

A Decade of Artificial Intelligence for Supply Chain Collaboration: Past, Present, and Future Research Agenda

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ABSTRACT

Due to its transformative potential, artificial intelligence is considered to be of growing importance for supply networks. As supply chain management faces a multitude of challenges, innovative organizational and technological concepts are required. As the application of artificial intelligence for supply chain collaboration has increased over the last years, a comprehensive overview of past and current developments in this heterogeneous and fragmented field could provide relevant insights into the main research streams and their developments. This paper presents a systematic literature review comprising 83 articles to assess the last decade of research and application of artificial intelligence for supply chain collaboration. The review adds clarity and richness to the field by enabling researchers and practitioners to navigate this topic and by facilitating the identification of future research avenues. The review outcomes are summarized in a conceptual framework of artificial intelligence inspired supply chain collaboration and a research agenda is derived.

KEYWORDS: Artificial intelligence · Supply chain collaboration · Supply chain management · Systematic literature review

1. INTRODUCTION

As the potential for digital transformation in supply chain management (SCM) becomes evident, cross-industry cooperation and transparency requirements drive the need for increased collaboration between companies [1-3]. The relevance of supply chain collaboration (SCC) as a distinctive research area focusing on supply chain partnership is frequently highlighted in the literature [e.g. 4] and can be characterized “as seven interweaving components of information sharing, goal congruence, decision synchronization, incentive alignment, resources sharing, collaborative communication, and joint knowledge creation” [1, p.55].

Artificial intelligence (AI), also referred to as a disruptive supply chain technology of transformative potential [5], is widely considered to be of growing importance for supply networks as data-driven approaches offer enormous potential for innovation [6]. AI is considered to be a relevant factor for the digitalization of future supply chain processes [e.g. 7, 8] as its potential impact on performance and innovativeness are discussed among researchers and practitioners.

While there are several papers investigating technological solutions in supply chains, there is no comprehensive review focusing on AI application for SCC. As innovative approaches are constantly being developed, the research field is becoming more difficult to navigate and the knowledge transfer to industry is becoming more challenging. Existing reviews approach the subject area with, for example, a broader perspective on the contribution of AI to the field of SCM [e.g. 9, 10]. Others focus on specific processes [e.g. 11, 12] or subsets of AI [e.g. 13]. Lastly, some contributions consider digital transformation without an explicit focus on AI [e.g. 7, 8]. Regarding the usage of AI in collaborative supply chain processes, the literature contains numerous analysis, for instance concerning AI collaboration requirements [e.g. 14] or intelligent collaborative platforms [e.g. 15]. In recent years,



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researchers have also highlighted the positive effect of information technology on SCC [e.g. 16]. Considering the growing interest in SCC occurring simultaneously with the increased focus on the potential of AI [e.g. 4], a comprehensive summary of research and application of AI for SCC could provide interesting insights as well as stimuli for future research. In-depth analysis of past and current developments in the area of research and application of AI for SCC could consequently help to bridge the gap between academia and industry and consequently drive the advancement of AI-based solutions.

Thus, the purpose of this paper is to systematically assess the past and current state of research and application of AI for SCC, and to explore potential future research avenues. Based on a systematic integrative literature review using multiple scientific databases [17-19], the paper provides an overview of the developments regarding the application of AI for SCC over the last decade. We find that SCC is a research field encompassing a great variety of research streams, thus requiring further consolidation and differentiation. In addition, it shows that the application of AI for SCC is increasing and diversifying.

The remainder of this article is structured as follows: Section 2 explores key concepts underlying the literature reviews and section 3 describes the review approach. Section 4 presents the research findings in detail, including general themes as well as a technology and a supply chain perspective. Section 5 discusses the literature review findings in the context of development over time, theoretical and practical implications, and limitations. Finally, section 6 concludes the paper.

2 KEY CONCEPTS

2.1 The collaborative supply chain

Logistics and SCM face a multitude of mega trends and modern challenges. To remain future-oriented and competitive, innovative logistics concepts and technologies are required [20]. Driven by technological enablers, the differentiation between internal and external boundaries is disappearing [21, 22]. In addition, the relevance of collaboration and partnerships within manufacturing, logistics, and SCM is frequently highlighted in the literature [e.g. 4, 23]. The wider application of SCC as a distinctive research area within SCM has been driven by multiple factors such as intensified global competition [24] and interaction between information technology and business [25].

SCC permeates all supply chain processes as summarized in the supply chain operations reference (SCOR) model [26] and can be characterized “as seven interweaving components of information

sharing, goal congruence, decision synchronization, incentive alignment, resources sharing, collaborative communication, and joint knowledge creation” [1, p.55]. These essential variables (see Table 1) are deemed to be central and sufficient elements which are required to define the occurrence of collaborative efforts. The relevance of supply chain collaboration (SCC) as a distinctive research area focusing on supply chain partnership is frequently highlighted in the literature [e.g. 4] and driven by the increasing relevance of supply chain resilience due to continuous challenges to global supply chains [e.g. 27]. The terms coordination, cooperation, and collaboration, the 3 Cs of the supply chain [28], are frequently used interchangeably in the literature. [29] refer to these terms as stages in an integrated supply chain, ranging from cooperation via coordination to collaboration. Collaboration is generally regarded as the most comprehensive concept and encompasses mutually sharing resources, information, objectives, and risks based on a shared vision and understanding among supply chain members or entire supply chains [30].

Table 1 Seven interweaving components of SCC as defined by [1].

