Working Papers

Working Paper No. 37

Applications of Artificial Intelligence in Supply Chain Management: Identification of main Research Fields and greatest Industry Interests

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ISSN 1614-7448

cite as: Sandra Lechtenberg, Bernd Hellingrath: Applications of Artificial Intelligence in Supply Chain Management: Identification of main Research Fields and greatest Industry Interests. In: Working Papers, European Research Center for Information Systems No. 37. Eds.: Becker, J. et al. Münster. May 2021

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Title

Applications of Artificial Intelligence in Supply Chain Management: Identification of main Research Fields and greatest Industry Interests

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Abstract

Advances in the area of computing power, data storage capabilities, etc., are changing the way business is done, particularly regarding how businesses use and apply artificial intelligence. To better understand how artificial intelligence is used in supply chain management, this paper identifies and compares the main research fields investigating this topic as well as the primary industry interests in it. For this, we performed a structured literature review that shows which methods of artificial intelligence are applied to which problems of supply chain management in the scientific literature. Then, we present industry-driven applications to provide an overview of fields that are most relevant to industry. Based on these results, indications for future research are derived.

Keywords

artificial intelligence; supply chain management; logistics; applications; industry-driven

1 Introduction

Technology has always been a driver of change – inventions such as the steam engine or the Internet have changed the way people live and work. Increased processing power, connectivity, and the capability to store and process more data than ever before change the way business is and can be done. It opens a wide range of possibilities to increase economic progress (Dobbs et al. 2015; Büyüközkan & Göçer 2018). This emergence of new technologies and the resulting digitalization of business is also changing supply chain management (SCM). A successful transition to a digital supply chain will create 'an intelligent, customer-centric, system integrated, globally-connected and data-driven mechanism that leverages new technologies to deliver valuable products and services that are more accessible and affordable' (Seyedghorban et al. 2020). However, even though digitalization is considered one of the most important SCM trends, its realization presents many companies with challenges. Many have started to develop concepts on how to digitize their supply chain. Still, only 5% of more than 300 interviewed executives from some of the largest global manufacturing and retail organizations are satisfied with the so far achieved results (Dougados & Felgendreher 2016).

A recent study conducted by the German Logistics Association (BVL) has shown that expectations for using artificial intelligence (AI) to digitalize supply chains are exceptionally high (Kersten et al. 2017). AI is not only a way to analyze data or automate decision-making but also to optimize the whole supply chain. In general, applying AI techniques in an SCM context is expected to show great potential and transform SCM (Min 2010). However, what exactly AI is and which methods do belong to the set of AI techniques remains unclear. Even when considering general, not SCM-related, AI literature authors cannot define a specific AI technique set. Moreover, the understanding of what can be considered as 'intelligent' has been changing over the years. As AI has a long history that has started in the 1950ies, new algorithms have been developed, and other ones have become more common (McCorduck 2004).

This lack of a common understanding of AI is also reflected when focusing on the SCM domain. Min (2010) examined AI applications in SCM and identified artificial neural networks (ANN) or machine learning in general, genetic algorithms, fuzzy logic, and agent-based systems as the AI techniques to address problems from the SCM domain. Although the review was able to show that AI techniques are already implemented, it has to be concluded that it 'has not been fully exploited to solve SC problems' (Min 2010). Moreover, this overview does not include recent advances in the field of AI, such as deep learning, reinforcement learning, robotics, computer vision, or natural language processing (Stone et al. 2016). Consequently, this paper aims at providing a current overview of existing applications of AI in SCM both in research and practice. Based on such an overview, the paper will derive suggestions for future research. Three research questions will be answered to achieve the stated goals. The first one focuses on existing applications in research:

- RQ1: Which techniques from the field of AI are applied to which tasks from the SCM domain?

This question focuses on both technical aspects as well as the domain of identified application cases. The result will be an overview of which methods are applied to solve specific SCM tasks. This research question will be answered based on a structured literature review (SLR) focusing on scientific literature.

Apart from research, industry-related AI applications are also of interest to give a broad overview of the application areas of AI in SCM. Of particular interest is whether the industry is interested in the same topics as research, i.e., might benefit from scientific results, or whether research does not fully satisfy the claim for relevance. Therefore, based on white papers published by companies, consultancies, or industry-related research organizations, the second research question will be answered:

- RQ2: To what extent do industry-interests resemble the main research fields regarding the application of AI in SCM?

Based on the answers to these two questions, i.e., an overview of how research and industry use AI in SCM, future research directions can be derived to answer the third research question:

- RQ3: What are the possibilities for future research in the area of AI for SCM?

By answering all three research questions, this paper will contribute to research in the field of AI for SCM. It will provide researchers with overviews of both scientific and industry-related interests and highlight promising future research options to streamline scientific work and support relevant research that also addresses industry needs.

The next section provides some basic knowledge regarding AI and SCM. It presents the working definition of both terms. Especially the one for AI has highly influenced the conduction of the SLR. Section 3 gives an overview of how the relevant literature has been searched, reviewed, and analyzed. The fourth section will then present the results of the scientific literature. It answers RQ1 by providing an overview of which AI techniques are applied and which SCM tasks are addressed as well as deriving the main research fields. Industry interest regarding AI applications and their similarities and differences to scientific research are presented in the fifth section to answer RQ2. It has to be noted that only very few companies publish their work in white papers, and even the number of press releases or similar is relatively small. Therefore, the chapter can only give a first indication of where an industry focus lies and provide a first overview of existing applications and possible high-interest areas. Moreover, the presentation might be biased to bigger companies and neglect advances made by smaller or medium enterprises since these are not publicly available. Having looked at existing applications both in research and industry, a discussion of future research possibilities is provided to address RQ3. The paper concludes with the last section summarizing the findings, highlighting important aspects, and pointing out limitations.

