi, and Regattieri 2005
		Chabots and intelligent assistants for operational procurement	Natural Language Processing	Davenport 2018
		Automatic spare part and service orders	Reinforcement Learning	Hellingrath and Lechtenberg 2019; Mortazavi, Khamseh, and Azimi 2015
	Quality control	Spare part demand forecasting	Neural Network	Amirkolaii et al. 2017
		Inventory control	Expert System; Reinforcement Learning; Artificial Neural Network	Paul, Azeem, and Ghosh 2015; Singh and Challa 2016
	Production planning and control	Automated quality control	Machine Learning	Tellaeche and Arana 2013
		Production optimisation /production capacity improvement/lead time reduction	Machine Learning	Min et al. 2019
	Services and Maintenance	Monitor and predict the conditions of the cutting tool and the bearing	Neural Networks; Machine Vision	Lee et al. 2019; Soleimani 2018
		Fraud detection/prevention	Machine Learning	Davenport 2018; Baryannis, Dani, et al. 2019
		Call Centre Automation (Switchboard)	Speech Processing	Brynjolfsson, Rock, and Syverson 2018
Smart connected products	Condition-based maintenance (predictive maintenance)	Recurrent Neural Network; Convolutional Neural Network	Lee et al. 2019	
	Situation aware products	Natural Language Processing	Jung, Hur, and Kim 2018	
Logistics	Transportation	Autonomous products	Deep Learning, Reinforcement Learning	Brynjolfsson, Rock, and Syverson 2018
		Accurate demand forecasting (Reduce the Bullwhip Effect)	Neural Networks	Singh and Challa 2016
	Warehouse	Post-processing monitoring	Neural Networks	Kousiouris et al. 2019
		Self-driving cars	Machine Vision	Brynjolfsson, Rock, and Syverson 2018
		Vehicle routing and scheduling	Evolutionary Computation	Levy 2018
		Voice picking	Speech Processing, Neural Network	Miller 2004; Gupta and Jones 2014
Retailer	Sales process	Robot picking	Machine Learning, Robotics	Hengstler, Enkel, and Duelli 2016
		Automatic container unloading	Robotics	Hengstler, Enkel, and Duelli 2016
		Virtual Assistants	Speech Processing	Hengstler, Enkel, and Duelli 2016
		Object inspection	Machine Vision	Jarrahi 2018
Customer	Customer interfaces	Fault detection	Neural Network	Hengstler, Enkel, and Duelli 2016
		Customer clustering	Machine Learning, Neural Networks	Knoll et al. 2019
Customer	Customer interfaces	Detecting process errors	Neural Network	Hellingrath and Lechtenberg 2019
		Suggesting better products and service	Machine Learning	Hengstler, Enkel, and Duelli 2016
		Customer requirements management	Machine Learning	Brynjolfsson and McAfee 2017
Customer	Customer interfaces	Chatbots and intelligent assistants for customer services	Natural Language Processing	Lyutov, Uygun, and Hütt 2019
		Get insights from the consumer preferences	Machine Vision	Dwivedi et al. 2019

the other hand, Lyutov, Uygun, and Hütt (2019) focussed on customer management. Both Goli et al. (2019) and Baryannis, Dani, et al. (2019) demonstrated how to predict and manage risks in the product portfolio and in the supply chain.

Based on this previous research, a model-training based AI approach is summarised for a general-purpose AI learning process. Figure 2 demonstrates the primary steps of developing and deploying AI models.

- Data collection and preparation:

This step includes two main activities. First of all, data collection means collecting data from industrial sensors and

entire IoT systems in real-time, and from business transaction-driven systems, etc. for the model training purpose (Min et al. 2019). Of course, other unstructured data are also collected, such as text and documents (Lyutov, Uygun, and Hütt 2019). The second activity is required to screen the raw data, drop duplicate or irrelevant data records, handle missing data attributes, and extract indicators and features by labelling the data needed in the learning/training process. It is crucial to map the data based on knowledge in business models (Lee et al. 2019; Min et al. 2019). Based on previous experiments, in order to train and validate the model the collected and transformed data must be divided into two groups: the training set and the test set, which are randomly divided by approximately

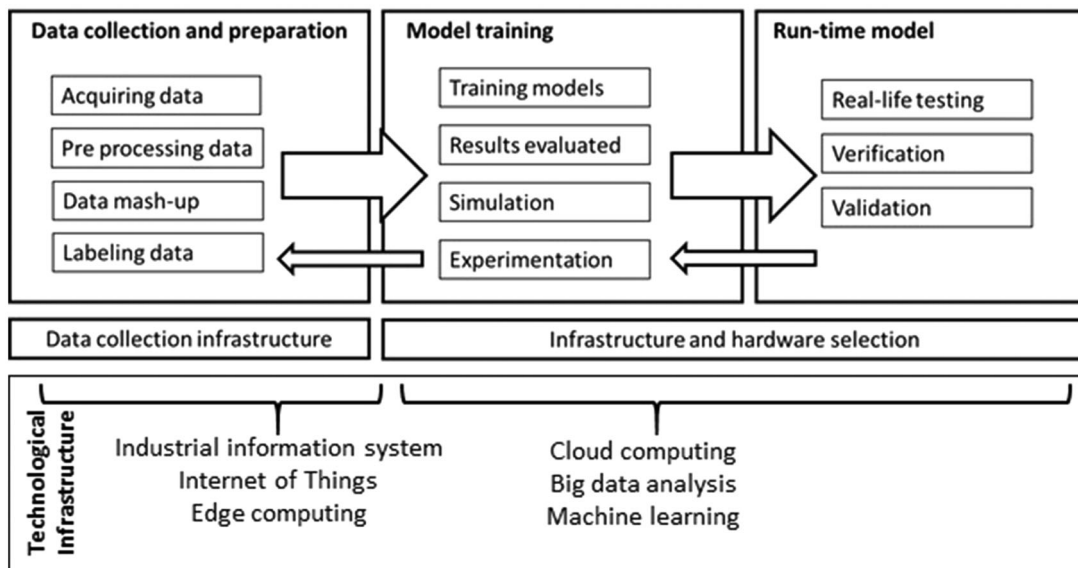


Figure 2. Process for developing and deploying AI models.

70% and 30% of the entire data set (Cavalcante et al. 2019; Goli et al. 2019; Baryannis, Dani, et al. 2019).

