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Review

Artificial intelligence applications in supply chain management

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A B S T R A C T

This paper presents a systematic review of studies related to artificial intelligence (AI) applications in supply chain management (SCM). Our systematic search of the related literature identifies 150 journal articles published between 1998 and 2020. A thorough bibliometric analysis is completed to develop the past and present state of this literature. A co-citation analysis on this pool of articles provides an understanding of the clusters of knowledge that constitute this research area. To further direct our discussions, we develop and validate an AI taxonomy which we use as a scale to conduct our bibliometric and co-citation analyses. The proposed taxonomy consists of three research categories of (a) sensing and interacting, (b) learning, and (c) decision making. These categories collectively establish the basis for present and future research on the application of AI methods in SCM literature and practice. Our analysis of the primary research clusters finds that learning methods are slowly getting momentum and sensing and interacting methods offer an emerging area of research. Finally, we provide a roadmap into future studies on AI applications in SCM. Our analysis underpins the importance of behavioral considerations in future studies.

1. Introduction

From Herbert Simon's well-known quote in 1965 "Machines will be capable of doing any work a man can do" until today, artificial intelligence (AI) has come a long way and far closer to what Simon predicted over 50 years ago. A movement that initially started with the development of expert systems and fuzzy logic, then further matured after 2010 with the emergence of big data, analytics, and numerous applications of graphical processing units and deep learning that has shaped what we refer to as modern AI. Since early 2010, the pace of AI applications has increased rapidly with promising results as well as some concerns about the future of work and business management (Manyika and Bughin, 2018; Samuel et al., 2019). While businesses are embracing AI and investing in AI solutions to improve their end-to-end supply chain operations (Chui et al., 2019; Hartmann and Moeller, 2014), it seems that the supply chain literature is still catching up with some recent efforts to incorporate modern AI methods within its core studies.

What triggered this study was our initial observation of the literature that seemed to be saturated with the use of decision support systems – primarily adopting fuzzy logic, expert systems, multi-criteria methods and/or heuristics and meta-heuristics optimization – for conducting supply chain management (SCM) studies. Yet, the literature still is following behind the industry in investigating applications of more advanced AI methods such as machine learning, deep learning, and image/text processing that are surely integral elements of modern supply chains today. Simultaneously, our investigations revealed significant fragmentation in AI research, highlighting the need for a reasonably acceptable and inclusive taxonomy that can guide operations and supply chain researchers to expand their understanding of the past, present and future scope of research into AI applications in SCM. Thus, in this systematic review of the literature we aim to address the following questions: *What is the current state of the literature of AI applications in SCM? What AI methods have been investigated, and in which supply chain contexts? What might future studies on AI application in SCM consist of? Which methods will be more widely embraced, and in which supply chain contexts?*

To address these questions, we utilize a multi-method approach to holistically review the related literature. This multi-method approach starts by developing a unique taxonomy of AI applications – an important tool that will be employed to systematically examine the entire field and the related studies. Our thorough co-citation and network analysis will help reveal existing patterns and interrelationships between/among different studies in this literature. This is an unprecedented attempt to review this literature and capture the research trends using a carefully designed AI taxonomy, holistic bibliometric and co-citation analysis, cluster analysis, and in-depth discussion on future research avenues.

The remainder of this paper is organized as follows. The proposed AI taxonomy is presented in Section 2. The AI taxonomy is developed based on our observations of the existing literature, validated by AI experts. In

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Section 3, we employ this AI taxonomy to categorize the articles we extract from the literature using a systematic keyword search. Section 4 presents a word frequency analysis and cluster analysis to further explore the clusters of knowledge that form the backbone of the existing literature. The clusters are then categorized according to our proposed AI taxonomy. Based on our findings from bibliometric and cluster analyses, Sections 5 and 6 discuss directions for future research, limitations of our review, and practical implications related to AI applications in SCM.

2. Artificial intelligence: definition and taxonomy

AI is a field in computer science encompassing the development of systems capable of performing tasks that normally necessitate human intelligence. Bughin et al. (2018) estimate the economic contribution of AI technologies to be around $13 trillion by 2030, and potentially boosting global GDP by about 1.2 percent annually. Despite its potential to disrupt the way organizations operate, Gartner (2018) estimates 37 % of organizations are still searching to outline their AI strategies, whereas 35 % are struggling to find the right application.