2 Theoretical Background

To provide an overview of existing literature, it is first necessary to develop a frame to classify results. A classification is essential to answer RQ1 and identify (1) which AI techniques are applied in SCM literature and (2) which tasks from the SCM field are addressed. Hence, a classification frame for AI techniques and SCM tasks is needed. These frames will be used to later on code the sources identified as relevant in the structured literature review. Section 2.1 describes the frame for AI techniques, and section 2.2. the one for SCM tasks. Both are derived from the primary literature and general sources discussing the fields.

2.1 Techniques of Artificial Intelligence

As described before, there is no common understanding of what can be considered as 'intelligent' and which methods can be subsumed under the term AI. Instead, definitions of AI remain somewhat vague and reach from focusing on 'agents that receive percepts from the environment and perform actions' (Russell & Norvig 2010) to the understanding of AI as 'computational systems that perform tasks commonly viewed as requiring intelligence' (Poole & Mackworth 2017). Russel and Norvig (2010) have organized the available definitions into four different categories: thinking humanly, thinking rationally, acting humanly, and acting rationally. They focus on 'acting rationally' and define AI as the study of rational or intelligent agents that act to achieve the best expected outcome. AI is not merely copying human behavior or inferring actions logically but also deals with the mathematically well-defined concept of rationality (Russell & Norvig 2010). Indeed, researchers have focused on designing intelligent agents for about 20 years (Russell et al. 2015). For this paper, we will also use the idea of rationally acting agents as a working definition of AI.

Such an intelligent agent exhibits certain capabilities, e.g., perceiving its environment or planning its actions, which are enabled by various algorithms. The number of these algorithms and their variations is too high to name all of them. Hence, a summarization into categories is reasonable. Based on Poole and Mackworth (2017) and Russel and Norvig (2010), the following AI approach categories could be identified. These have been iteratively adapted based on the literature later on identified in the literature review. The following list provides short explanations for each group; more details can be found in the sources mentioned above.

- *Neural Networks:* The human brain serves as an example for creating a neural network, which consists of neurons, i.e., nodes that are connected and arranged in layers. Each connecting link has a certain weight, and each neuron an activation function. Neurons receive inputs and calculate output values based on their activation function. They then send that output to neurons on the next layer until a final output is derived.

- *Bayesian Networks:* The structure of a Bayesian or belief network is similar to the one of a neural network. However, the connection of neurons represents conditional dependencies among the set of input variables. Variables are ordered according to their interdependencies, and the result is a directed graph.

- *Multi-agent Systems (MAS):* In a MAS, different agents follow their individual goals and strategies. Based on these, they perform actions and propose different solution alternatives, which are often presented to a human decision-maker to make the final decision.

- *Support Vector Machines (SVM):* SVMs aim at establishing a hyperplane to separate data points into classes. This hyperplane is the boundary with the most significant distance to all data points and hence separates the classes best.

- *Decision tree/Random forest:* Comparable to a real-world tree, a decision tree consists of nodes and branches connecting them. The nodes at the end of a branch are leaves, and each leaf represents a class. The other nodes are decision nodes, and when moving along the branches, the decision at each node determines which branch to select to move on. The set of possible classes decreases with each decision, leading to one class assignment when reaching a leaf. A random forest consists of several decision trees, which are typically created based on different data subsets. This way, it is ensured that different trees using various features as decision nodes are built.

- *Reinforcement learning:* With reinforcement learning, an agent can perceive its environment and current state and act based on that perception. For each action, the agent receives a reward and learns which actions are good or bad. After each action, the environment's and agent's state changes, and the agent chooses its next action.

Another approach class often mentioned in the context of AI are metaheuristics. Independently on whether one agrees that these belong to AI, the application of metaheuristics in SCM has been highly researched. Indeed, there are already some sources providing an overview of this field (cf. for example, Griffis et al. (2012)). Due to the available research, this paper does not consider metaheuristics.

2.2 Tasks from Supply Chain Management

Numerous definitions are available for SCM. This paper uses the definition established by the Council of Supply Chain Management Professionals (CSCMP), an association of SCM professionals whose research is widely recognized in the domain. According to their definition, SCM 'encompasses the planning and management of all activities involved in sourcing and procurement, conversion, and all logistics management activities. Importantly, it also includes coordination and collaboration with channel partners, which can be suppliers, intermediaries, third party service providers, and customers. In essence, supply chain management integrates supply and demand management within and across companies' (Council of Supply Chain Management Professionals 2013). Different tasks need to be done to fulfill the activities mentioned in the CSCMP's definition. The Supply Chain Operations Reference (SCOR) model, established by the supply chain council now merged with the association for supply chain management, is well-known and highly acknowledged. It categorizes those tasks into plan, source, make, deliver, and return. Each of these categories contains planning, execution, and enabling tasks (e.g. Holten & Melchert 2002).

Stadtler (2005) proposes a more detailed division of the planning task: the advanced planning matrix. This matrix depicts SCM tasks along two dimensions: the planning horizon (long-term, mid-term, short-term) and the type of supply chain process (procurement, production, distribution, and sales). However, this matrix focuses on planning tasks as well as on the forward flow of material. Hence, extensions are necessary to depict all tasks according to SCOR and serve as a categorization frame. In addition to the planning horizons, an execution layer is added. This layer subsumes all tasks related to executing and controlling a supply chain. The second extension is a functional support layer that includes all tasks to support material flow and resembles the 'enable' function of SCOR. Exemplary tasks of this layer are performance measurement or finances. The return process is also not included in the initial matrix by Stadtler (2005), so another addition is needed. Figure 1**Fehler! Verweisquelle konnte nicht gefunden werden.** shows the p