SCC component	Definition
Information sharing	“extent to which a firm shares a variety of relevant, accurate, complete and confidential information in a timely manner with its supply chain partners” [1, p.58]
Goal congruence	“extent to which supply chain partners perceive their own objectives to be satisfied by the accomplishment of the supply chain objectives decision synchronization” [1, p.58]
Decision synchronization	“process by which supply chain partners coordinate activities in supply chain planning and operations for optimizing the supply chain benefits” [1, p.58]
Incentive alignment	“process of sharing costs, risks, and benefits amongst supply chain partners” [1, p.58]
Resources sharing	“process of leveraging assets and making mutual asset investments amongst supply chain partners” [1, p.58]
Collaborative communication	“contact and message transmission process among supply chain partners in terms of frequency, direction, mode, and influence strategy” [1, p.59]

SCC component	Definition
Joint knowledge creation	“extent to which supply chain partners develop a better understanding of and response to the market and competitive environment by working together” [1, p.59]

The SCOR model is used as an orientation as it provides an internationally recognized categorization and facilitates access and understanding for practitioners along the process categories plan, source, make, deliver, return, and enable (see Table 2). It has been developed to describe all phases of satisfying customer demand along the main business activities.

Table 2 SCOR model process categories [26].

SCOR process category	Definition/Description
Plan	“describe the activities associated with developing plans to operate the supply chain”, including requirements, information, and resources gathering and balancing [26, p.139]
Source	The ordering, receipt, and storage of goods and services, excluding the supplier identification and qualification as well as contract negotiation [26].
Make	“describe the activities associated with the conversion of materials or creation of the content for services” [26, p.139]
Deliver	Any activities regarding the fulfilment of customer orders, for instance delivery scheduling, picking and packing, and shipment [26].
Return	All activities concerning the reverse flow of goods [26].
Enable	All management activities, such as performance management, procurement, data management, resource management, network management, and risk management [26].

2.2 The digital and intelligent supply chain

Currently, a development from technology-enabled to technology-centric SCM can be observed, as information management plays a central role in SCM [31]. According to a statement by [25, p.9], “today and looking at the near future [...] the supply chain is as

good as the digital technology behind it” suggesting that digital transformation profoundly impacts organizational strategy and change [32]. While inter-business data exchange has already been applied within SCM and SCC, there still lies great potential in big data and digital interoperability [8, 33, 34]. AI can be defined as “[...] the branch of computer science that is concerned with the automation of intelligent behavior” [35, p.1], view which is also described as symbolic AI [36]. More recently, the definition has shifted toward the training (i.e., machine learning (ML) approaches) rather than the programming of systems. AI can thus be defined as a “perpetually learning model-growing system” [36, p.336] that consists of multiple sub-fields such as machine learning, multi-agent systems and agent-based modeling, expert systems, fuzzy logic and fuzzy sets, metaheuristics, and decision support systems. ML “can draw inferences from the given input data of a specific domain after a learning process” [37, p.164620]. Expert systems simulate human cognitive skills and perform complex reasoning to support decision-making [38]. Multi-agent systems (MAS) comprise multiple intelligent agents perceiving and interacting with their environments [39]. Fuzzy logic and fuzzy sets conceptualize partial truth to handle imprecise or vague information [38]. metaheuristics are concerned with optimization problems [39]. Decision support systems (DSS) are “information systems that provide assistance to humans involved in complex decision-making processes” [40, p.8].

3 REVIEW APPROACH

This paper aims to systematically assess the past and current state of research and application of AI for SCC, and to expose potential research avenues by conducting a systematic and integrative literature review [17, 19]. We follow the cyclic framework for conducting information systems literature reviews proposed by [41]. At the same time, we incorporate elements of the approaches suggested by [18], [42], [43] and [44]. The review comprises five phases: I Definition of the review scope, II Conceptualization of the topic, III Literature search, IV Literature analysis and synthesis, and V Summary and research agenda.

Phase I consists of the definition of the appropriate review scope which is explained in the introduction. According to the taxonomy for literature reviews presented by [45] and additional characteristics derived from [46] and [44], this review can be characterized as a standalone representative review. The focus of the review is research outcomes and applications, including a potential research agenda. This review aims to conceptually integrate and present central issues of the research field from a neutral perspective. Both practitioners and scholars might find this review useful.

Phase II is concerned with the conceptualization of the topic. Several iterations of keyword tests using Google Scholar and search phrase tests using the Scopus database are conducted and result in the keywords Supply Chain, Collaboration, Coordination, Cooperation, Artificial Intelligence, Machine Learning, Machine Intelligence. Despite the prior testing of the keywords, the selection of certain keywords unavoidably results in biased search results and thus research findings. The choice of either a broad or in-depth selection of keywords clearly restricts either the thoroughness of the resulting analysis and discussion or the generalizability of the findings. However, the iterative and thorough testing of keywords and search phrases leads to a list of the potentially most suitable search keywords.

Phase III comprises the literature search and is based on the following search and selection structure for literature collection and critical appraisal:

- (1) Search the literature to locate the body of literature.
- (2) Evaluate the titles and abstracts according to pre-defined exclusion criteria to identify the relevant literature.
- (3) Evaluate the full texts according to the pre-defined exclusion criteria to identify the core literature.
- (4) Critically appraise the publications to determine the consideration set for further analysis and synthesis.

The search process (1) took place in June 2022 and considers the last decade (2013-2022) of AI applications in SCC. Since this literature review is interdisciplinary in nature, we selected databases with a variety of area-specific resources in the field of information systems and SCM: two databases focusing on information

systems, i.e. IEEE Xplore Digital Library and ACM Digital Library; and two on business and management, i.e. Scopus and ScienceDirect. For additional conference proceedings, AIS Electronic (AISEL) was additionally searched. This search resulted in an initial body of the literature comprising 403 publications. The complete literature search and assessment process, including details on the exclusion criteria, is illustrated in Figure 1. A paper was deemed to have insufficient focus on review question when, keywords appear only in the title, abstract or reference list, or in an unconnected manner that does not relate to the aim of the review, or if an insufficient application of AI technology or an insufficient focus on collaboration can be observed. Exclusion due to publication type occurred when the paper has a publication type which is not included in the scope, for example editorials. Significance and contribution refer to the potential impact of the source, for instance a low citation count or insufficient research contribution and innovativeness. Papers excluded based on accuracy concerns had not been peer reviewed. The final consideration set comprises 83 publications.