- Model training:

This is where the actual learning happens. The machines can extract knowledge by repeat learning and achieve acceptable forecasting accuracy, regardless of the size of the data set (Zhu et al. 2019). Different types of training algorithms are applied to a data training set (a subset of the entire data to learn from). The training target is used to construct an accurate mapping relationship based on available data and current algorithms (Min et al. 2019). The training set is used to train the model and construct an accurate mapping relationship based on available data and current algorithms (Min et al. 2019). The training datasets should contain all the features needed for the model and should have low noise (Paul, Azeem, and Ghosh 2015). The model training and the result evaluation steps are iterated until the best predictive model is found to be then actually used in the real world.

- Run-time model:

The final step is a try-out step that deploys the model within the actual business process in a real-life environment. The testing data set will be used to test the accuracy of the model (Lee et al. 2019). This testing set, while independent of the training set, follows the same probability distribution. The model must be revalidated in the latest environment and optimised according to the results and feedback (Min et al. 2019). In some instances, additional features may need to be included in the model and this is a necessary step before actually using the training model for security and effectiveness reasons (Min et al. 2019). Now the well-trained models can automatically predict or forecast in actual business processes and make an optimal decision to a given problem.

Step 1 to step 3 is not a one-time process but a repeating cycle. In the first round of the practice loop, a lot of manual work is needed for preparation and business understanding. But in the subsequent rounds, all tasks are expected to be executed automatically by the computers between the physical IoT (data sources) and the cyber-network (internet). The frequency of repetition depends both on the business requirements and on computing performance (Min et al. 2019).

2.3.2. Technological infrastructure

Based on Figure 3, the technological infrastructure can be considered from two main parts, namely Data Collection Infrastructure and Model Training Infrastructure.

The Data Collection Infrastructure is designed for the centralisation of collecting real-time and historical data to be used by the model training (Min et al. 2019). Various industrial information systems are integrated to support the data and information communications (Min et al. 2019; Haas 2020), such as manufacturing execution system (MES), which realises real-time and dynamic monitoring and control of the entire production process; supervisory control and data acquisition (SCADA) system and the programmable logic controller system (PLC), which directly controls the reaction parameters of machines; and warehouse management system (WMS), which utilises complex algorithms to direct the personnel in performing warehouse tasks, etc. (Min et al. 2019; Gupta and Jones 2014).

In addition to data from industrial information systems, the Internet of Things (IoT) makes it possible to collect more relevant data from manufacturing shop-floors by enabling remote sensors to communicate with central networks or even with other products. Technologies such as radio frequency identification (RFID), wireless sensor networks (WSN), and Bluetooth low energy devices, e.g. beacons, are used (Xu, Xu, and Li 2018; Cavalcante et al. 2019). Moreover, the

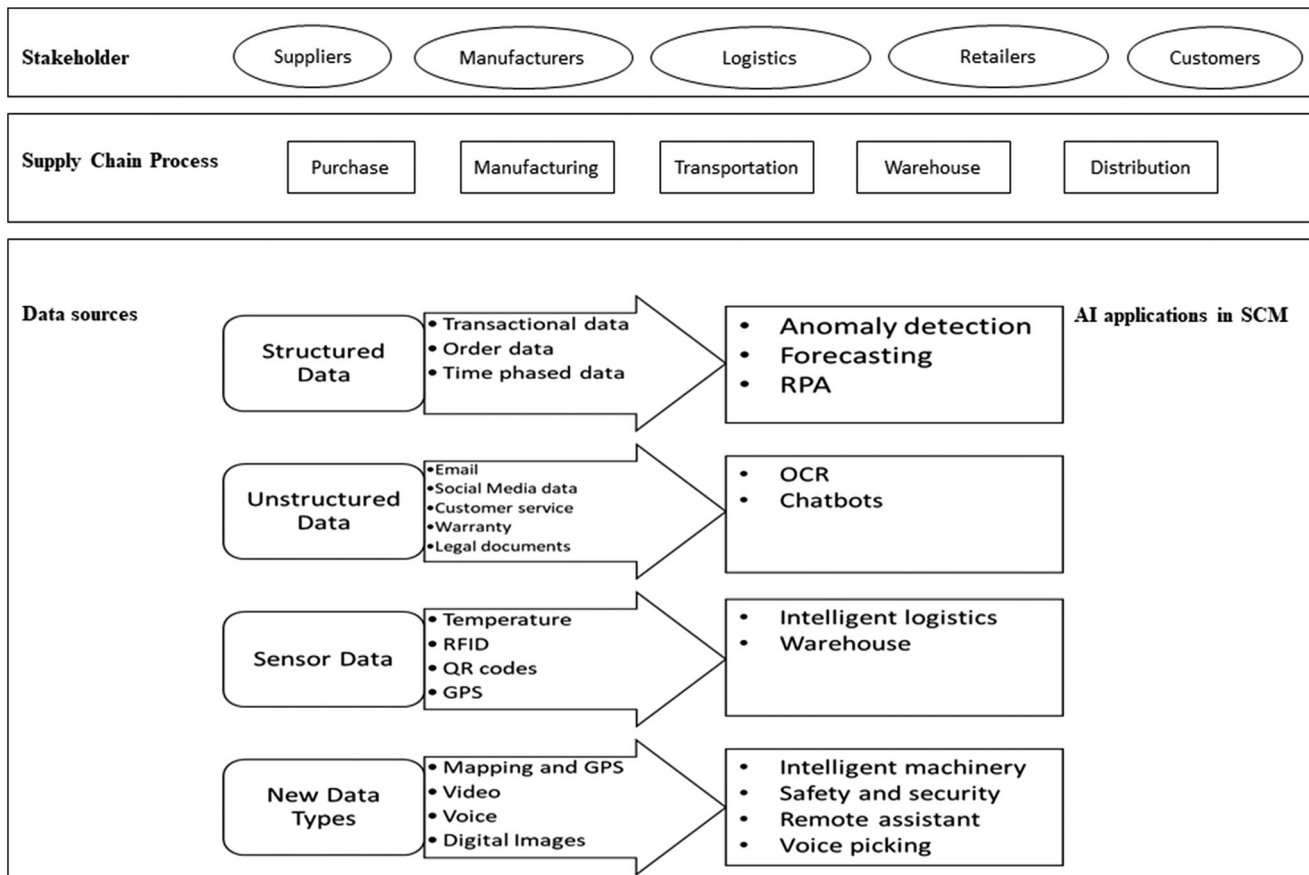


Figure 3. Links between different data sources and their use cases in the supply chain.

IoT system should have specific edge calculation abilities and automatic analysis functions (Min et al. 2019). In edge computing architecture, distributed edge nodes are connected to several sensors and analyse the data from the sensors and IoT devices at distributed servers. Therefore, both data collection and computational tasks are completed in a distributed manner. A distributed and decentralised way for processing the data can release the stress of centre computing because training data needs a lot of computation power. The participation of more edge nodes to increase the training dataset can also increase the accuracy of the training model compared to the traditional approach (Singh et al. 2020).