The term "artificial intelligence" was first coined by John McCarthy in 1955 to explore the ability of machines to use language, solve problems that are typically reserved for humans (McCarthy et al., 1955). An agreed-upon and standard definition of AI is virtually non-existent (Legg and Hutter, 2007; Nilsson, 2010). Russell Stuart and Norvig (2009) consider two dimensions for AI. The first dimension is about comparing the system performance with the way humans think or with ideal rationality. The second dimension is whether the system matches human performance in acting rationally. We adopt the widely accepted definition provided by Marvin Minsky, the founder of MIT Artificial Intelligence Lab (Minsky, 1968): *"the science of making machines do things that would require intelligence if done by men"*. Since its early conceptualization in the 60s, AI research has witnessed extensive variations, from low interest in this topic to its rapid growth, also known as AI frenzy (Baryannis et al., 2019b). However, it wasn't until recently when AI started delivering its promised value to businesses. Well-known examples are IBM Watson that is used for medical diagnosis and Fleet Learning developed by Tesla that allows vehicles to anticipate changing condition by continuously sharing fleet data (Deloitte, 2018).

Several factors contribute to the recent momentum that AI has received in both academia and industry, including (i) significant improvements in computational power (Duan et al., 2019), (ii) availability of large datasets for training the algorithms as a result of widespread adoption of Internet of Things devices (Leary, 2013) and (iii) development of novel learning algorithms (Al-Jarrah et al., 2015). Furthermore, recent developments are fueled by significant investments made by the leading companies such as Google, IBM, Microsoft and Amazon to become the frontiers of emerging AI marketplace (Lohr, 2016).

While there is agreement on defining the key characteristics of AI and the values that can be derived from various AI applications, the absence of a taxonomy that clearly explains the primary branches of AI is evident. AI is an extremely fragmented field, with its branches overlaying each other in terms of type and methods. Therefore, any attempt to categorize various AI methodologies are often associated with inevitable shortcomings. For instance, some consider machine learning and Natural Language Processing (NLP) as two branches of AI, since one can use machine learning techniques to solve NLP problems (Trappey et al., 2020).

To apply AI techniques to a domain, a preliminary step is to understand the key branches of AI. In this section we aim to produce an AI taxonomy that classifies AI methods to a reasonable degree. The key areas were initially identified through various academic sources followed by informal face validity (Salkind, 2010) through interview consultations with AI experts. The use of expert opinion for face validity is widely practiced in business research (Hardesty and Bearden, 2004). Five academics with extensive AI expertise and two supply chain practitioners were involved in the validation process, including a supply chain director from the food industry, a supply chain analyst from the telecommunication industry, a full professor, an associate professor, two assistant professors and one postdoctoral fellow. The length of each interview varied between 20 minutes and 1 hour in an open discussion format to avoid any bias and maximize information capturing (Dieckmann et al., 2017; Langfeldt, 2004).

The experts were asked to validate the proposed taxonomy and make suggestions to improve its structure/formatting, if applicable. The initial taxonomy was developed as a result of this collective consultation, which was then shared with the experts once again for further refinement. The final taxonomy was principally agreed upon by all experts with only minor differences in some areas due to variations in their background and expertise (e.g., applied mathematics vs. computer science). The final proposed taxonomy (Fig. 1) shares similarities with some of the existing AI frameworks (Kotu and Deshpande, 2018; Mata et al., 2018). However, our taxonomy provides a more fine-grained perspective in terms of main branches and applications of AI methods. Specifically, the taxonomy provides a three-layered perspective into the field: (i) 'branch', which specifies the key functional area, (ii) 'application' that indicates the specific use of AI, and (iii) 'method', which stipulates the technical basis. Due to the large number of algorithms and heuristic methods, we will not attempt to elaborate on individual algorithms and methods. Instead, we aim to capture the crux of the AI applications and provide examples to explain those applications. Fig. 1 presents the proposed AI taxonomy and the remaining of this section briefly explains the key branches of AI, their applications and methods, which will be further utilized to achieve the objectives of our review. According to Fig. 1, AI can be broadly classified into three branches given their function in a system. The first branch consists of approaches that are associated with *sensing and interacting* in various forms such as text, audio and video (Ramos et al., 2008), namely speech, vision and NLP. The second branch includes applications and their methods intended to *learn from data*. Most Machine Learning methods such as deep learning could be labelled under this category (Al-Jarrah et al., 2015). The third branch comprises applications and methods related to *decision making*, including expert systems, planning, simulation, modelling, scheduling and optimizations (Duan et al., 2019; Pan et al., 2020; Soleimani et al., 2018). Classifying AI into sensing and interacting, learning, and decision making is also consistent with one of the well-known definition of AI by (Kaplan and Haenlein, 2019) as a system's ability to "correctly interpret external data", "to learn from such data", and "to use those learnings to achieve specific goals and tasks".