4 REVIEW RESULTS

4.1 General Characteristics and Themes

Within the consideration set, 35 publications represent conference papers and 48 are journal papers. The most frequently appearing journals and conferences are summarized in Table 3. In general, the heterogeneous nature of the research field and the topic's interdisciplinarity are confirmed by the variety of journals and conferences.

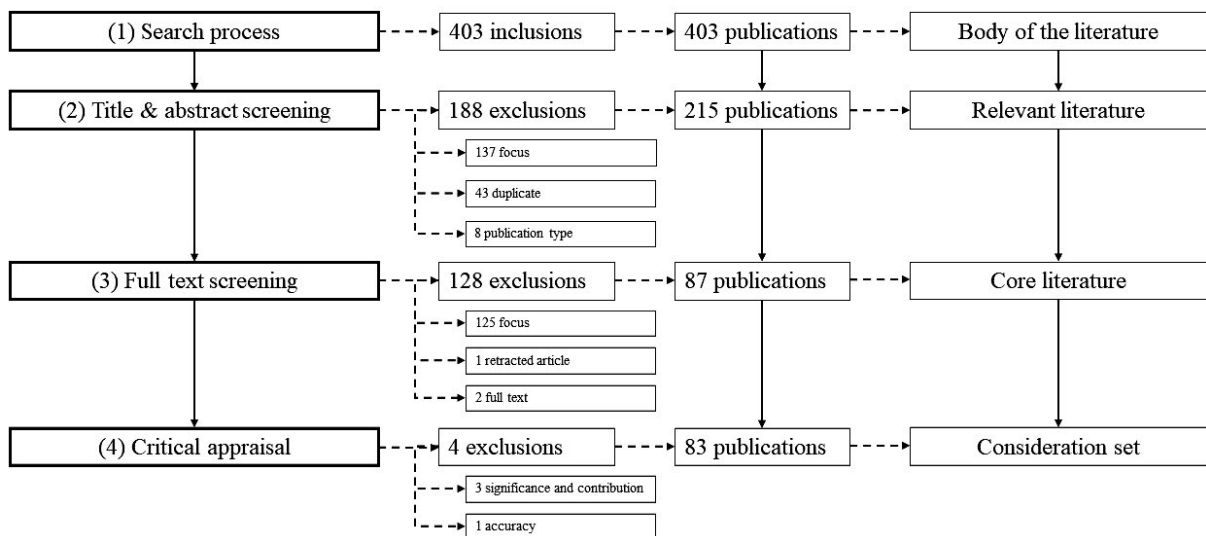


Fig 1 Search and selection process overview

Table 3 Most frequently appearing journals and conferences.

Journal name	Number of publications	Conference name	Number of publications
International Journal of Production Research	5	IFIP Advances in Information and Communication Technology	4
Expert Systems with Applications	4	International Conference on Advanced Logistics and Transport	2
Sustainability (Switzerland)	4	International Conference on Industrial Engineering and Engineering Management	2
Computers in Industry	3	Winter Simulation Conference	2

Journal name	Number of publications	Conference name	Number of publications
European Journal of Operational Research	3	-	-

The analysis of the consideration set is based on the thematic analysis approach proposed by [47] and results in the visualization of themes as a thematic map. The thematic map (see Figure 2) reveals two main perspectives on the review topics, i.e. a technology perspective (AI application) and a supply chain perspective (collaborative processes). These two perspectives can again be divided into three categories: AI sub-fields and techniques, collaboration within the SCOR processes, and components of SCC.

As shown in the thematic map, the first category (AI sub-fields and techniques) contains seven themes: *AI*, *artificial neural network (ANN)*, *decision support system (DSS)*, *fuzzy logic and fuzzy sets*, *ML*, *metaheuristics*, and *MAS*. Within this category, the most papers can be found in the *ML* theme, followed by *AI* in general, *DSS*, and *MAS*. The second (collaboration within the SCOR processes) and third (components of SCC) categories consider the topic of AI inspired SCC from the supply chain perspective. The SCOR processes *source* and *deliver* contain the same number of papers. The *make* process, however, is referred to considerably less and the *enable* process considerably more within the consideration set literature. Similarly, the seven interweaving components of SCC exhibit