The second part of the technological infrastructure is the Model Training Infrastructure, which mainly consists of cloud computing, big data analysis, and machine learning. These are connected to the Data Collection Infrastructure in the first part to provide decentralised and secure big data analysis of collected data.

Cloud computing is a fundamental technology. It is used to support the collection, selection, and analysing of data from ambient environments using centralised methods. AI-enabled data centres must be run on a cloud-based server. All these sensor and computing systems store and manipulate a massive amount of data, which is highly heterogeneous (including both structured and unstructured data points) and diversified (Choi, Wallace, and Wang 2018), and requires very speedy processing. This requirement leads to the rapid development of big data analytics.

Additionally, the successful implementation of machine learning generally requires training data. The ability to continuously learn from training data can improve the machine learning algorithms and also create a more competitive advantage (Choi, Wallace, and Wang 2018). Davenport (2018) emphasises the importance of training data and incremental learning in AI rather than the mastery of AI technology. However, this approach is very challenging. It not only requires the presence of good computing memory so that the knowledge discovered by the trained datasets will be well-stored (Choi, Wallace, and Wang 2018), but also high level of requirements in terms of IT architecture related to its security, privacy, and resource constraints (Singh et al. 2020).

2.3.2. Data sources

As noted in the training of AI models, the processing of training and testing requires the collecting and then preparing of the data for analysis. In both steps, it must be understood in the data pre-processing what data needs to be obtained and why. It is paramount to collect relevant data and create a proper dataset. SCM strategies often depend on rapid and adaptive decision-making based on potentially significant, multidimensional data sources (Baryannis Validi, et al. 2019). As analysed in Baryannis, Dani, et al. (2019), data sources concerning the supply chain are numerous and can be divided into internal and external ones. Internal data sources include purchasing, production, delivery and sales records, GPS and container sensor information, firm finances,

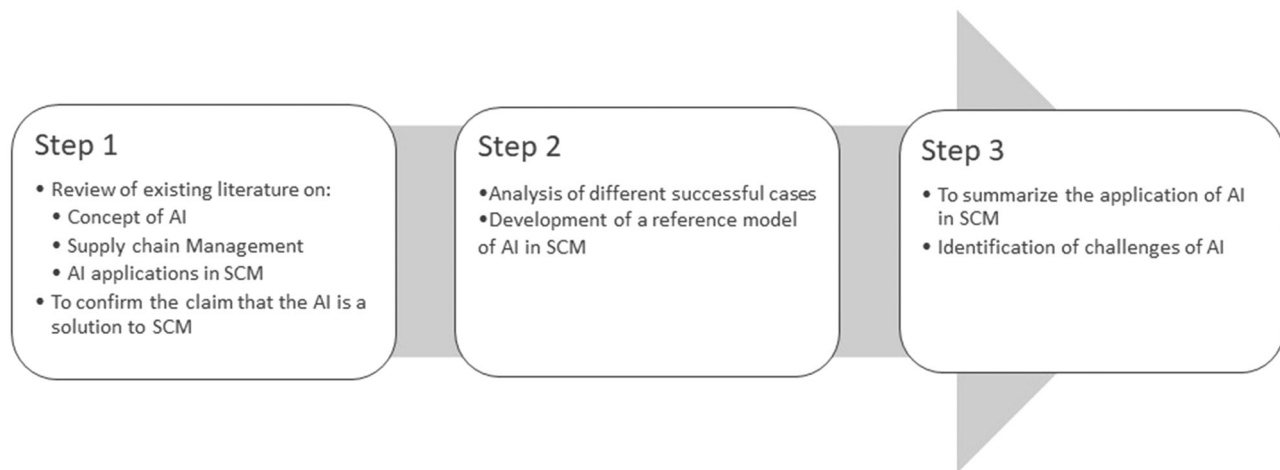


Figure 4. The approach of exploratory research.

and human resources data. External sources are not directly related to the supply chain and can include news items, weather reports, social media activity, national and international policies, and so on. Haas (2020) considered the data from four different information carriers: transactional data, analytical data, unstructured data, and linked data. Successful AI algorithms must be trained on the right data sources, or they will not be able to make the right decisions.

- **Structured data:** Structured data, even in tabular form, can usually be found without substantial effort in standard software systems for classic processes such as warehouse or order management. Machine data, which are also mainly subject to a structure, can be called up either via machine-specific or standardised interfaces. As automation progresses, these processes are increasingly confronted with big data, meaning that machines or monitoring systems (e.g. driving behaviour or temperature) generate large volumes of data (Haas 2020). Recording, processing, and interpreting human data and information sources require completely different instruments than the mechanical extraction of data from tables and machines.
- **Unstructured data:** Unstructured data consist of textual documents, social media, and ratings from customers. One of the critical features of machine learning is its capability of processing unstructured data to identify contextual patterns in the conversation. It can improve the knowledge extraction process. Social media information can be used for sentiment analysis and emotional detection, which is valuable for customer relationship management.
- **Sensor data:** Several applications can be envisioned by sensor data, such as reducing the uncertainty of customer demand based on consumer behaviour, mitigating transportation-related risks by real-time monitoring of the distribution centres, increasing visibility and trust among suppliers (Baryannis, Validi, et al. 2019), and also enhancing industrial products through machines' 'digital twins' (Davenport 2018).

- **New data types:** Advanced technologies, such as speech recognition and natural language processing, are now providing more unique types of data, for instance voice transcripts, or information from an image/video. This intangible information can be converted into editable text and easily interpreted with no manual work being required anymore. GPS can capture location information and convert it into numerical data, which can be used easily. Therefore, new opportunities and new use cases can be created with new data types.

3. Methodology

In order to illustrate and demonstrate how AI can be implemented in SCM and improve SCM overall performance, exploratory research is conducted in this particular study. Childe (2011) and Choi, Cheng, and Zhao (2016) pointed out the importance of an exploratory case study with a literature background review in the research community. It is widely recognised that the case study approach is widely used in supply chain-related research (Skender and Zaninović 2020; Ramanathan et al. 2017). Based on the fundamental nature of exploratory research, qualitative research through multiple case studies is adopted as a best-fit technique (Yin 2003).