2.1. Sensing and interacting

This section outlines the AI methods related to sensing and interacting. *Natural language processing (NLP)* is an application of AI comprising development of systems to perform tasks under human language instructions. The key methods of NLP are text extraction, classification, translation, text generation and question answering (Collobert et al., 2011; Manning et al., 1999). NLP has been recently used to establish improved human-system interfaces (Zanon et al., 2020). For instance, Wichmann et al. (2020) examine how NLP can be employed to automatically verify and generate supply chain maps for enhancing structural visibility of a supply chain from unstructured text (e.g., newspapers or blogs).

Other AI methods have proven to be the ultimate solution for solving cognitive problems using voice-driven applications and speech recognition (de Barcelos Silva et al., 2020; Graves et al., 2013). Speech recognition encompasses the methods that can automatically and accurately recognize spoken words for conversion to text and vice versa (Lu et al., 2018; Ramos et al., 2008). While speech recognition is far from perfect and there remain challenges in terms of accent, word similarity, and sound quality (Ricketts and Hornsby, 2005; Yang et al., 2018), the accuracy of the existing software packages have been

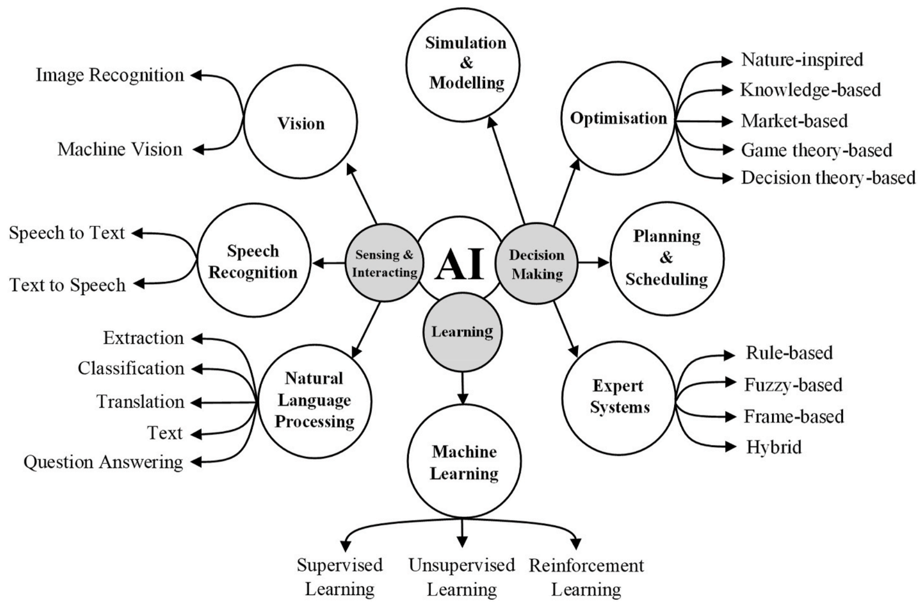

Fig. 1. The proposed AI Taxonomy.

improved significantly over the past decade (Ogawa and Hori, 2017). Some of the widely used industry examples of speech recognition include Google Home, Amazon's Transcribe, Alexa from Microsoft and Apple's Siri.

With the recent advancements in AI capabilities, vision-based methods for image and video analytics have received significant interest in the field of computer science. Vision has gradually become a mainstream in the field of AI, aiming to enable computers to analyze and interpret meaningful information using data collected from vision-based sensors (Zhang et al., 2020). AI-based vision methods can be loosely categorized into machine vision and image recognition. While image recognition refers to the process of identifying and detecting an object or a feature in a digital image or video, machine or computer vision encompasses the methods that enable a machine to capture, process and interpret images to intelligently undertake a given task. In recent years, computer vision has received additional momentum in the area of mobility, enabling autonomous vehicles to effectively interact with their surrounding environment (Das et al., 2020).