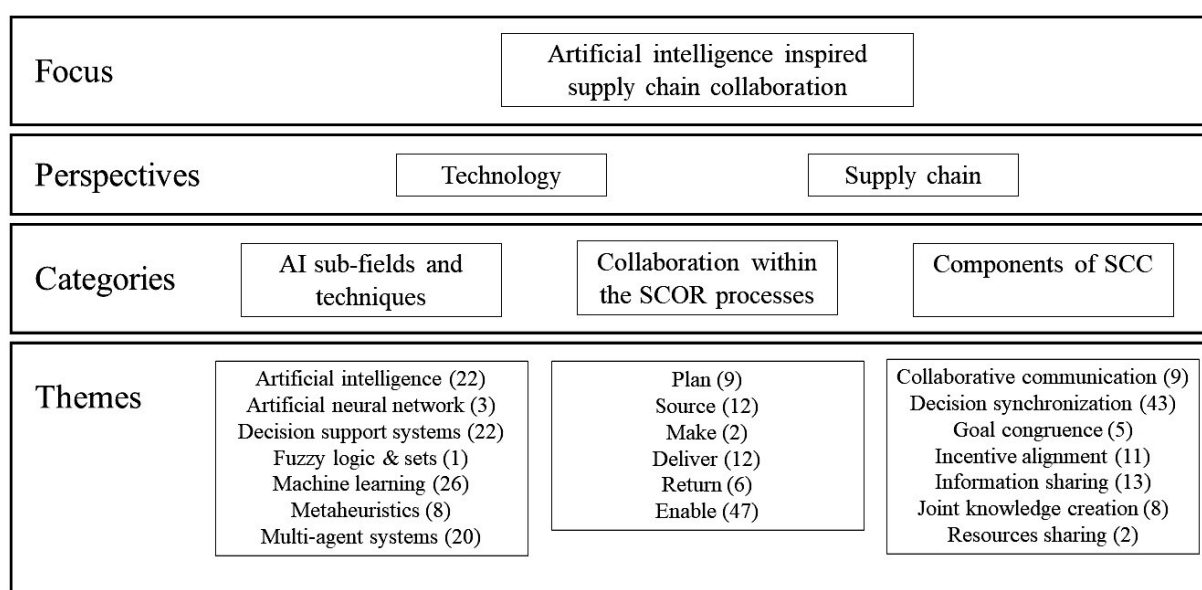


Fig 2 Thematic map of artificial intelligence inspired supply chain collaboration including the number of papers per theme indicated in brackets (multiple mentions)

differing paper quantity distributions. The most papers could be allocated to *decision synchronization*, whereas *resources sharing* and *goal congruence* have the lowest paper count. The other themes within this category contain a similar number of papers.

4.2 Supply chain perspective – Collaborative processes

4.2.1 Collaboration within the SCOR processes

Within the consideration set literature, references to all five SCOR processes could be identified, however, the *enable* process was most frequently referred to. Applications include, for example, co-competition for supplier selection [e.g. 48], network-oriented finance management [e.g. 49], outsourcing risk coordination [e.g. 50], and lean coordination [e.g. 51]. Agility and resilience enhancement [e.g. 52] as well as information and data management [e.g. 53] as well as risk and performance management represent applied cases [e.g. 54]. The collaborative orientation is also highlighted by [51] who describe negotiation optimization for win-win targets.

Regarding the *plan* processes, for instance, authors mentioned collaborative planning under constraints such as environmental uncertainties [e.g. 55, 56]. Other examples comprise green supply chain and sustainability management [e.g. 9, 57] and digital strategy alignment [58].

Source processes occurring in the consideration set literature include order aggregation [59] and beer game optimization [60]. Further, joint replenishment policy determination and coordination [e.g. 61, 62] and inventory routing and allocation are part of these source processes [63, 64]. For instance, [65] describe a VMI collaboration where optimal replenishment is determined between the supply chain partners.

The *deliver* process is frequently referred to in the consideration set literature, for example concerning cooperative and dynamic last mile delivery [28], delivery operations coordination including cooperative routing and information sharing [e.g. 66, 67] as well as multimodal transport cooperation [68]. Other SCOR process papers refer to autonomous fleet coordination [69, 70] and event-driven information sharing to foster collaborative behavior [71].

Concerning the *return* processes, for example, AI is applied for reverse chain network-based cost forecasting and reduction [63, 72], shared recycling and circular economy flow capacity planning [73, 74], and closed-loop return vehicle routing [40].

The *make* process is the least mentioned SCOR process as only two papers could be allocated to it. [75] discuss monitoring and improving the production process for collaborative decision-making, while [76] debate the agro-industry supply chain.

4.2.2 Seven interweaving components of supply chain collaboration

As the thematic analysis revealed, all components could be identified in the consideration set literature. According to the frequency of appearance in the consideration set literature, *decision synchronization* is the most relevant SCC component. It could include calculating optimal production lot size [e.g. 77], collaborative planning and scheduling considering supply chain goal alignment [e.g. 78] and integrated waste elimination and lean coordination [e.g. 51]. Shared DSS among supply chain partners [e.g. 79], coordinated key performance indicators [e.g. 80], and transparent risk and crisis management [e.g. 81] could be other factors to be included.

Information sharing is used, for instance, regarding optimal planning of routes and dispatchers through efficient information exchange [82], optimal replenishment and forecasting to ultimately enable better alignment of demand and supply [e.g. 83, 84]. In addition, the importance of digital interoperability, transparency and visibility, and overcoming information asymmetry is acknowledged [e.g. 8, 85]. [86] also state that information sharing is the prerequisite for intelligent logistics.

Different *incentive alignment* activities were mentioned in the consideration set literature. This includes credit risks assessment in a supply chain finance network [87], bulk order discounts [59], profitability analysis [88], and sustainability achievements [57]. In addition, supply chain costs sharing between buyers and suppliers [89, 90] as well as total costs of chains [63] and collaborative cost management [89] are mentioned.

Collaborative communication could, for instance, refer to connectivity and interoperability for live information transmission and Physical Internet [28, 37], intelligent dispatching system with dynamic coordination among all actors [91], and coordination between supply channels [92]. Other potential strategies and modes could be multi-agent negotiation, interaction and relationships [e.g. 93, 94], or effective software systems [95].

In the consideration set, *joint knowledge creation* includes the cooperation of smaller organizations to achieve better procurement deals [59], the development of a shared knowledge framework [96], and customer requirements management [64]. Furthermore the conceptualization of new interaction designs and business models [97], collaborative smart supply chain innovation [98], and the transparent analysis of used parts business data are included in the consideration set [72].

For example, authors express *goal congruence* as aligning global goals of the supply chain to, on the one side, make decisions autonomously and maximize individual utility, and, on the other side, to align the global supply chain goals [99], and win-win negotiation

[100]. A frequently appearing goal is sustainable and green SCM [e.g. 81].

Resources sharing appears to be a less dominant SCC component in the consideration set literature. [101] mention resource flows coordination regarding, for example, logistics, capital, or information, to achieve synergy effects. Similarly, [58] refer to harmonizing implementations.

4.3 Technology perspective – Artificial intelligence application

4.3.1 Artificial intelligence sub-fields and techniques

As highlighted by the thematic map, a variety of AI sub-fields and techniques are mentioned in the consideration set literature: *ML, ANN, AI, DSS, MAS, metaheuristics*, and *fuzzy logic and fuzzy sets*.