3.1. Research design

Figure 4 shows the procedure of exploratory research that is applied in this particular research. In the beginning, it is essential to perform an in-depth analysis of existing literature to create a comprehensive understanding of basic concepts. It is vital to follow an acknowledged literature guideline to conduct a rigorous literature review. Therefore, a structured literature review has been conducted to identify (i) the basic concept of AI, (ii) its applications in previous research on the topic of AI and SCM, and (iii) the technical requirements for implementing AI in SCM. This systematic literature review helped to better understand the technological background of AI and its related features. However, there are still research gaps on how to implement an integrated AI

solution to support the entire supply chain management. This paper seeks to fill the research gaps, and also aims to gain familiarity with the concept of AI, and acquire new insight into AI-powered SCM.

The second part of this research is an exploratory case study. Different applications of AI in SCM are analysed to investigate the contemporary phenomenon in real-life, and also to discover the state of the studied phenomenon (Yin 2003). The case study method was selected because its characteristics are suited to the purpose of this research. Multiple case studies can help researchers to understand the studied phenomenon (Stake 2005) and also develop new approaches to operations management.

The combination of case study and other research methods offers a wide range of data acquisition and analysis. Therefore, the last step of this research is to generalise the concept of AI-powered SCM. Each case should be studied separately in-depth to understand the phenomenon, but also all the cases should be analysed holistically to fulfil the overall research purpose (Stake 2005). This study summarises the systematic investigation of how different case companies utilise different AI techniques in improving their SCM overall performances. A cross-case analysis is suitable and is considered more reliable in this particular research (Ramanathan et al. 2017) because cross-case analysis enables comparisons of differences and similarities between the cases. This method is suitable for identifying general trends and also for verification (Yin 2003).

3.2. Data Collection and analysis

A semi-structured interview process was developed to collect data from the case companies. The interview questions were open questions raised during the interview. In order to analyse the potential impact of using AI technologies in operations/supply chain, four exploratory case studies were selected. Access to case study data was provided by an IT consulting company assisting industrial companies in their transformation to the use of artificial intelligence. For each case company, different process sections were used in the analysis. Additionally, each case company had a different kind of implementation technology.

Several interviews with the development teams building the AI-powered SCM were conducted separately in each case company. Project management and application development experts were included. During the initial stage of each interview, a brief description of the study and its objectives were given, and the interview process involved was explained to the interviewees. Each interview took about an hour. Since the scope of this study falls within their job responsibilities, it is expected that the information gathered meets the objectives and purpose of the study.

The study invited four international companies operating SCM to participate in the interviews. They varied in size, focus and mission. They were selected due to their high level of supply chain participation and high level of innovation technology acceptance. The participating companies were labelled case companies 1, 2, 3, and 4. Because the purpose

of this research was to focus mainly on exploration, this case number can be considered sufficient and appropriate to give a valid grounding to this empirical research (Roden et al. 2017).

The interview data were analysed and compared through cross-case techniques (Caniato et al. 2012). Correspondingly, all the data were labelled and classified and used for comparing and identifying the similarities of each company. The results obtained through a cross-case analysis were used to derive and generalise the summary of the cases in the following sections. This open coding approach is widely used in case studies (Shaharudin et al. 2015).

4. Exploratory case analysis

The main question for each case was to analyse the objectives of the AI implementation, the used technology, the expected and delivered impact on key performances and persons involved. The interviews were targeted on persons working with the responsible project manager of the company.

4.1. Case 1: sales configuration

Case company 1 is an industrial company manufacturing various sizes of distribution transformers based on customer needs. The sales include communication with the customer in order to have a valid specification and then deliver a quotation which accords with the production specification. Pricing decisions, giving delivery time estimates and other related communication with the engineering/production team is important. Very often in the sales phase, several rounds take place until the final configuration is fixed and specifications are delivered to order fulfilment.

Sales configuration is the process part of the sales and distribution and is sometimes referred to as CPQ – Configure Price and Quote. The objective of sales configurator tools is to help maintain a fast communication between customer interface and engineering/production at the company. In practice, such software packages have been developed initially as rule-based systems, which store the key product information in a certain format. Today, this kind of system may comprise several technologies, including constraint satisfaction engine solving different conflicting rules and communicating with external systems such as ERP for delivery time and Production Planning for schedules. Sales personnel or knowledgeable customers can use the system with a web-based user interface and access up-to-date product information all the time.

Based on the configuration history, product selections can be clustered, e.g. using so-called shopping cart analysis, and information regarding the selected products are often bundled and can be utilised in R&D process (Figure 5).

The main objectives for using AI technology have been (1) reducing the speed for quotation process, (2) improving the quality of the documents, and (3) reducing the manual work in the process. The objectives for configuration system implementation have been set in the investment project and