2.2. Learning from data

Perhaps the most broadly known and popular branch of AI is machine learning, which is classified into the major application of "learning" in the proposed taxonomy. *Machine learning* is associated with the development of algorithms that can learn by training data to solve problems using knowledge obtained from previous problems (Priore et al., 2019). For example, machine learning has been extensively used for time series forecasting (Carbonneau et al., 2008). Machine learning can be classified into three main methods of supervised learning, unsupervised learning, and reinforcement learning (Overgoor et al., 2019). Supervised learning is about training a machine with a known dataset (training samples) to predict an output. Supervised learning models can primarily contain decision tree models, linear regression, support vector machines, and neural networks (Cui et al., 2018; Friedman et al., 2001). In unsupervised learning, the machine will learn to recognize patterns without any trained data or pre-labelled information. Unsupervised learning is widely used in clustering problems to identify similarities (Sharma et al., 2020). Reinforcement learning is similar to unsupervised learning, with the difference that the machine receives feedback after completing the task. In other words, the machine improves its performance by trial and error, where the attempts are guided (Mnih et al., 2015). While supervised learning mainly deals with classification and regression problems (Guillaumin et al., 2010; Ponulak and Kasiński, 2010), unsupervised and reinforcement learning are concerned with clustering and reward-based problems, respectively (Chen et al., 2005; Mahadevan, 1996). Other machine learning methods such as deep learning (LeCun et al., 2015) can span across the three categories of learning methods (see the recent review by Kraus et al., 2020). The applications of machine learning have received further momentum in recent years, mainly because today's digitally operated business processes are inundated with large volumes of data (Hazen et al., 2014). For further reading, a review of the machine learning methods for big datasets is provided by Choi et al. (2018).

2.3. Decision making

AI applications in supply chain decision making can be broadly grouped into *optimization, expert systems,* as well as methods related to *planning and scheduling* and *simulations and modelling.* While many of the existing methods used for solving optimization problems were introduced in the early 60s, it was only in 2000s when such methods were employed to address more dynamic problems using large datasets (Abbasi et al., 2020; Allam and Dhunny, 2019; Dey et al., 2018; Fischetti and Fraccaro, 2019; Jiang et al., 2016). Optimization methods can be grouped into nature-inspired (e.g., ant colony optimization and genetic algorithm), game theory-based (e.g., cooperative models), market-based (e.g., negotiation and auction algorithms), decision theory-based (e.g., Bayesian approaches) and knowledge-based methods. These methods have been employed to solve a range of operations and supply chain optimization problems (see, Diabat and Deskoores, 2016; Melo et al., 2009; Saghaei et al., 2020).

Expert systems – also known as knowledge-based systems – is another application of AI that encompasses a variety of domains and problem-solving methods aiming to enable systems to accomplish tasks that are otherwise performed by human experts (Giarratano and Riley, 1998; Tecuci, 2012). Kusiak and Chen (1988) outline the components of an expert system as (i) knowledge reorientation where knowledge is framed, (ii) interface engine which outlines the control strategy and (iii) knowledge acquisition that enables the system to acquire data and knowledge for problem solving. Examples of expert systems methods can include rule-based, fuzzy, frame-based and hybrid methods that benefit from the combination of more than one intelligent system

(Zarbakhshnia et al., 2018). Research suggests that expert systems perform very well in areas where human intelligence can be formalized and structured (Jakupović et al., 2014). When such formalization is not possible, the performance of expert systems could drastically fall (Haenlein and Kaplan, 2019). This issue is more evident when expert systems are employed for solving cognitive problems.

In recent years, the use of AI techniques for modelling and simulation of complex systems has become more commonplace (Chen et al., 2008). Applying AI in modelling and simulation allows for advanced scenario-based analysis; thereby enhancing decision making through better understanding of system behavior (Bennett and Hauser, 2013; Moayedikia et al., 2020). Agent-based computing techniques could be named as one of the key methods to model the interplay of system components and examine performance in real-world scenarios (Abar et al., 2017; Rolón and Martínez, 2012).

AI planning and scheduling are the methods for making intelligent system decisions given a set of constrains (i.e. resources in a production facility) (Barták et al., 2010). Planning is concerned with decisions to optimize the order of activities to occur, whereas scheduling is about the temporal allocation of tasks to resources (Kreipl and Pinedo, 2004). Not only have recent AI advancements enabled managers to detect and predict disruptions that may impact normal system operations (e.g., fraud detection, predictive maintenance and system failures), but they have also assisted with system recovery in a more responsive and data-driven fashion (Abedinnia et al., 2017).

3. Review methodology

3.1. Extracting relevant scholarly articles

A few review papers have been published since 2015 (and especially in the last couple of years) that either directly or indirectly address AI methods and their applications in SCM. Table 1 provides a summary comparison of these review papers. There have been of course other reviews prior to 2015 (e.g., Min, 2010), but given the fast pace of changes in AI and the rise of big data and innovative analytics especially in the past few years (Rowe and Pournader, 2017), we limited our comparison and analysis to the more recent debates on the topic.