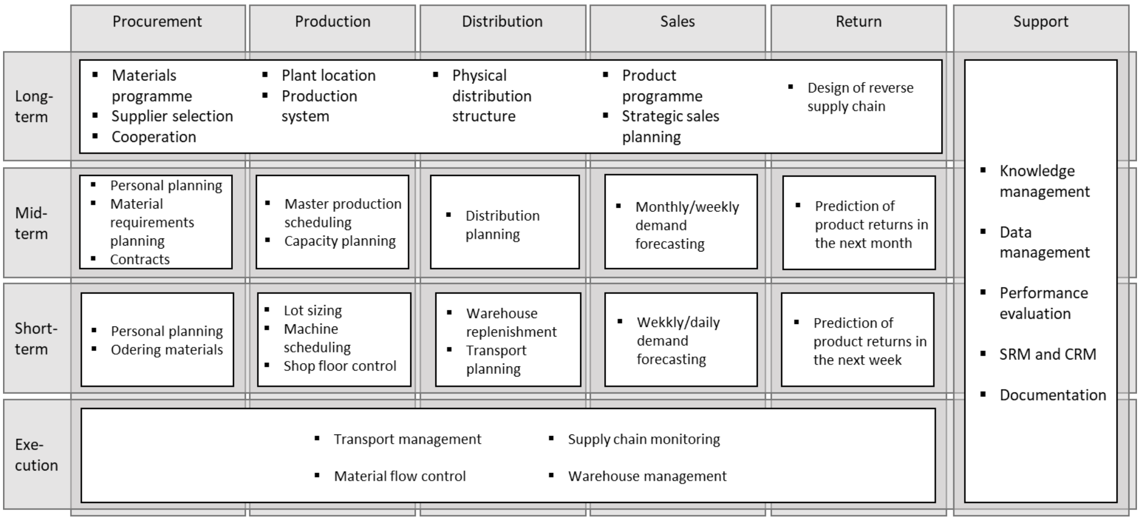

Figure 1: Extended Supply Chain Planning Matrix (based on Stadtler 2005)

roposed categories and exemplary tasks.

These categories are quite general, and their configuration depends on the specific situation at hand. Therefore, they can group all tasks related to SCM according to the definition provided above. Moreover, the tasks provided within each category in figure 1 are simply illustrating examples; the set of tasks is neither complete nor immutable.

3 Methodology

This paper aims to provide an overview of existing AI applications in SCM and derive future research fields based on it. Literature reviews are a suitable method to achieve this goal. They help answer a specific research question by summarizing and criticizing available and relevant literature on the topic of interest. A structured approach ensures a relevant and rigorous search and review process (Thomé et al. 2016). After identifying a body of relevant literature, it is necessary to extract relevant content and information, summarize and interpret it. Content analysis is a method to do so and 'represents an effective tool for analysing a sample of research documents in a systematic and rule-governed way' (Seuring & Gold 2012: 546). Hence, this paper follows the steps proposed by Seuring and Gold (2012) for content analysis: material collection, descriptive analysis, category selection and material evaluation, and research quality. The step of material collection is conducted by applying the process for structured literature reviews (SLR) proposed by Thomé et al. (2016). The unit of analysis is single papers.

To collect suitable material, i.e., identify relevant literature, the SLR scope has been defined based on a taxonomy for literature review proposed by Cooper (1988) (cf. Table 1 for a characterization of the conducted SLR).

Characteristic	Selected category	Explanation
Focus	Practices or applications	The focus of this SLR is to identify existing applications of AI methods to the SCM domain.
Goal	Integration (Generalization)	The goal of this SLR is to summarize identified applications and to provide an overview of existing research.
Perspective	Neutral representation	It is tried to evaluate and present identified literature on a neutral basis to give an as objective as possible overview of already existing research and deduce potential future research areas.
Coverage	Representative	Due to the afore-mentioned issue that no complete list of AI methods is available, this SLR cannot claim to be exhaustive. Instead, it aims at presenting a sample that is big enough to reflect all existing literature.
Organization	Methodologically	Results are presented based on a grouping regarding applied AI methods as well as addressed SCM tasks.
Audience	General scholars	The SLR is not intended solely for AI nor SCM specialists but for a more general audience. This circumstance profoundly influences the level of detail in which results are presented, e.g., functionalities of AI methods will not be explained in detail.

Table 1: Characterization of conducted SLR (according to Cooper 1988)

After deriving the SLR's scope, the general literature on AI and SCM has been used to derive the working definitions presented in section 2. Moreover, an initial literature search using the keyword combination 'artificial intelligence' AND 'supply chain' has been conducted to get a first overview of which techniques are used in the SCM domain and be later able to define more specific and suitable keywords. Therefore, "Artificial Intelligence" has been used as an umbrella term in the initial search and has been combined with "Supply chain" to search for relevant sources in ScienceDirect, Web of Science, and Scopus databases. Using the term "supply chain" instead of "supply chain management" leads to a greater search generalization. Hence the risk of excluding relevant sources is reduced. The results have been analyzed to understand what kind of applications are already existing in the literature. Together with the sources used to create the working definitions, the result of this initial analysis has served as a basis to create more specific keywords for further searches (as suggested by e.g. Vom Brocke et al. 2009).

Based on the results of this initial search, four additional search terms have been derived, aiming at the identification of more relevant applications:

- ("machine learning" OR "self-learning" OR "neural network" OR "support vector machine") AND "supply chain"
- "natural language processing" AND "supply chain"
- ("image recognition" OR "object recognition") AND "supply chain"
- ((intelligen* OR smart OR knowledge OR reasoning) AND agent) AND "supply chain"

The four search terms reflect the categorization of AI techniques derived in section 2. Instead of searching for concrete methods, choosing more general terms as keywords ensure a sufficiently broad search. For example, specific AI techniques such as recurrent neural networks will still be identified by looking for the more general term 'neural network'. At the same time, this generalization ensures not to miss any form of neural network. It has to be noted that looking for clusters of AI techniques might accidentally exclude relevant results. Nonetheless, these four search terms are derived from the primary literature (cf. section 2) and an initial literature search. Therefore, they are believed to cover the majority of applied AI methods. Moreover, as the goal of the SLR is to present a representative overview of AI applications in SCM, it can be considered as sufficient to identify the majority of relevant sources. Literature was searched in Scopus and ScienceDirect, looking at titles, keywords, and abstracts. Book (chapters), journal articles, and conference papers are suitable source types. To explicitly get an overview of recent advances and applications of AI in the field of SCM, again, only sources since 2013 have been considered. After the elimination of duplicates, two people have reviewed the abstracts of 1043 remaining results independently. Only if both agreed that one of the following exclusion criteria applied to a source it was excluded from the relevant list:

- *The application field is not related to SCM:* A source has been eliminated if it does not apply an AI approach to an SCM task but another domain.
- *No AI technique is applied:* Some results appeared even though not using an AI approach. As elaborated before, there is no comprehensive list of AI techniques, but methods such as mixed integer programming cannot be considered 'intelligent' and have therefore been excluded.
- *Not a specific application:* This exclusion criterion has been fulfilled by all sources not trying to apply an AI technique to a particular problem of the SCM domain. Among them have been reviews, conceptual work, model development, or sources focusing on different aspects such as improving algorithms regarding their solution quality. These have been excluded due to the focus of the SLR towards already existing applications. However, their content has been influencing the discussion of future research possibilities described in section 6.
- *Formal criteria:* This category subsumes all exclusion criteria not related to the paper's content, such as languages other than English.

After abstract review, 327 papers remained for full-text review, where an additional 38 sources were excluded. The final set of 289 articles was the basis for the content analysis.

Descriptive information about the final set of papers - such as the yearly distribution of publications, the most relevant journals or conferences, or highly cited papers - are presented in the next section together with the category analysis' results.

The individual papers are assigned to the categories presented in section 2, as proposed by Seuring and Gold (2012). Sources' assignment to the classes (AI techniques and SCM tasks) has been based on a full-text review. In most cases, authors of the relevant papers specifically name and describe the AI technique they are applying, and it can be assigned to one of the categories unambiguously. In the rare instances that authors utilize more than one AI technique, the source has been assigned to 'combination'. Sometimes authors do not describe or name their method. Instead, they use more general terms such as 'machine learning approach'. For such cases, another category 'not further specified' has been defined. Both groups account for only 9% of the identified sources (4% use a combination of techniques, 5% could only be assigned to 'not further specified'), which shows that the utilized classification of sources can account for the majority of literature. Regarding the addressed SCM task, an assignment to the extended SCM matrix was also done based on a full-text review. As the matrix has been chosen due to its suitable level of detail and been adapted (cf. section 2), all cases could be assigned to its class unambiguously. The results of the category analysis are discussed in the next section.

4 Applications of AI for SCM in research

This section presents the results of the SLR. First, the final papers' descriptive profile is described, and then the main research fields regarding the application of AI for SCM are identified. To do so, each document has been categorized according to their utilized AI technique and addressed SCM task (cf. section 2 for categories). Based on this classification, the main research fields could be derived. For each of them, general trends are mentioned, and exemplary applications are given.

4.1 Descriptive Profile of Selected Articles

The overview of publications per year (cf. figure 2) shows a linear trend. Especially in 2019, there has been an increase in publications leading to 63 within one year.

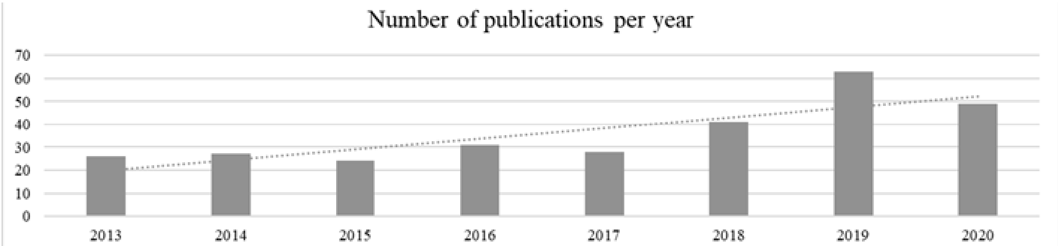

Figure 2: Number of publications per year (until July 2020)

Based on the increase in the linear trend line and the fact that by the end of July 2020, 49 papers have already been published, one can assume rising research interest in the topic of AI applications for SCM.

Author	Year	Title	No. of Citations
Kar	2015	A hybrid group decision support system for supplier selection using AHP, fuzzy set theory and neural network	72
Jaipuria et al.	2014	An improved demand forecasting method to reduce bullwhip effect in supply chains	59
Tuncel et al.	2014	Solving large scale disassembly line balancing problem with uncertainty using reinforcement learning	41
Tavana et al.	2016	A hybrid intelligent fuzzy predictive model with simulation for supplier evaluation and selection	41
Singh et al.	2018	Social media analytics to improve supply chain management in food industries	40

Table 2: Top five Articles based on No. of Citations (based on Scopus citation count)

Overall, more than 160 different journals, conferences, and books contain articles, highlighting the diversity and variability of research. A similar picture emerges when considering the top five articles by the number of citations (cf. Table 2). The five most-cited articles deal with various topics, including supplier selection, supply chain configuration, social media analytics, demand forecasting, or production line balancing. In summary, the profile of selected sources shows that the research regarding AI for SCM is somewhat scattered and that various topics are discussed. Hence, the main research fields presented in the next section also cover a wide range of topics.

4.2 Main Research Fields

Table 3 gives an overview of how many sources have applied which AI technique to which SCM task. The last column and row sum up the values for task and technique categories, respectively. The medium- and short-term planning tasks have been combined. As the distinction between these planning horizons is somewhat blurry, the sources could often not specifically be assigned to one of them. Besides, the numbers for the categories examined separately have often been too small to be well interpretable. For ease of representation and due to low numbers for many AI categories, technique classes except for the top three ones (neural networks, SVMs, and MAS) and combination approaches have been subsumed under the term 'other'.