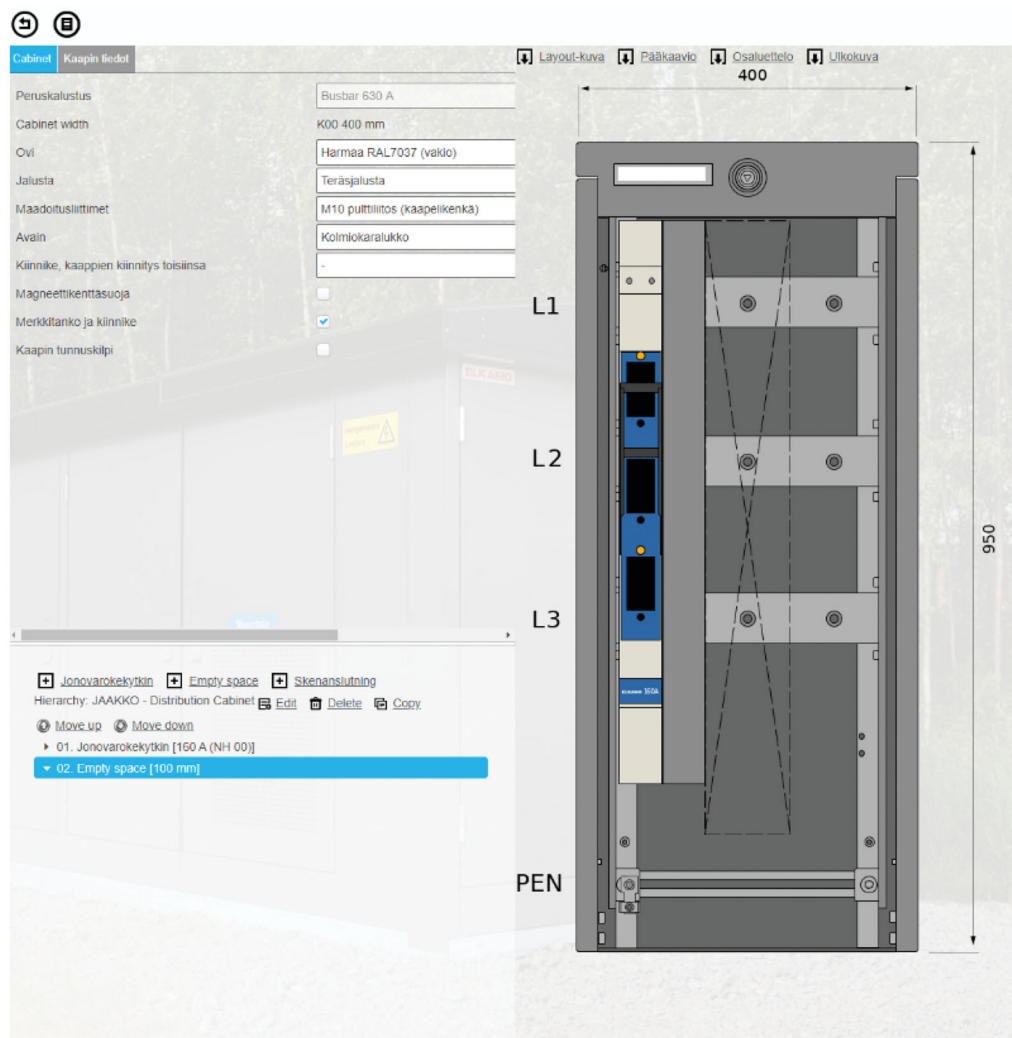


Figure 5. Configurator system for sales.

the configuration model has been updated and revised during the product life-cycle updates.

4.2. Case 2: production planning and control

Case 2 is a company building sheet metal manufacturing equipment, including machinery for cutting, bending, shearing and bending. Equipment is sold to customers as separate machines or as a complete line. Production planning is a key activity at the customers' sites, ensuring good utilisation of the machinery. Understanding the patterns and principles of the machines and design processes related to producing manufacturing instructions, lots, nests and schedules is a complicated task. Controlling various dependencies and conflicting objectives under varying situations requires experience.

The company decided to invest in AI technology to support production planners with automated decision support. In practice, the smart connected machinery connects to a cloud-based AI, which reacts to any changes in the production system or customer order list. The AI uses genetic algorithm-based optimisation to suggest new alternatives for production schedules, material changes and tool changes.

The decisions improve the impact of production planning, although the decisions are not used to replace humans completely from the system (Figure 6).

The main objectives for this case driving the implementation are: (1) improved capacity utilisation of machinery, (2) a more systematic and quick-to-adapt approach for production planning, and (3) separation of control domain and physical assets. The key metrics include on-time delivery, machine utilisation, and order lead-time. Previous performance can be compared with that delivered by the AI system. Another important feature behind investing in AI technology was to build a connected service for the customer's equipment to provide online guidance for production planning tasks. A centralised AI service links customer machinery to the machine-builder's fleet, and further services can be introduced in the cloud.

4.3. Case 3: quality control of products

Case company 3 is a food production plant producing various types of consumer-packaged foods in various packing and stock-keeping units. The production processes include both manual and automatised sections. A large variety of

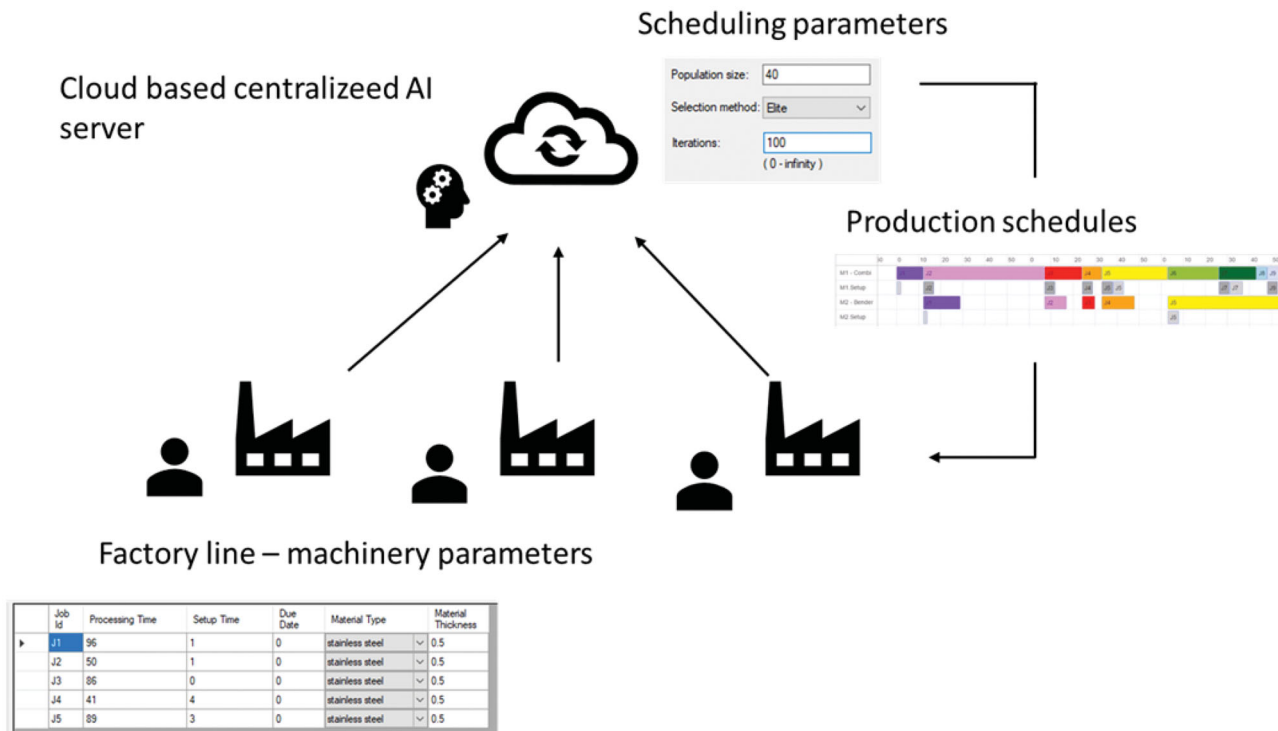


Figure 6. Centralised cloud-based AI servers in several factories to deliver better production plans as a service.

quality control is required in the stock-keeping unit level, and this has been based on visual inspection. AI based camera stream analysis on the production line can provide detection of products and analysis of possible errors in packaging. The analysis is based on trained image materials and different features matching these. Deep neural networks (DNN) are used in this application, and new product features can be trained in a relatively short time.

Figure 7 below illustrates a high-level principle of how local AI can use video stream in real-time and by using the trained material find if the quality reference is met and the level of confidence of the analysis. DNN detector can be trained to recognise a large variety of product errors and understand even if the product rotation is different from the expected one.