Out of the four most recent reviews, none provide a basic understanding of the scope of AI methods, nor a framework/guideline to sort the searched articles. The AI taxonomy we presented in Section 2 serves two major purposes, i.e., categorizing various AI methods under the umbrella of a cohesive framework of reference for future research, and it will be used to categorize the clusters emerging from co-citation analysis in the following Section 4. Moreover, except for Toorajipour et al. (2021) the scope of these reviews are either very specific (i.e., Baryannis et al. (2019b) on supply chain risk) or too broad (i.e., Dhamija and Bag (2020) and Grover et al. (In press) on operations management). Equally important, the AI keyword search in these reviews is quite limited to specific methods. Finally, to our knowledge, no review to this date has gone through the lengths of providing an in-depth co-citation analysis to reveal the existing and emerging research areas in this domain.

The primary purpose of this review is to shed light on the less explored, yet important, aspects of AI applications in SCM. Using the proposed AI taxonomy to construct our keyword structure to search for relevant articles, we primarily focused on the keywords that represent ‘learning and sensing’ and ‘interacting’ aspects of the taxonomy. Excluding the well-explored research areas in our review allows us to focus specifically on an in-depth analysis of the clusters that contain the emerging areas of research.

We relied on the definition of SCM by Mentzer et al. (2001) to outline the keywords needed for finding the relevant papers using advanced AI methods. Mentzer et al. (2001) describe a supply chain as: “a set of three or more entities (organizations or individuals) directly involved in the upstream and downstream flows of products, services, finances, and/or information from a source to a customer”. While this definition emphasizes on the multi-tier nature of supply chains (i.e., buyer-supplier relationship) it excludes references to marketing, logistics and production, which were recently used by Toorajipour et al. (2021). We also excluded general terms that are categorized under the umbrella of Operations Management such as “inventory management”, “manufacturing”, “procurement”, and “newsvendor/newsboy model” (see Slack et al., 2016). Instead, we have used keywords that are exclusive to supply chain management and its multi-tier nature such as “supply chain”, “supply network” and “buyer-supplier”. We also tested the keyword “supplier” in our search attempts, but the number of irrelevant outcomes using this keyword prompted us to exclude it from the keyword set (see the online Appendix A1).

Scopus (www.scopus.com) and Web of Science (www.webofknowledge.com) are the two major search engines for searching scholarly sources. Scopus, particularly, offers a wide range coverage of literature and is commonly used for network and co-citation analysis (e.g., Fahimnia et al., 2019; Pournader et al., 2020b). We have therefore opted for Scopus for the purpose of this study. To ensure maximum coverage of the literature that adopted AI methods (see Section 2) in the context of SCM, we employed a trial-and-error method to keep the most relevant keywords, while discarding keywords that either introduced too many irrelevant articles or did not introduce articles that are not already

Table 1
Comparison of related review papers.

Article	Method	No. of reviewed articles	Review Timeline	AI Framework (Yes/No)	AI methods	Supply chain areas
Baryannis et al. (2019b)	Systematic literature review (keyword search and bibliometric analysis)	276 (not all AI-related)	1996–2018	No	No specific AI-related keywords	Supply chain risk management
Dhamija and Bag (2020)	Systematic literature review (keyword search and bibliometric analysis)	1854	2018–2019	No	Artificial intelligence, genetic algorithms, agent-based systems, expert systems, big data analytics	Operations management (used in the keyword search)
Toorajipour et al. (2021)	Evidence-informed, systematic literature review (keyword search and bibliometric analysis)	64	2008–2018	No	No specific AI-related keywords. Classified AI methods based on supply chain areas.	Demand forecasting, facility location, supplier selection, supply chain network design, supply chain risk management, inventory replenishment, crisis management, global value chains, supply chain process management, supply chain planning, maintenance systems, sustainability
Grover et al. (In press)	Literature review (keyword search, clustering and word cloud) and social media analytics	181	Not specified	No	No specific AI-related keywords	Operations management (used in the keyword search)

captured by the existing keywords. The process is shown in the online Appendix A1. As shown in this Appendix, a variety of AI and SCM keywords were examined in 26 consecutive iterations. The inclusion criterion for a keyword was to introduce new and relevant papers. The criteria for the exclusion of a keyword were either brining too many irrelevant papers or no papers at all. We terminated the trial-and-error after several iterations, where adding new keywords introduced no new papers. The final keyword set is as follows:

> “artificial intelligence” OR “machine learning” OR “deep learning” OR “unsupervised learning” OR “supervised learning” OR “reinforcement learning” OR “computer vision” OR “natural language processing” OR nlp OR “support-vector machine” OR “support vector machine” OR svm OR “self-learning” OR “self learning” OR “transfer learning” OR “cognitive computing” OR “logic programming”) AND (“supply chain” OR “supply network” OR “buyer-supplier” OR “supplier selection” OR “supplier evaluation”)

The search covers the published papers until January 2020. The earliest publication we found on this topic dated back to 1998, which makes our coverage of the literature from 1998 to January 2020. While we did not limit the timeline of the search, finding relevant articles no earlier than 1998 sounds logically correct as the term “supply chain” slowly started to enter the academic literature in this decade as a result of globalization and outsourcing. To ensure the inclusiveness of our keywords, we cross-checked the articles we found with the existing reviews that are somewhat relevant to AI and SCM (i.e., Baryannis et al., 2019a; Baryannis et al., 2019b; da Silva et al., 2020; Dhamija and Bag, 2020; Mišić and Perakis, 2020). While our keyword set showed a +90 % coverage of the papers in these reviews, we manually added the missing papers to the pool of articles we extracted from Scopus.

3.2. Bibliometric analysis

Our search attempts revealed 261 peer-reviewed articles published between 1998 and January 2020. We went through a multi-level screening process to finalize the set of articles for our review. First, we omitted the articles that were not ISI-indexed or from unknown publishers. The publisher coverage in Scopus is quite extended, therefore we needed to be selective and only opt for articles from the following publishers: Elsevier, Springer, Wiley-Blackwell, Taylor & Francis, Sage, Emerald, and IEEE that represent the bulk of the operations and supply chain outlets. Next, we filtered out the articles that either did not fit in the AI taxonomy introduced in Section 2 or did not fit in a supply chain context. This process resulted in a total of 150 journal articles. The frequency of publications per year is shown in Fig. 2 below.

37 journals have contributed to the publication of these 150 articles. The most contributing journals in terms of publication frequency are *International Journal of Production Research* (33 articles), *International Journal of Production Economics* (17 articles), and *European Journal of Operational Research* (15 articles). John Colins, Angappa Gunasekaran, and Manuj Kumar Tiwari, each with 3 articles, have the highest count of publications. At least two of the authors of this paper were involved in reviewing every article to extract information such as the supply chain context and AI method(s). The authors then compared their classifications and addressed the discrepancies to ensure reliable outcomes. Overall, we found a variety of supply chain topics that were addressed within the pool of articles, from supply chain forecasting and risk management to supplier selection and procurement. Based on our AI taxonomy and despite filtering out the decision-making keywords, we still found that a majority of all articles were related to decision making methods, a few used learning techniques or a hybrid of decision making and learning, and only one article used sensing and learning methods. Table 2 summarizes the frequency of AI methods used in each supply chain context.

We found 15 review papers in our pool of articles that either focus on

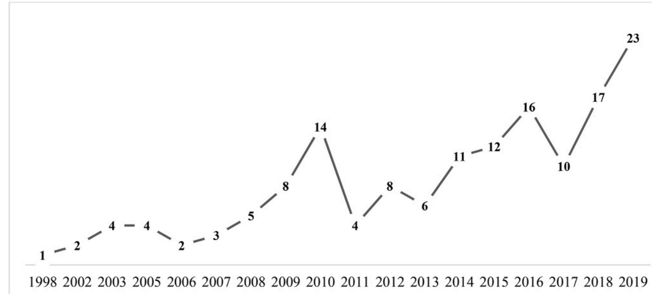

Fig. 2. Frequency of publications per year.

the application of AI methods in a particular supply chain context (e.g., Baryannis et al., 2019b; Carbonneau et al., 2008; Syntetos et al., 2016), or discuss the application of a certain AI method in SCM (e.g., Groves et al., 2014; Pontrandolfo et al., 2002; Tako and Robinson, 2012). It is true that in our keyword search we excluded topics that are generally categorized under Operations Management (e.g., “inventory management” or “quality management” or “lean”); however, they may still appear in Table 2 if these topics have been used in a supply chain context (multi-tier operations) along with the application of an advanced AI method. We observe that *Forecasting* has been the most popular supply chain context that primarily uses AI learning methods. Most of the articles that use decision making methods, apply *stochastic programming* and *fuzzy logic*; whereas *agent-based models* and *neural networks* are the dominant techniques used for learning methods. The excel file containing the citation details of the pool of articles and the AI methods used is presented in online Appendix A2.