The *ML* theme appears to be the most dominant. While many papers specify which kind of ML technique or algorithm they apply, some only mention ML in general [e.g. 100, 102]. ML is described as an enabler for digital transformation [58], and linear collaboration synergies in supply chains [92]. Supervised ML is specifically mentioned and used for classification and prediction tasks, e.g. for risk information sharing [87]. Similarly, the review literature suggests the application of unsupervised ML with the purpose of goal congruence [52, 103]. Reinforcement learning is another relevant ML technique used in several papers to solve complex sequential goal congruence decision problems [e.g. 60, 65].

Deep learning and *ANNs* are mentioned in several papers and can be applied for collaborative communication [e.g. 88, 91]. Some authors also refer to combinations of ML techniques, such as deep reinforcement learning [e.g. 60, 65], supervised and unsupervised algorithms [e.g. 55], or integrated models of ML and ANN [e.g. 84]. The SCC applications include decision synchronization and incentive alignment. Transfer-learning approaches can be used to ensure quick adaptation of collaborative communication for other agents and settings [60].

As some papers on SCC do not specify the applied AI sub-field or technique, the theme of *AI in general* is required [e.g. 86, 104]. The review literature suggests that AI drives information sharing and collaborative communication in the form of information alignment, interconnectivity, and interoperability and thus supports the evolution of Physical Internet [8, 105]. Several enabling or accompanying technologies for AI are mentioned in the literature, e.g. blockchain [69, 106]. These developments however, should not distract from fundamental information sharing issues concerning data quality and data sharing [37].

The theme *DSS* is used for decision synchronization, collaborative communication, and goal congruence [e.g. 77, 107]. As a knowledge-based decision aid

tool [96], DSS can be combined with a variety of systems, e.g. ERP [79, 82] or graph database [108]. These applications focus, for instance, on incentive alignment and goal congruence. In addition, [74] use a simulation-based system dynamics approach for information sharing. [102] suggest that the integration of ML and big data could create valuable interfaces with legacy DSS such as business activity monitoring, thus ultimately advancing SCC.

MAS or agent-based modeling are used to represent the collaboration and interactions of autonomous agents and their environment to achieve imitations of real-world systems [49], including collaborative supply chain networks [99]. MAS approaches are applied by several authors in the context of goal congruence and incentive alignment [e.g. 100, 109]. [100] find that the joint utility of agents increases self-adaptive learning success rates compared to ML with regards to incentive alignment.

The theme *Metaheuristics* comprises different optimization models, e.g. for collaborative inventory management [110]. Many approaches consist of evolutionary heuristic algorithms, e.g. Genetic Algorithm for supplier or inventory collaboration [90, 111] or Ant Colony Optimization for transportation and delivery collaboration [67, 91]. Sometimes, hybrid heuristic models combining different heuristic algorithms or evolutionary approaches are used for collaborative transportation of similar resource sharing use cases [e.g. 63, 91].

Fuzzy logic and fuzzy sets stem from the 1960s fuzzy sets theory. Only a small number of papers on SCC mention fuzzy approaches [e.g. 50].

Overall, hybrid approaches combining different AI sub-fields and techniques can be observed. For instance, Genetic Algorithm based DSS [111], agent-based modeling with reinforcement learning [70, 99], or deep learning with DSS and MAS [89]. However according to [39], many AI hybridization approaches consider combinations with more traditional operations research tools.

4.3.2 Potential benefits of artificial intelligence

The literature suggests several benefits of AI application for SCC. These positive effects can concern the firm itself (intra-organizational collaboration), several companies or systems (inter-organizational collaboration), or even larger networks or regions (trans-organizational collaboration).

On the *intra-organizational collaboration level*, the consideration set literature mentions the development of managerial insights for goal achievement [90] which is related to the SCC component of goal congruence. AI is referred to as a leverage mechanism for supply chain enhancement through collaboration [75] and business sustainability as a relevant incentive alignment element [53, 75]. The accuracy and precision of AI-based models and decision-making is highlighted

regarding the SCC component of goal congruence [e.g. 77, 87]. For example, some authors specifically mention how AI could provide user friendly support for analysis and information sharing [e.g. 64, 112]. Overall, collaborative process improvements regarding performance, productivity, flexibility, and efficiency can be achieved [e.g. 53]. Several authors indicate a potential for strengthening competitiveness within the collaborative supply chain through visibility and real-time information transparency [e.g. 108, 112]. For customer collaboration, the perceived quality level can be increased [e.g. 82, 91].

On the *inter-organizational collaboration level*, the improved flow of live information, i.e. information sharing, between organizations is mentioned [28]. Inventory and forecasting optimization through intelligent collaboration, for instance in vendor managed inventory systems, can be achieved through AI application aiming for goal congruence [e.g. 61, 113]. Additionally, the resilience and risk-management collaboration of supply networks can be enhanced through information sharing [50]. The application of AI can furthermore achieve greater levels of trust and sustainable partnerships as information is shared, incentives are aligned, and decisions are made by a centralized tool [64, 89]. Collaborative negotiation and a focus on achieving win-win-situations are enabled in collaborative AI inspired supply chains [100, 114]. [105] show how information alignment can positively impact agility. Moreover, the well-known bullwhip effect and the associated costs and challenges can be minimized in collaborative supply chains [e.g. 92, 110]. [75] describe how AI can be used to improve supply chain integration and relationship management, thus enabling incentive alignment.

On the *trans-organizational collaboration level*, AI can enable efficient transfer learning, collaborative communication, and information sharing [28]. Several authors argue that AI can reduce the environmental impact concerning traffic congestion, energy consumption, and harmful emissions, thus aligning incentives and advancing sustainability goals [e.g. 28, 92]. Economic and social sustainability can also be improved through AI support regarding waste elimination and recycling [e.g. 73, 96]. AI in SCC also enables further technological innovation [8], data dividends [98], smart city development [115], and the emergence of new business models [97].