The main objectives for the quality control case are: (1) moving from sampled quality control to 100% inspection without adding personnel, (2) building a systematic learning loop on QA (quality assurance) results from production and earlier parts of the process, (3) reducing waste in the process. AI based video stream can improve the quality inspection process, and quality criteria can be stored in a systematic training material format for the AI.

4.4. Case 4: spare parts and maintenance orders

The case company is a manufacturer of mobile machines used in constructions. The machines have planned schedules for maintenance based on the calendar and running hours. The basic maintenance includes service tasks which an operator can do, but also events which are required to be

completed by authorised service personnel. Each service requires certain spare parts, tools, additives such as lubrication oils, and personnel in order to be completed.

The company has invested in IoT, which connects the installed base to the manufacturer's portal. In the first phase, remote information collected was used to give guidance to customers on asset management. Later, EDGE level processing capability was added to the machines. In practice, IoT continuously monitors use of the machine and analyses early signs of part wearing, fatigue and possible breakdowns. Each machine has specific types of failure modes, which are predicted by clustering time-series data and detecting anomalies.

Anomaly events are categorised by the local machine AI on different levels based on training data. Once the confidence level of a certain type of possible failure event triggers the pre-set level, the machine AI sends a message to the machine manufacturer's centralised portal to make a condition-based maintenance request. The manufacturing service organisation maintains service orders in the ERP system. In case of a high confidence condition-based analysis, the construction machine AI can book service and spare parts automatically to the site and notify the fleet owner of the service plan triggered by the AI (Figure 8).

The main objectives for the spare part case were (1) improved life-cycle of assets by ensuring correct spare part procedures, (2) moving from a calendar-based system to condition-based maintenance, and (3) reduced operational expenses and life-cycle costs. Condition-based service is enabled by a local machine-level AI system in combination with the manufacturer's centralised ERP. Service contracts need to be up-to-date, and authorisation to monitor the fleet

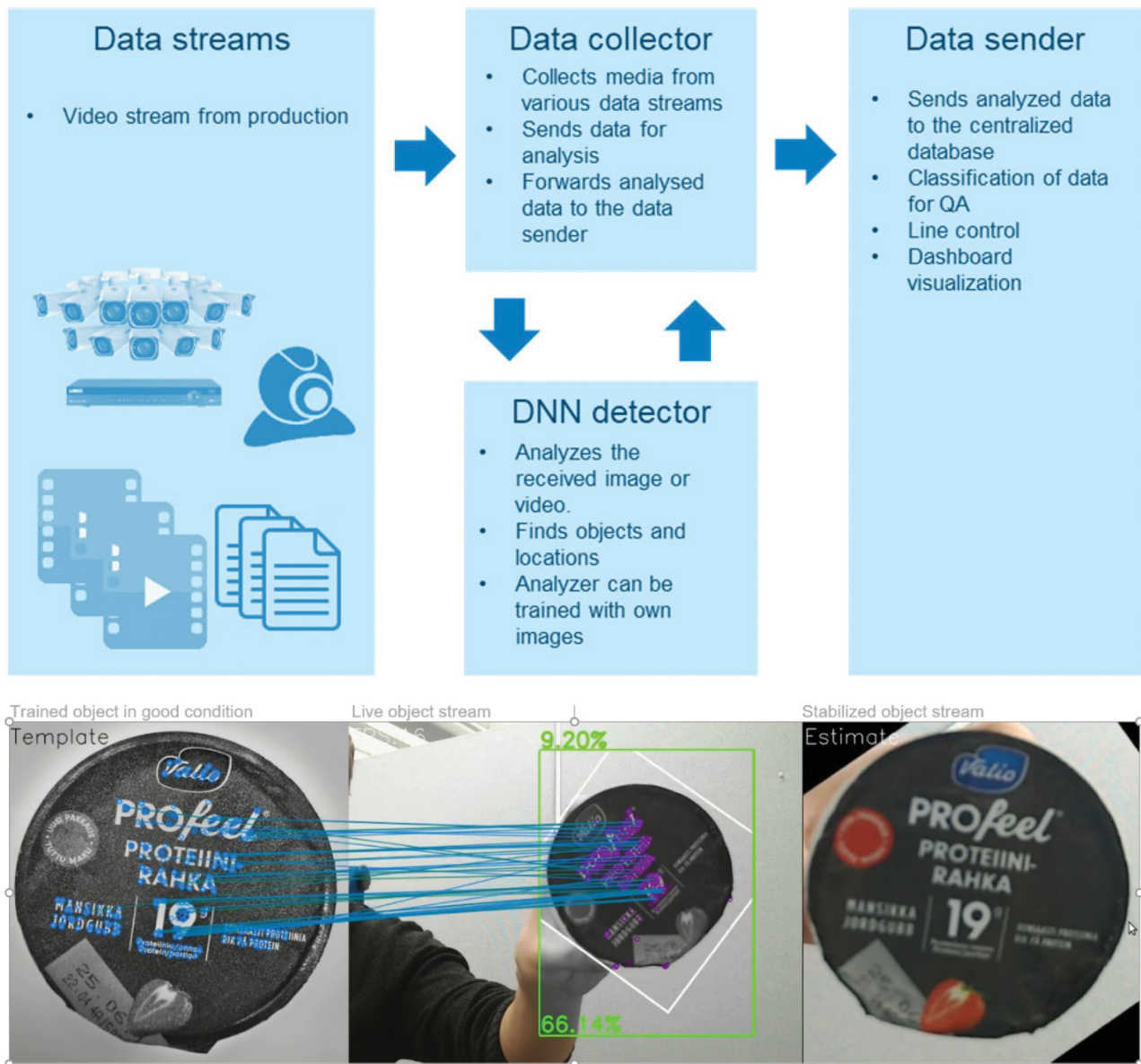


Figure 7. Feature detection demonstration for product quality control based on machine vision and DNN.

is needed. Overall, the operational benefit for the end-user is that the machine builder is able to offer improved service planning and better capacity utilisation of the fleet.

4.5. Analysis

The four described cases have had an impact of different organisational parts of the companies. In the case of sales, production planning and service, the persons affected have been domain experts. In the case of quality control, the task is not complicated, but high volume and repetitive. Purely human-based quality inspection would not cover all the products, and some sampling would be required. Improved resource utilisation is the case in production planning and the spare parts management case. In none of the cases have humans been replaced by machines completely, but they take some tasks which have become possible with the new AI technology stack. The systems are not completely

autonomous, but rather assist humans at a high-level in repetitive tasks. Figure 9 shows the matching of business processes, potential use cases and data sources connected for AI implementations.