3.3. Co-citation network analysis

To identify the forming clusters of research, we complete a co-citation analysis as a commonly accepted approach (e.g., Ben-Daya et al., 2017; Fahimnia et al., 2019; Fahimnia et al., 2015; Khorram Niaki and Nonino, 2017; Pournader et al., 2020b; Xu et al., 2018). Compared to various other methods of network analysis for literature mapping, such as citation analysis and bibliographic coupling, co-citation analysis is to be analogous to bibliographic coupling in terms of coverage and accuracy of clustering (Perera et al., 2020; Boyack and Klavans, 2010; Yan and Ding, 2012). Moreover, citation analysis is subject to a number of limitations that makes it a less preferred tool to network analysis and literature mapping in general (see Arvan et al., 2019; Pilkington and Meredith, 2009).

In simple terms, co-citation analysis forms clusters of scholarly sources that are frequently co-cited in a pool of articles (Small, 1973). The idea behind clustering through co-citation analysis is that the higher the frequency of the co-citation of each pair of references, the higher the likelihood of these references forming a cluster and converging to a similar topic (Clauset et al., 2004; Leydesdorff, 2011). Each cluster therefore contains a set of co-cited references that have strong connection among them and weaker connection with the rest of the clusters (Perera et al., 2019).

We adopted a two-step approach to conduct the co-citation analysis. First, we used Sci2 Tool (Sci2, 2009) software to conduct the required graph analysis for the co-citation analysis. The network was shown to be strongly connected, which means there are much stronger connections between the co-citated references in each cluster rather than across cluster connections. Overall, the co-citation network had 12,501 nodes (i.e., the total number of scholarly sources cited by the pool of 150 articles) and 488,456 edges, which gives an average of 39 edges per node – indicating a strongly connected network. Next, we visualized these clusters using Gephi 0.9.2 (https://gephi.org/) software. Forming and visualizing the clusters in Gephi requires a modularity analysis. Modularity index varies between −1 and +1 and the closer the index is to +1

Table 2
AI methods used in each supply chain context.

Supply chain context	AI methods			Review	Sensing/Interacting	Special Issue	Total
	Decision Making	Decision making/Learning	Learning				
Auction			1				1
Capacity Management	2						2
Configuration			1				1
Decision Making	2		2	1			5
Finance	2		2				4
Forecasting	5		13	2			20
Inventory Management	6	1	7				14
Lean	1		1				2
Logistics	10		3				13
Manufacturing	10			1			11
Performance Measurement	4						4
Planning	5			1			6
Procurement			1	1			2
Quality Management			1				1
Review	2		3	1			6
Risk Management	5		3	1			9
Social Media					1		1
Supplier Selection	11		3				14
Supply Network Design	12		5				17
Sustainability	10		2	1		1	14
Technology			2	1			3
Total	**87**	**1**	**50**	**10**	**1**	**1**	**150**

is an indication of more strength between nodes within clusters and weaker connections between nodes in different clusters. The latter ensures that different clusters are sufficiently differentiated. The modularity index of our network is 0.895 with the degree filter of 120 forming 14 clusters. Then, we used Gephi toolbars to choose a layout for the clusters, making each cluster color-coded and preferably change the sizes of nodes/references in each cluster based on the degree of co-citation. The larger a node is within a co-citation network, the more prominent the node is in the literature as this is an indication of the node being frequently co-cited. The labelled network containing all 14 clusters is presented in online Appendix A3. The full list of all references in all clusters are included in online Appendix A4.

4. Cluster analysis

An important step in cluster analysis is determining the primary theme(s) or focus area(s) of each cluster. Due to the high frequency of the sources in each cluster (most of our clusters have between 100 and 250 sources), we initially used text and word frequency analytics on the titles of all sources in each cluster using NVIVO 12 software. The word frequency analysis helped us gain a basic understanding of the theme(s) of each cluster. Subsequently, we further investigated the sources of each theme to better understand its relevance. Upon this investigation, we realized that we can provide a higher-order classification of clusters based on the AI taxonomy presented in Section 2. Of 14 clusters in our co-citation analysis, 7 can be labelled as decision making and learning clusters. The sources in these clusters often revolve around the application of certain AI techniques in a variety of supply chain and operations management contexts. The remaining clusters were focused on specific supply chain contexts where multiple AI methods were applied. We labelled the latter clusters as hybrid clusters. There are 2 clusters that do not necessarily focus on a supply chain context or a particular AI topic. These clusters are labelled as miscellaneous and are discussed briefly at the end of this section. In what follows, we present the outcomes of our cluster analysis. The examples provided below in the description of each cluster are chosen carefully to reflect the impact of the related studies on the existing literature.