		Neural network	SVM	MAS	Combination	Other	Sum
Long-term		11.4%	3.3%	7.1%	1%	1%	**23.8%**
Mid- and short-term	Procurement	0%	0%	1.9%	0%	1%	**2.9%**
	Production	2.4%	0.5%	1.4%	0%	2.8%	**7.1%**
	Distribution	6.1%	0%	0.5%	0.5%	1.9%	**9%**
	Sales	15.2%	2.9%	0.5%	1.4%	2.4%	**22.4%**
	Return	0.5%	0.5%	0%	0%	0%	**1%**
Execution		8.6%	3.3%	5.2%	0%	2.4%	**19.5%**
Support		6.7%	2.4%	1.4%	1%	2.8%	**14.3%**
Sum		**50.9%**	**12.9%**	**18%**	**3.9%**	**14.3%**	**100%**

SVM: Support vector machines; MAS: multi-agent systems (for short explanations cf. section 2)

Table 3: Applied AI technique and addressed SCM task

The percentages show the tasks and techniques mainly discussed by the identified literature and which areas have not received much attention. In the following, the most prominent research streams extracted from the identified sources will be presented. The result answers the first research question and gives an overview of AI applications in SCM in research. So far, under-represented application areas are mentioned and discussed in section 6, where future research possibilities are proposed.

Long-term Planning

Long-term planning is the most researched area of SCM tasks (23.8%). Sources focus mainly on two different problems: supplier selection and the analysis of various supply chain configurations.

Supplier selection is usually made by predicting each possible suppliers' performance and selecting one based on this information (Tavana et al. 2016; e.g. Kamble et al. 2017; Vahdani et al. 2017). Sometimes authors focus on specific types of supply chains/suppliers such as agricultural supply chains (Guo & Lu 2013), hospital drug suppliers (Khaldi et al. 2017), or service supply chains (Zhang et al. 2016).

Apart from the prediction of supplier performance, sources focus on analyzing different supply chain configurations and their effects on supply chain performance or similar. The method most often used for this problem class is multi-agent systems (MAS), which are applied by 17% of all relevant sources. They are utilized to either automatically configure a supply chain (e.g. Ameri & McArthur 2013; Greco et al. 2013; Shukla & Kiridena 2016) or to model the behavior of different supply chain actors and examine its effects on the whole supply chain (e.g. Craven & Krejci; Perera & Karunananda 2016; Sergeyev & Lychkina 2019).

One of the main advantages of using MAS systems is to model complex systems by depicting individual actors, their beliefs, and their goals. This way, it is possible to understand the system's emergent behavior based on its agents' actions and analyze how changes in these actions affect the overall system behavior.

Sales planning

Sales planning is the second-most researched group of SCM tasks (22.4%) and by far the most addressed group within mid- and short-term planning.

The vast majority of papers in this category apply an AI technique to forecast demand (e.g. Jaipuria & Mahapatra 2014; Sarhani & El Afia 2014; Kilimci et al. 2019). Indeed, demand forecasting is the task most often addressed with AI techniques in the literature. Among the sources dealing with demand forecasting, most address either a particular type of supply chain, industry, or demand structure. Examples for specific supply chains addressed are cross-border (Ji et al. 2019) or regional (Watanabe et al. 2016) supply chains. Agriculture (Li 2014) or retail (Islek & Ögüdücü 2015; Chawla et al. 2019) are specifically addressed industries. Authors focussing on particular forms of demand discuss intermittent (Nemati Amirkolaii et al. 2017; Fu et al. 2018) or non-linear (Singh & Challa 2016) demand.

AI techniques show a variety of strengths when using them to forecast demand. Their main advantage is providing more accurate results, i.e., they result in lower forecasting errors than standard statistical methods such as exponential smoothing or any form of regression. The papers highlight that AI techniques can deal with higher amounts of data, which leads to even more reliable forecasts as a greater number of influencing factors can be considered. Additionally, these techniques can handle nonlinearity, making them applicable to a variety of demand situations.

Production planning

Even though production planning is only addressed by 9% of the sources, it has been identified as a significant emerging research stream since especially more recent sources focus on this category. Moreover, their number is increasing, supporting the claim that AI for production planning is an emerging research field. All the sources in this category focus on two tasks: (1) predicting machine failures, i.e., fault diagnosis, and (2) predicting completion or lead time.

Especially the first task seems to be of increasing interest for researchers. Fault diagnosis tries to assess the current condition of machines or their parts and extrapolate when it breaks or needs maintenance based on this information. It not only helps to detect or predict failures but can also be used to identify root causes for such failures. (e.g. Aqlan & Saha 2015; Cherukuri & Ghosh 2016; Regan et al. 2017; Islam et al. 2018).

Similar to predicting how long machines are still capable of operating or when spare parts and maintenance actions will be needed, sources apply AI techniques to estimate completion or lead time prediction (e.g. Ahmarofi et al. 2017; Gyulai et al. 2018; Lingitz et al. 2018). Completion or lead time is dependent on multiple criteria, and a prediction of it can highly increase the quality of production planning and scheduling.

In general, authors applying AI techniques to production planning problems report that they have increased prediction accuracy. Aqlan and Saha (2015) even state that their approach can detect production-related faults earlier and replace human root cause analysis. Besides, good generalization and the ability to deal with large-scale and complex problems are further strengths mentioned by the sources.

Supply chain execution

Following long-term planning and mid-and short-term sales planning, execution is the third most addressed SCM task. 19.5% of sources have applied AI techniques to solve issues from this field. A high amount of these sources aims at automating tasks from supply chain execution.

Many sources address recognition problems in the context of automating supply chain execution. With these problems, the goal is to either recognize something from images or objects in a 3D space. Such techniques are mainly used for quality control in food supply chains (e.g. Cavallo et al. 2018; Gong et al. 2018; Xu & Sun 2018) or for checking the quality of parts to detect counterfeited ones or estimate their reusability (e.g. Alam et al. 2016; Frazier et al. 2016; Schlüter et al. 2018).