From the data source point of view, the cases presented have different raw materials. Sales configuration and production planning are based on structured data. Quality control and spare part control rely on processing sensor data close to the source. Smart connected devices are common factors for production planning and quality control cases. Tables 2 and 3 below summarise the results of the case analysis.

5. Discussion

In this research, we conducted a systematic literature review and exploratory case studies. Based on both theoretical and practical research, several examples and possible applications have been presented. Multiple case studies were carried out

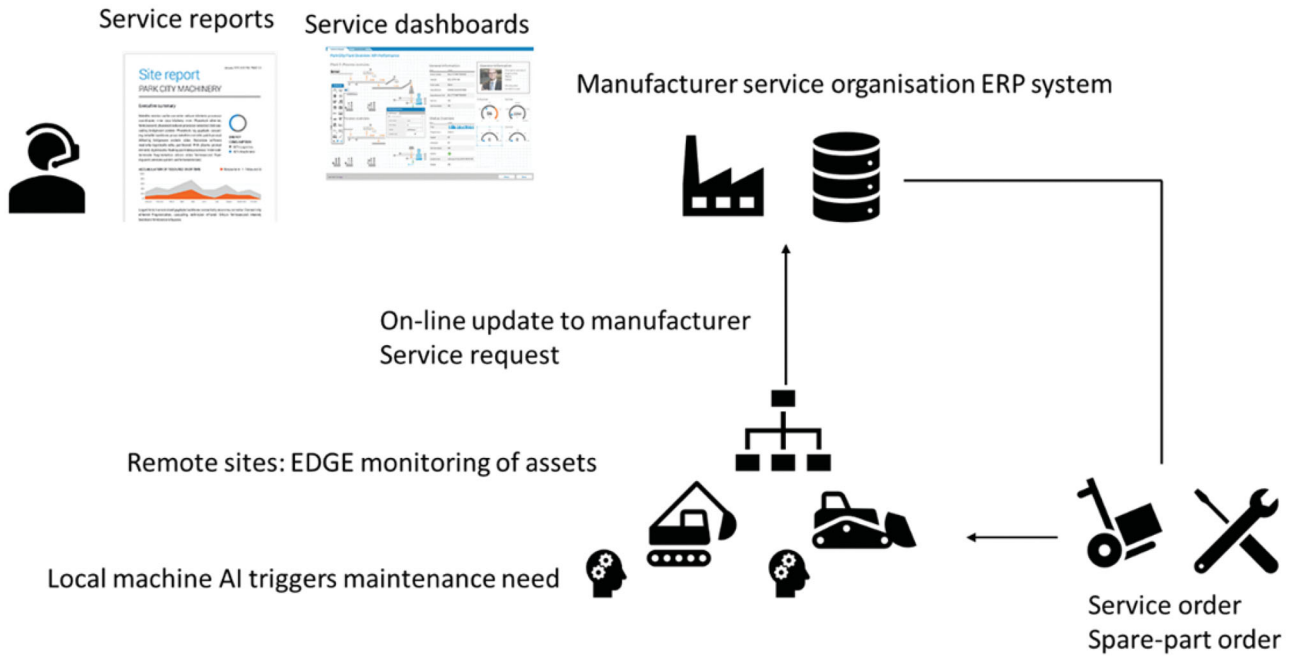


Figure 8. Automated spare part orders generated by smart connected product.

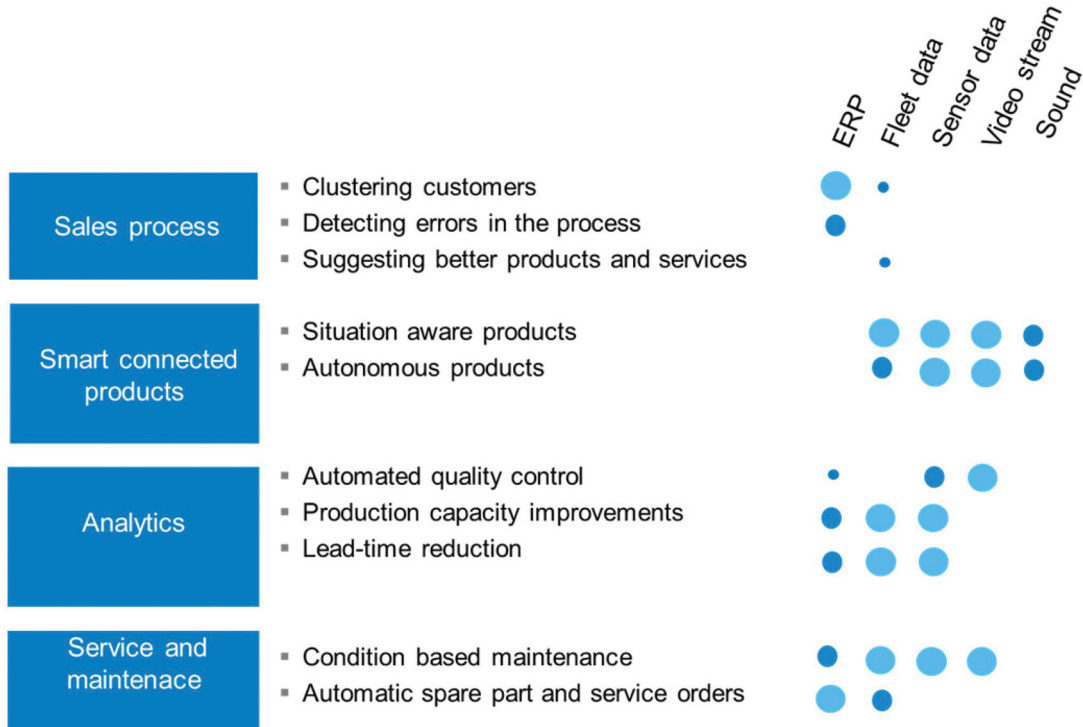


Figure 9. Matching business processes, potential use cases and data sources connected for AI implementations.

to compare the various features of AI in SCM. We can see that multiple AI technologies are used to make the SC leaner (reduce waste) and more efficient. This finding coincides with the literature review in the theoretical background section, concluding that different AI technologies interplay with each other and are used together to implement an application. An appropriate level of IT infrastructure helps to build

process automation and process optimisation for SC tasks. Some common objectives for these planned and expected impacts seem to be:

1. Reduced time needed in decisions or decision support. Computers can pre-screen order documents, make forecasts, plan production, but a human makes the final

Table 2. Case overview.