5 DISCUSSION AND FUTURE RESEARCH DIRECTIONS

5.1 Development over time

Following the analysis of the consideration set literature regarding content and focus, it is interesting to look at the distribution of publications and the development of

topics over time. A steady increase in the number of publications can be observed over time (tripled quantity in 2021 compared to 2013). Thus, a continued growth of publications on AI application for SCC in the next years is likely. The development of AI application for SCC over time is summarized in Figure 3. The development is depicted from the supply chain and technology perspectives.

In 2013, the first year considered in this literature review, DSS appear to be the prevalent tool applied for SCC as five out of six publications focus on this sub-field of AI [e.g. 77, 116]. [117] highlight the relevance of data for DSS while [74] employ a system dynamics based DSS. The prevalence of DSS underlines the focus on efficient supply chains and the role of collaboration therein, especially regarding decision making and goal congruence. Application areas for DSS are demand uncertainty management, lean supply chain, carbon emissions accounting and management to achieve reduced overall emissions along the supply chain, and demand-driven capacity planning for optimal collaborative production lot size determination. The only exception within this consideration set is the application of MAS for assisted collaborative decision-making [118].

In 2014, only one publication refers to a DSS application in the context of collaborative overcoming of shortage situations in delivery management [64]. In contrast, the use of MAS appears to have increased as three papers report agent-based applications for negotiation, aligned KPI planning, and transport cooperation [68, 93]. This appears to show the shifting from collaborative but centralized towards agent-based decision making in supply chains. In addition, fuzzy logic is used for risk coordination [50] and metaheuristics and ML are applied for aligned performance management [103]. Collaborative risk management as well as performance management and evaluation are gaining in importance, showcasing the complexity and interconnectedness of global supply networks.

DSS again play a minor role in 2015, with two papers referring to their application for order aggregation among smaller supply chain actors and to support fast and efficient shared decision making wood supply chain [59, 112]. DSS appear to be slowly replaced by a greater variety of AI based approaches as well as combinations of those. Heuristics are mentioned again one time for cooptation scenarios enabling optimal order quantity allocation among the supplier network [90]. Studied agent-based solutions include collaborative planning, scheduling, and execution [56, 95], thus showing the wider application of this approach. In 2015, hybrid combinations of AI techniques appear for the first time, including multi-agent reinforcement learning for collaborative planning [99] and Genetic Algorithm based DSS for vendor managed inventory cooperation [111].

	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Supply chain perspective	Closed-loop supply chain Decision-making Lean supply chain Uncertainty Sustainability	Delivery/ transportation scheduling Negotiation Planning Performance Risk	Cooperation Operations Planning Procurement Inventory Scheduling Supplier management	Cost Inventory Performance Supply chain integration Transportation scheduling	Emergency supply chain Fleet coordination Relationship management Scheduling	Decision-making Freight pooling Negotiation Performance Planning Relationship strategy Risk Sustainability Unmanned operations	Circular supply chain Event processing Finance management Last mile Planning Production/delivery operations Relationship management Reverse supply chain Supplier management Sustainability	Business ecosystem Crisis management Information management Inventory Planning Profitability analysis Risk Smart city Supplier management Sustainability Transportation scheduling	Agility Circular Economy Closed-loop supply chain Finance management Information management Inventory Interoperability Inventory Lean supply chain Performance Resilience Risk Sustainability	Beer game Capacity management Collaboration efficiency Cost management Decision-making Delivery/scheduling optimization Order management Sustainability
Technology perspective	Data Decision support systems Multi-agent systems System dynamics	Decision support systems Fuzzy logic Machine learning Metaheuristics Multi-agent systems	Decision support systems Fuzzy logic Machine learning Metaheuristics Multi-agent systems	Decision support systems Fuzzy logic Metaheuristics	Decision support systems Digital transformation Machine learning Metaheuristics Multi-agent systems	Artificial intelligence Decision support systems Fuzzy logic Machine learning Multi-agent systems Robotics	Artificial intelligence Decision support systems Fog computing Machine learning Multi-agent systems	Artificial intelligence Decision support systems Blockchain Machine learning Multi-agent systems	Artificial intelligence Decision support systems Big data Machine learning Physical Internet	Artificial intelligence Decision support systems Machine learning Metaheuristics Multi-agent systems

Fig 3 Conceptual framework of artificial intelligence inspired supply chain collaboration

Only two papers within the consideration set have been published in 2016. For example, DSS is used for event-driven transportation management that provides transparent information as well as network-oriented behavior suggestions [71], in line with the trend towards resilience and risk awareness and mitigation. At the same time a hybrid heuristic model is applied for vendor managed inventory cost optimization [63]. Again, hybrid combinations of AI techniques are mentioned. This increasing hybridity appears to show the growing curiosity and creativity of researchers in the field of SCC.

In 2017, metaheuristics are applied for overall cost-improved transportation scheduling [67]. Interestingly, the use of ML increases as it is applied for port logistics digital transformation taking individual IT strategies into account and harmonizing them [58], collaborative relationship prediction [119], and as a hybrid combination of reinforcement learning and agent-based modeling for autonomous fleet coordination [70]. This confirms the description in the literature of a shift toward the training, i.e. ML approaches, “perpetually learning model-growing system” [36, p.336]. Lastly, MAS and DSS are used for collaborative emergency supply chain management [66], again underlining the increasing relevance of supply chain resilience and flexibility.