Automated supply chain monitoring and control is another highly researched topic. Monitoring is often realized based on radio-frequency identification (RFID). The collected information is usually analyzed, and whenever irregularities are detected, suitable countermeasures are either proposed or directly introduced (e.g. Abed et al. 2013; Emenike et al. 2016; Mercier & Uysal 2018).

Moreover, authors have developed systems to automate supply chain execution tasks. The most prominent tasks among those are ordering (e.g. Dogan & Güner 2015; Mortazavi et al. 2015), inventory control (Zhang et al. 2013; Dev et al. 2016), production control (Higuera & las Morenas 2014), or even tasks along the whole supply chain (Lee & Sikora 2019).

Advantages that have been realized by automating supply chain execution are better efficiency, increased flexibility, a reduced dependency on human domain experts, and, in general, a greater amount of freed human capital that can be used for other tasks.

Application of neural networks

Apart from specific task categories, there is also a focus evident regarding the applied AI techniques. Neural networks and their variants, such as convolutional neural networks or recurrent neural networks, are by far the most popular method for applications in the SCM domain (50,9%). Additionally, almost all sources combining different AI techniques use neural networks. These are combined with decision trees, SVMs (Kilimci et al. 2019), or other techniques such as genetic algorithms (Liu & Zhang 2017) to improve their performance and increase the prediction accuracy.

There is a wide variety of things that neural networks are applied to. They are mostly used to predict something, and most application cases stem from long term planning (11.4%, cf. section 4.1) or sales planning (15.2%, cf. section 4.2).

The high number of usages indicates that neural networks show great potential for applications in the SCM domain, mostly for prediction problems. Besides, many authors compare different methodologies and assess their performance concerning e.g., solution quality or convergence speed (e.g. Aengchuan & Phruksaphanrat 2018; Ma et al. 2018). Within these comparisons, neural networks outperform other methods such as logistic regression or decision trees. They are capable of achieving a higher prediction accuracy, dealing with nonlinearity, noise, or uncertainty as well as providing greater generalizability.

5 Industry-driven applications

So far, only application examples from scientific literature have been discussed. Nevertheless, as the industry is also highly interested in applying AI techniques to SCM tasks, many industry-driven application cases have been established. Often, these have been developed, implemented, and tested independently from research. Hence, the industry might have addressed different tasks than research with different AI methods. This section provides an overview of the greatest industry interests and discusses differences from resp. similarities to the afore-identified main research streams to answer RQ2. A look at industry-driven applications can give indications on industry interests, check whether research produces results relevant to the industry, and support the identification of future research possibilities that also benefit the industry.

Publications from the industry have been retrieved using general search engines and combining keywords from three groups: (1) AI techniques such as neural networks or MAS, (2) ‘supply chain’ and (3) ‘application’, ‘use case’, ‘business case’ or names of consultancies/companies known for publishing reports or white papers. Each search resulted in a relatively high number of hits. Therefore, the review was restricted to the first few result pages as the relevance of hits decreased drastically afterward. The retrieved results were analyzed similar to the scientific literature, i.e., the utilized AI technique and addressed SCM task were derived. However, it is not as common as in the research community to publish successful applications' results. While there are some white papers or similar publications, their number and exhaustiveness are very low compared to scientific literature. It is not possible to provide percentages as in the section before since one cannot identify 100% of the applications nor estimate how many more non-reported ones there might be. Therefore, we will only provide estimations on the level of industry-driven applications instead of specific percentages (cf. Table 4). Those estimations are based on the analyzed industry publications and how often application cases from particular categories have been described within those.

<table>
<tr><th></th><th>Procurement</th><th>Production</th><th>Distribution</th><th>Sales</th><th>Return</th><th>Support</th></tr>
<tr><td>Long-term</td><td colspan="5">low</td><td rowspan="3">medium</td></tr>
<tr><td>Mid- and short-term</td><td>low</td><td>high</td><td>medium</td><td>high</td><td>low</td></tr>
<tr><td>Execution</td><td colspan="5">high</td></tr>
</table>

Table 4: Industry applications: Adressed SCM task

In general, the industry regards AI as a suitable tool to achieve cost reduction, efficiency increase, and customer experience improvements by a reduction of manual processes, human effort in these processes, and increased quality in decision making by reducing the human failure rate (Gesing et al. 2018). Having reviewed industry-related publications, it becomes imminent that AI often only refers to methods of machine learning or even only deep learning. The set of methods discussed and covered in the industry is not as diverse as in research. Hence, table 4 only gives information about the addressed SCM task. While research shows a clear tendency towards applying neural networks, SVMs, and other machine learning techniques, the industry seems to concentrate on these entirely or at least does not report about other techniques' applications. In the context of applying machine learning techniques, the following general use cases are mentioned as suitable: resource allocation, predictive analytics, predictive maintenance, hyper-personalization, the discovery of new trends, anomaly detection, forecasting, price, and product optimization (Henke et al. 2016).

5.1 Similarities to main research fields

Regarding mid- and short-term planning tasks, the level of existing application cases resembles the situation of research. Procurement planning is the by far least represented category, and only slightly more application cases could be identified for mid- and short term distribution planning.

Following research, there is a high interest in mid-and short-term production and sales planning. For the latter, the main focus is also demand planning. Interestingly and differnet from research, all industry applications incorporate external data to improve forecasting accuracy. Examples are global economy data to indicate future development of global trade and the resulting demand for air and ocean freight (Gesing et al. 2018) or weather data to predict energy demand (Bughin et al. 2017). A German online retailer has even reached a 90% accurate forecast of the next month's sales and now builds up inventory only based on this forecast, i.e., in anticipation of and not based on actual orders (Bughin et al. 2017). Overall, it is estimated that forecasting errors can be reduced between 20 and 50% with machine learning. Moreover, it is feasible to reduce lost sales due to unavailable products by up to 65% and inventory by 20 to 50% (Bauer et al. 2017).