	Case 1: Sales configuration	Case 2: Production planning and control	Case 3: Quality control of products	Case 4: Spare parts and maintenance orders
Organisation	Sales, configure-price-quote	Sales/Operations Planning	Production	Service
Primary method	Rule-based system with constraint satisfaction programming	Genetic algorithm running optimisation	Deep Neural Network conducting visual inspection	Clustering analysis and anomaly detection with machine learning
Objectives	Automation of quote processing, replacing human knowledge with artificial intelligence to process offers and orders	Ensure that all orders are processed on time and maximise capacity utilisation of production	Perform a thorough quality inspection for all parts in the manufacturing phase	Processing condition analysis of assets in the field (installed base) and placing automated maintenance and spare part orders
Persons involved and how role has changed	Salespersons – focus on customer communication; product knowledge and rules are maintained by AI	Production planners – daily scheduling is conducted by automated machinery sending order information to central cloud scheduling AI	Quality assurance can focus on corrective actions rather than operative inspections	Service planning – service calendars are maintained by AI
Key performance indicators	<ul style="list-style-type: none"> • Number of orders • Order quality • Speed to process offers 	<ul style="list-style-type: none"> • Capacity utilisation • Later orders 	<ul style="list-style-type: none"> • Number of inspections / hour • Type A/B errors 	<ul style="list-style-type: none"> • Life-cycle costs of asset • Number of rush orders

Table 3. Case AI data, learning and control.

	Case 1: Sales configuration	Case 2: Production planning and control	Case 3: Quality control of products	Case 4: Spare parts and maintenance orders
Data	Product data, sales offers and orders from ERP	Production orders	Production camera stream	Smart machine collected data from the EDGE
Closed-loop learning	Analysis of customer offers and orders in terms of product parameters	Information updates from factory, machine unavailability triggers re-optimisation of the schedules	Camera data is collected from production, manual retraining needed	Measuring equipment behaviour from IoT data
Learning adjusts	Product parameterisation suggestions based on clustering	Production schedule	New product failure types, improved detection	Condition- based maintenance

decision. Better preparation has been conducted, but the processes are not fully autonomous. A single person can handle a large volume of cases and concentrate on higher-level problems. This yields a faster response rate and improved process throughput.

- Human resources for repetitive tasks will be reduced. This affects back-office work, which is needed to complete various paper work between organisation entities, including customer front end, production, and services. Process automation, combined with decision support, has a direct impact on jobs that require less knowledge and have been focussing on handling items.
- A higher capacity utilisation rate is a common objective for several planning activities. Artificial intelligence can conduct operations that give close to real-time guidance for humans on how to improve the current setup. Learning from the past and forecasting future states present practical use cases for this. Higher utilisation is a common objective for smart connected machines, but also production-related assets and all resources.

Figure 10 shows examples and possible mechanisms that are driving AI implementation related to operations and supply chains. The expected impacts and pressure from the market are quite high, and there is a risk that some objectives are unrealistic in the short term at least. This research comes with limitations. Qualitative research, as such, is often

criticised for its lack of scientific rigour. Four case examples do not cover all sectors very well, such as online sales or specific transportation tasks, and further research on implementation patterns is needed.

6. Conclusions

The supply chain (SC) is crucial in moving products across vast distances and in supporting interconnection among different stakeholders, such as raw materials suppliers, manufacturers, retailers, logistics companies, and consumers. Therefore, an effective and efficient SC means that these connections can be made accurately, quickly, and at least cost. The critical success factors for SC are information sharing, process integration, and collaboration (Fatorachian and Kazemi 2020). Therefore, SC will have to be digitalised and increasingly dependent on technology in the form of IoT and sensors all across the SC, and this will enable them to collect data in real-time.

Our study is inspired by the increasing amount of AI implementation recently. Many pieces of research point out that AI has been adopted intensively in SC and has created the most value in the manufacturing industry (Chui and Malhotra 2018). The results of the wide usage of AI have played a critical role in improving supply chain management. In general, AI and AI applications are one of the

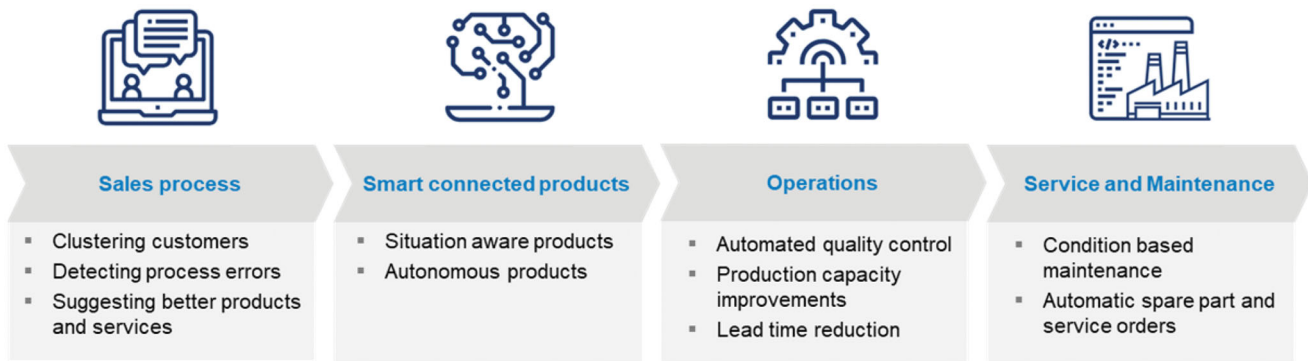


Figure 10. Key application areas.

most exciting and valuable current fields of research. AI is not only applied in humans' everyday lives, but also in operations and supply chain management. AI-based SC is a comprehensively integrated technology and management system based on information and intelligent technology to realise intelligence, network, synergy, integration, and automation. By means of integration with AI, supply chain management is becoming autonomous SC with the characteristics of being self-aware, self-governing and self-determining, and self-optimizing.

Our study addresses an important gap in the literature as to how AI can be implemented in the supply chain management area and how it helps to improve operational performance. Our study is innovative in that it summarises the most recent research and also investigates four real cases in the fields of SCM: customer management, production management, quality management, and also services management. The findings provide a holistic and meaningful understanding of the adoption of AI for SCM in dynamic environments. This research makes contributions to both theory and managerial methods that are usable in practice in the future.

As this study was conducted through exploratory case studies, it can lay the foundation for the development and emergence of AI in SCM and impact the SCM's business performance. This research can also offer other future research opportunities. For instance, it considers the critical success factors of the implementation of AI in SCM. Other interesting future research could focus on the investigation of organisational and cultural factors influencing the adoption of an AI operational perspective in the SCM. Although AI has enormous potential in SCM, it has a long way to go to realise its real value (Chui and Malhotra 2018).

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