In 2018, the application of DSS increases again, for example for freight pooling and carrier collaboration [82, 108], and supply chain planning for overall inventory reduction [79]. ML is used for win-win negotiation optimization [100], which is potentially driven by the growing sustainability movement, as, for instance, the Fridays for Future movement and similar initiatives are established. MAS are prevalent again and mentioned in the context of supply chain cooperation [114] and logistics flows management [120]. This is the first year with mentions of AI in general. This includes risk and performance management [54], supply chain and customer interaction designs and business models [97], and autonomous port logistics [69]. The reference to AI as a general term marks the beginning of a continuing trend towards to buzzword of AI and general growing academic and public interest in the topic.

Publications in the year 2019 are dominated by MAS application, for example for agile and customer-oriented supplier selection and economic relationships [48, 94], and collaborative approaches to improve financial performance [49]. [113] amalgamates MAS as a hybrid combination with ML for demand and supply alignment. In addition, DSS are prevalent and used in reverse supply chain coordination [72], sustainable supply chain planning enabled by greater network transparency [30], and as a hybrid combination with ML for event processing [102]. [28] mention AI application for connective and interoperable last mile processes. Individual segments of the supply chain,

e.g. last mile delivery or sourcing, are investigated regarding sustainability and collaborative alignment.

In 2020, the field of AI application for SCC becomes even more versatile and ranges from the use of AI for smart city management using a collaborative urban cockpit [115], fair and transparent information management [39, 106], and business ecosystem management [86], to DSS for agro-industry supply chain [76]. Potentially, this development is related to increasing consumer awareness of the role, importance, and impact of supply chains. The collaborative aspect appears to thus be further extended from supply chain internal to external partners as well as different aspect of public live such as urban management. This might be due to the emergence of the COVID-19 pandemic and the related strain on global supply networks. Moreover, ML is applied for logistic planning [55]. (Deep) reinforcement learning is used in the context of joint replenishment [62, 65] and ANN is applied for supply chain network profitability analysis [88]. This highlights the potential and versatility of ML solutions and could point towards the future growth of this approach. [109] also mention the use of MAS for crisis management supply chain and [121] refer to metaheuristics for collaborative transportation scheduling. Hybrid combinations also appear in 2020 as AI, MAS, and ML for sustainability and risk management through stakeholder interaction [81].

2021 exhibits a steep increase in paper numbers and shows a great variety in applied AI sub-fields and techniques for SCC. DSS are again a dominant feature and are used for supply chain network financing [87], collaborative vehicle routing [40], and synchronized risk and opportunity management [107]. Similarly, ML is frequently applied in circular economy [73], information collaboration patterns [53], and transparent demand forecasting [61]. In hybrid forms, ML is applied in integrated replenishment and forecasting [84] and resilience management through aggregated risk indicators [52]. It is striking that a total of nine publications refer to AI in general, thus indicating an increasing use of AI as an umbrella term. This development confirms the observations of the previous years in the scope of this review. For instance, AI is applied for collaborative risk management [104], larger-scale enterprise transformation [85] as well as information alignment and agility [105]. Other examples are interoperability-based Physical Internet [8, 37], resource coordination synergies [101], collaborative innovation [98] as well as vendor managed inventory [122], and shared environmental performance [9]. Both the terms AI and ML are mentioned for lean supply chain [51] and supply chain performance management and integration [75].

In 2022, ML appears to become even more relevant and is applied for collaborative decision-making [123, 124] and coordinated capacity enhancement [92]. Deep learning is also gaining in importance and is used to play the beer game [60], and as a hybrid combination

with DSS and MAS for partnership-based cost management [89]. In combination with metaheuristics deep learning is used for optimization purposes across the supply network [91]. [57] mention AI for sustainable supply chain collaboration and [110] refer to heuristics for order policy coordination. Possible future developments derived from these observations are presented in the next section.

5.2 Theoretical contributions and implications

As argued by [125], literature reviews can constitute a baseline and orientation for future research. Thus, this systematic review highlights several research gaps. As an outcome of this review and to make scholarly and educational impact [126] we suggest a future research agenda built around six promising research areas containing nine exemplary research questions that may guide future investigations in the field.

(1) Hybrid intelligence

The role of human involvement and human-machine or human-system collaboration needs to be addressed. Incorporating both artificial and human intelligence and enhancing capacities is regarded as a crucial element by [97]. [105] similarly state that demanding and complex activities such as disaster SCM require human coordinators. Hybrid intelligence, referring to the integration of human intelligence into AI approaches, could complement and strengthen AI tools by enabling a reinforcing feedback loop [127, 128]. Thus, different SCC components could be extended and strengthened by incorporating both AI and human intelligence aspects elements. For instance, collaborative communication and information sharing could potentially benefit from a balanced human perspective. Similarly, decision synchronization could be enhanced by AI and thus lead to a more cooperative supply chain.

Research question #1: How can AI support human operatives during collaborative supply chain processes on operative, tactical, and strategic levels?

Research question #2: Which AI activities in SCC could benefit from the integration of human intelligence?

(2) Ethical aspects

Ethical aspects, along with sustainability concerns, need to be considered and respective guidelines should be developed to consider current and future developments in the fields of AI and hybrid intelligence. Due to the increasing cooperation and interconnectedness of supply networks, transgressions of one partner could have severe impacts for any collaborating entities. For example, [39] mention the FAST track principles: fairness, accountability, sustainability, and transparency. These should be developed and advanced

by the supply network to ensure joint knowledge creation.

Research question #3: Which updates and extensions for ethical guidelines in SCC are required to sufficiently incorporate aspects of AI and hybrid intelligence to protect all collaborators?

(3) Hybridization

Hybridization is referred to as a central future research area as the strengths of different (and potentially currently unknown) AI sub-fields and techniques can be combined. Due to the variety of AI sub-fields and techniques as well as the constant new developments in this field, a great variety of application potential for different tasks remains. In addition, combinations with classical approaches and methods from operations research and similar fields could provide improved tools which have not yet been researched in detail [39]. Hybridization could also include enabling technologies such as RFID, thus providing potential regarding transparent collaborative flow of goods in supply chains.