Mid- and short-term production planning tasks show two major focus points: predictive maintenance and yield optimization. Predictive maintenance refers to the analysis of machines' sensor data enhanced with information about the working environment etc., and the estimation of the remaining useful life. While the term 'predictive maintenance' is rather industry-shaped, this field's tasks and problems are also represented in the scientific literature but preferably under terms such as fault diagnosis (cf. section 4.3). Hence, a similarity in interests regarding production planning can be subsumed. By using AI techniques in this context, companies have been able to increase productivity by up to 20% and reduce maintenance costs by up to 10% (Bauer et al. 2017). For example, IBM Watson has successfully been utilized to identify and classify damages as well as to decide on appropriate repair activities for wagons based on images taken by cameras installed along the train tracks (Gesing et al. 2018). Volvo has developed a truck with lots of integrated sensors to identify where and when maintenance is required (DHL 2016).

Another task class that is highly represented both in research and industry-related publications is execution. The industry puts particular emphasis on warehouse management and – similar to research – on supply chain monitoring. Applications for warehouse management include, e.g., automated guided vehicles (AGV), which are controlled by AI algorithms that determine where to store or pick a product and which route should be taken to retrieve or deliver it. Moreover, computer vision techniques can be used to make robots able to recognize empty shelf space or to recognize items in retail store shelves and automatically extract information such as its brand, the price on the price tag or the shelf condition (Bauer et al. 2017; Gesing et al. 2018). However, the literature's focus on quality control with image recognition could not be replicated in industry publications.

In contrast, the focus on supply chain monitoring is shared by industry. For example, DHL has implemented its Resilience360 Supply Watch module that monitors the content and context of 8 million entries from social media and other online sources. These are analyzed with machine learning and NLP algorithms to extract their sentiment and then identify risk indicators ahead of time. Indeed, the analysis of sentiment within a text is of high importance. It can also improve the machine-based understanding of, e.g., product reviews, social media content, or online articles (Gesing et al. 2018).

Overall it can be summarized that industry interests resemble the identified main research fields to a great extent. The SCM task categories addressed most often are almost the same, and within the categories, similar focus points are set.

5.2 Differences to main research fields

The main difference observable between industry and research interests is the topic of long-term planning. Even though industry publications express the need to adapt supply chains to make them more flexible and customer-centric, there are only very few examples of industry-driven AI applications in long-term planning. One of the rare examples a Japanese retailer utilized machine learning to get to know about profitability drivers and then picked new store locations based on the algorithm's results (Bughin et al. 2017). Independently from a specific use case, DHL mentions the possibility to base location decisions on capacity and demand forecasts to avoid unnecessary investments in storage or fleet capacity (Jeske et al. 2013).

Apart from long-term planning tasks, there seem to be no other significant differences between research and industry interests. This supports the impression that research mostly examines questions and issues relevant to the industry as well.

6 Proposals for future research

Having looked at already existing applications of AI both in SCM research and industry, it becomes apparent that already some impressive research streams are established. Benefits such as increased prediction accuracy, the generalizability of approaches, dealing with nonlinearity, and processing of more data have been realized with AI techniques. On the other hand, many SCM tasks have been addressed with AI rarely. Besides, authors still state open issues such as the availability of sufficient training data, lacking applicability to complex real-world scenarios, and the general functioning of AI techniques as black boxes. Based on the overview of existing applications as well as open issues and future research mentioned by the examined papers, we propose promising areas, which should receive (more) attention in future research.

Applicability of AI-based long-term planning

Comparing which tasks have been addressed with AI techniques in research and practice, there is an evident difference when looking at long-term planning tasks. While almost a quarter of all scientific sources identified in the SLR deal with this category, only very few industry-related examples show how an application for this problem class could look like. So far, this might be because rather big companies, which have already established a supply chain network, publish their successful AI applications. In contrast, smaller enterprises that deal with questions on how to design a supply chain do not report their results. However, the real reasons for the different consideration levels cannot be identified for sure. Therefore, it is interesting to examine whether the approaches for supply chain configuration or supplier selection developed in research are applicable to practical scenarios.

AI techniques for procurement planning

Neither research nor practice has given much attention to AI for procurement planning tasks. However, the very few ones that did, report successes especially about enhancements in collaborative procurement or to the identification of discrepancies between paid and received goods (Pal & Karakostas 2014; e.g. Chen et al. 2018) So the sources do not hint at general unsuitability of AI techniques for procurement planning. Hence, the identification of other application cases in the context of procurement appears to be a possible research topic. New advances in AI techniques, such as incorporating more unstructured and external data, might lead to more procurement tasks to be better solvable with AI.

Return process and supply chain sustainability

While only 1% of the identified papers deals with applying AI in return processes and only low interest of industry could be identified, it is clear that the general interest in sustainability and green SCM issues is increasing (Tseng et al. 2019). Aspects already addressed with AI include forecasting return products (Kumar et al., 2014) or assessing whether machine parts can be recycled (Schlüter et al. 2018). These first attempts accomplished to use AI for supporting return processes and enabling sustainable SCM. These first successes, combined with the increasing interest in supply chain sustainability and the general strengths of AI techniques, strongly suggest applying AI to this area as a highly interesting research field. Indeed, this is in accordance with Chehbi-Gamoura et al. (2020), who identify the return process to be of increasing interest for big data analytics, a field related to AI. They also gain the impression that research on sustainability aspects in SCM becomes more critical and that combining it with new technologies can be a profitable opportunity for future research.

Incorporation of unstructured, external data

One aspect that has already been of interest to some researchers is improving AI techniques' results by incorporating information gained from external data sources. Authors have, e.g., succeeded in using social media data, product comments, or weather information, especially for increasing the quality of demand forecasts (Ye et al. 2015; Watanabe et al. 2016; Lau et al. 2017). Since the amount of data to be processed increases significantly when including external sources, the strength of AI techniques to deal with these greater amounts comes into play. Using such techniques makes it possible to feed algorithms with more data and base their results on more information, hence increasing their accuracy or reliability. However, authors mention the incorporation of unstructured information as a current issue. Moreover, the insufficient availability of training data needed for AI algorithms and lacking data quality are problems that need to be addressed before taking advantage of external data sources (e.g. Alireza et al. 2013; Vhatkar & Dias 2016; Wang et al. 2017).

Despite the mentioned issues, Cui et al. (2017) assessed the value of using social media information and constitute that using such data improves sales forecasting significantly. This claim can most likely be extended to other SCM tasks, but this would need further examination. Already realizable advantages such as improved prediction accuracy and the possibility to automatically process text and human-voice combined with recent improvements of AI techniques, e.g., the increased applicability of deep-learning techniques, hint at promising future results.

Application of natural language processing

Industry-shaped visions of the future for AI applications in SCM contain, e.g., anticipatory logistics, meaning to deliver goods to customers based on anticipated demand before they have issued an order or even realized their need for the product. Another vision is the utilization of enhanced voice technology to allow for conversational interaction with IT systems, which is not limited to pre-defined expressions but can also consist of colloquial or informal phrasing (Gesing et al. 2018). The focus on processing and using language and text has already gained some research attention, but there seems to be a higher interest in the industry. While Schniederjans et al. (2020) even claim that the application of AI, in general, is more prevalent in the industry than in research, our results at least support this regarding the utilization of natural language processing (NLP) techniques. Only very few scientific sources apply NLP techniques, but many industry-related application cases regarding text classification and extraction or automatic voice recognition and communication have been identified. So apparently, there is still lots of research potential, especially in this area. Again, improvements in AI techniques will most likely allow for more successful applications (Stone et al. 2016).

AI as a non-technical endeavor

Looking at the proposals for future research stated by the identified papers, a focus on technical aspects becomes evident. Authors typically propose to improve algorithms concerning accuracy or solutions speed or to integrate additional capabilities. However, the application of AI not only concerns the development of the algorithms itself but also requires a well-managed transition of organizational processes. Even though AI techniques have started to become common, there are still challenges surrounding its application, such as legal issues, employees' resentment, or the fear of machines replacing humans (cf. e.g. Bauer et al. 2017; Bughin et al. 2017). While many companies see potential value in using AI, there is a lack of skills and knowledge on how to adopt it, leading to unsuccessful or non-existing adoption efforts. Hence, the application of AI techniques is not only a technical endeavor but also involves organizational, process- and human-related issues, which must be dealt with for successful utilization of AI (Hartley & Sawaya 2019). So far, research does – to the best of our knowledge – not answer how the implementation of an AI technique can be organized best, how change management should be done and what needs to be managed to apply AI successfully.

7 Conclusion

In summary, this paper aimed at (1) giving a literature-based overview of existing applications of AI techniques in SCM, (2) identifying greatest industry interests and comparing them to the main research fields, and (3) deriving suggestions for future research.

RQ1 was answered based on an SLR. Identified sources were categorized according to their used AI technique and the addressed SCM task. Based on this categorization, the following primary research streams could be identified: Long-term planning (supplier selection & analysis of supply chain configurations), sales planning (demand forecasting), production planning (fault diagnosis & the prediction of completion/lead time), supply chain execution (automating tasks & supply chain monitoring and control), and application of neural networks.

An analysis of industry-driven publications, white papers, and similar provided the ground for examining main industry interest. These were compared to the results of RQ1 to discuss differences and similarities and finally answer RQ2. It became evident that apart from the focus on long-term planning, there a no significant differences to industry. This allows claiming that research mostly accomplishes relevant and practicable results.

However, some smaller differences, e.g., the application frequency of NLP techniques, have been noticed. In combination with future research possibilities mentioned by papers, those and the comparison of main interests have led to identifying future research trends, thereby answering RQ3. Six possible areas could be derived: applicability of AI-based long-term planning, AI techniques for procurement planning, return process and SC sustainability, incorporation of unstructured, external data, application of NLP, and AI as a non-technical endeavor. These areas range from focussing on specific tasks over applying certain techniques to more general issues and provide various opportunities to streamline future research regarding the application of AI in SCM.

While the paper can give a representative overview of research in AI for SCM and estimate which applications exist in the industry, it cannot claim to be a comprehensive elaboration. First, the conducted literature review has some limitations starting with the definition of keywords, which might have excluded relevant sources on accident. It has tried to be avoided by following a structured framework and base the definition of keywords on general sources on AI techniques. Still, an extension of the literature search might lead to more relevant results. However, it is highly unlikely that the percentages based on the identified set of relevant sources will change significantly, even when considering more publications. Regarding the industry-related literature, it has already been mentioned before that since not many companies publish white papers or similar reports about their applications, the set of considered examples is limited and possibly biased towards consultancies and bigger companies. Therefore, only an estimate on the level of existing applications could be given. However, this overview is still capable of giving a good impression of where industry interests lie regarding AI applications. Case studies or expert interviews are opportunities to improve this section and gain more in-depth insights into industry interests.

Overall, it surely is possible to extend the conducted searches, but the used set can provide an insight into the current state of AI applications in SCM sufficiently.

Since the identification of research possibilities is based on the SLR results and the retrieved industry-related sources, there is also the possibility to have missed interesting research possibilities. However, the presented suggestions give a good indication of where improvements can be made or where research can provide valuable results in the context of AI applications for SCM.

Overall and while keeping its limitations in mind, the paper succeeds at answering its research questions. It provides an overview of current applications of AI for SCM, both from research and industry. It hints at major research streams that have been followed, identifies the greatest industry interests, compares them to research, and highlights some promising ideas for future research.

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