Research question #4: How can AI techniques be combined to optimize results in SCC?

Research question #5: How can AI techniques in SCC be supported by novel technologies?

(4) Physical Internet

Greater degrees of interconnectivity and interoperability are required for the Physical Internet, thus driving future research into interconnected network and the digital internet [37, 62]. Promising future application contexts need to be identified based on the availability of goods and information flows.

Research question #6: How can the smooth interaction between and integration of physical flows and information flows in supply chains be supported through (intelligent) and collaborative information and communication structures and enterprise architecture?

(5) SCOR make process

The make process is the least mentioned SCOR process as only two papers within this literature review could be allocated to it [75, 76]. This is somewhat surprising as the goods flow associated with the conversion of materials or the creation of the content for services is a key component of the supply chain process. Especially the emerging relevance of digital twins in the industry could represent an ideal data source for AI applications regarding information and resources sharing or also concerning joint knowledge creation, for instance in a production research and development context.

Research question #7: How can the collaborative and transparent make process be enhanced through AI application?

(6) Resources sharing

Resources sharing is observed as a less dominant SCC component in the consideration set literature [e.g. 58, 101]. Possibly, this is due to existing barriers to leveraging assets and making mutual asset investments, e.g. legal restrictions or set corporate forms. Comprehensive resources sharing might consequently result in greater costs than benefits from the collaboration.

Research question #8: How can governments or other administrative bodies foster resource sharing between supply chain partners?

Research question #9: Which AI applications could enhance the benefits of asset leveraging in collaborative supply chains?

5.3 Implications for practice

This paper has several practical implications that offer helpful guidance for managers involved in SCC and related processes. First, managers involved in SCC can use this review to navigate the complex and heterogeneous field of AI application for SCC. The conceptual framework of AI inspired SCC constitutes a valuable roadmap for promising AI technologies. Users may apply the framework to select adequate literature depending on their specific sector or practical focus. Thus, it becomes easier for managers to select the appropriate AI tools in relation to their organization's aims and performance goals. Second, the review findings can be used to derive information on promising investments in high-potential AI tools. Thus, relevant investment strategies can be defined, and pitfalls can be avoided. Similarly, the review supports managers striving to identify promising SCC areas for AI application such as last mile networks. Following the analysis of suitable areas, market entry or expansion decisions can be made. Third, the Physical Internet and thus the integration of information and material flows is becoming increasingly relevant for supply networks. Collaboration within these smart networks needs to be supported by sufficient investment in the extension of integration levels. Similarly, managers should strive to secure supply network competitiveness by ensuring data availability, integrity, and adequacy as a basis for the further development of AI application. Fourth, as the review findings suggest, AI applications should consider the human users they are designed to support. To adequately involve human actors and to respect organizational perspectives during the process of implementing novel technologies, dedicated frameworks could be consulted.

5.4 Limitations

This paper has its recognized limitations. First, systematic literature reviews have been criticized for being too mechanistic [129] and thus restricted regarding their conclusions. Second, the literature

review is limited in its selection of databases. The resources available at the time were used to achieve the best possible result and a comprehensive review. However, not all sources of academic literature can be covered. Third, the choice of an in-depth instead of a broad approach restricts the comprehensiveness of the resulting analysis and discussion. Despite the exhaustive literature search process, this review cannot claim to provide a full overview of AI application for SCC due to restrictions concerning the choice of keywords. While prior testing of the keywords is included in the review approach, it cannot be claimed that all relevant articles are included in the final consideration set. Fourth, the use of a specific time period, the adoption of specific analysis and synthesis approaches and the defined exclusion criteria restrict the scope and depth of this review. Overall, the validity of the research results is influenced and restricted by these four main limitations and the authors' interpretations. This mainly concerns the exhaustiveness and completeness of the literature search results and resulting consideration set as well as the structure, content, and discussion of the review results. Consequently, while the thorough and best-practice-based review approach leads to valid results, the findings do not necessarily offer a complete or entirely accurate representation of the review focus area.

6 CONCLUSION

In this paper, a systematic literature review of 83 published articles is presented to determine how AI techniques have been applied in SCC in the last decade and to derive potential roads forward. The review resulted in a comprehensive conceptual framework of AI inspired SCC and concludes that SCC is a research field encompassing a great variety of research streams, thus requiring further consolidation and differentiation. Different subsets of AI are applied with varying intensity for SCC processes and frequently also combined as hybrid forms. The framework shows that ML and ANN, DSS, and MAS are frequently used in this context. The main AI inspired SCC processes reported in the literature sample include, for example, decision-making, data and information sharing, and supplier selection.

The literature review shows that AI technologies have only been applied in a limited way for the development and improvement of SCC. Over the last decade, a constant increase in application fields as well as AI tool variety and versatility can be observed. A clarification of the implications of AI application for SCC and a better understanding of the required changes in policy and practice are necessary to utilize AI efficiently. However, few studies have focused on how to transform supply chain networks and collaborative processes for AI implementation. Future research could build on this

literature review by comparing the next years' research findings regarding the implementation of AI for SCC. For example, consecutive research could discuss if the collaborative processes supported by AI have changed or for which it would have the most impact. Also, which further applications are conceivable and how does this differ from past development as described in this literature review? Still, potential misuse as well as challenges during the implementation of AI also need to be examined [58, 130]. Likewise, AI should not be regarded as a panacea and potential misuse needs to be acknowledged [131].

This paper confirms the overall trend of publication growth, which could indicate the topicality of AI application for SCC as well as a future increase in research and development activities in this direction. This finding supports the initial statement that there is an increased focus on the advancement of technological solutions and that the research field is becoming more difficult to navigate. This paper thus provides relevant insights into the main research streams as well as potential future research avenues. The literature review confirms the relevance of digitalization and related enabling technologies as a prerequisite for AI implementation, especially concerning the availability and quality of a supply network data.

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