4.1. Decision making clusters

4.1.1. Cluster 0: simulation and system dynamics

Most of the articles in this cluster are concerned with adopting *simulation* approaches to tackle a range of problems related to supply chain network design, planning, and scheduling. Examples of studies in this cluster include Van Der Zee and Van Der Vorst (2005) that provide insights into simulation modelling qualities and using the findings to define an object-oriented modelling framework to facilitate supply chain simulation. In a similar vein, Holweg et al. (2005) adopt simulation in a multi-tier supply chain and examine the effect of changing key factors in scheduling to identify plausible developments in supply chain responsiveness. In a later relevant study, der Zee (2011) argues that Petri Nets visual simulation models cannot be easily understood due to their complexity. Therefore, a structured method is proposed guiding the analysts to achieve more perceptive models. The fundamentals of the proposed method are domain-related reference architecture and unchanging guidelines for mapping high-level concepts onto low-level Petri Nets.

System dynamics is the second major theme in this cluster. Specifically, system dynamics integration with discrete-event simulation is repeatedly used in this cluster. For instance, by integrating discrete-event simulations and system dynamics models, Reiner (2005) explores the role of customer focus (orientation) on supply chain assessment and improvement. Greasley (2005) proposes that delivery performance problem of organizations cannot be solved by merely using discrete-event simulation. Therefore, a decision-making framework is developed using system dynamics in sales and production process leading to a deeper understanding of supply chain performance. Greasley (2005) argues that system dynamics can provide a human aspect into discrete-event simulation analysis. In another study, Tako and Robinson (2010) empirically compare the modelling and processes of discrete-event simulation and system dynamics. They investigated how the same modelling task can be tackled differently using simulation and system dynamics. Discrete-event simulation modelers focus significantly on model coding, verification, and validation; while system dynamics modelers pay more attention to the conceptual modelling.

Overall, studies in Cluster 0 aim to improve supply chain data-driven decision-making using simulation, system dynamics, or both. Most articles in this cluster are published before 2010 with the highest frequency between 2000 and 2006, implying the established maturity of this research area. *Systems theory* is the most common theory adopted in this cluster. Table 3 provides further examples of the research themes in this cluster as well as a selection of the relevant number of articles and the theoretical and methodological sources. This information is also provided for all clusters and will be further discussed in more details in the following sections. The last column of Table 3 contains the top 5 publishing journals in each cluster.

4.1.2. Cluster 1: genetic algorithm and agent-based modelling

Looking at the publications in this cluster, the dominating theme appears to be the application of *Genetic Algorithm (GA)* and *agent-based modelling* in supply chain forecasting, optimizing and problem solving. In one of the earliest works included in this cluster, Malmborg (1996) compares GA with alternative heuristic algorithms to solve vehicle scheduling problems. Malmborg (1996) explores GA's potential advantages through its application to a service-level based vehicle scheduling problem and concludes that GA can be useful for finding good quality solutions with only limited search of the solution space. This study was further extended by Min et al. (2006) who propose an integrated model of GA and a nonlinear mixed-integer programming to solve a reverse logistics problem with product returns. The framework is applied to a hypothetical problem with returned products for validity and feasibility testing. Pasandideh et al. (2011) develop an economic order quantity (EOQ) model for a two-level supply chain in which the supplier delivers on retailer's orders according to (R, Q) policy. The proposed EOQ formulation is a nonlinear integer programming model. GA is employed to find order quantities and the maximum backorder levels to minimize the total inventory costs.

Another stream of research in this cluster is agent-based modelling for supply chain optimization and forecasting. Some instances of earlier relevant publications in this cluster include Swaminathan et al. (1998) who explore the shortcomings of applying simulation to supply chain analysis and evaluation. Using a multiagent approach, Swaminathan et al. (1998) develop a supply chain modelling framework to overcome simulation limitations. Another example of the application of agent-based modelling in SCM is Xue et al. (2005), who propose an agent-based framework for construction supply chain coordination, which integrates construction organizations and a multi-attribute negotiation model into a multi-agent system for better supply chain coordination. Liang and Huang (2006) develop a multi-agent system simulating a supply chain with three types of independent demand inventory systems (i.e., periodic review, continuous review, and optional systems) to minimize total cost and reduce the bullwhip effect. The outcomes of the proposed agent-based system show reduction in total supply chain cost and smoother ordering variation curve. The primary methodological framework adopted in Cluster 1 is mathematical modelling.

4.1.3. Cluster 7: stochastic programming

The main theme of this cluster is the application of stochastic programming to supply chain planning. For example, Leung et al. (2007) address a multi-site production planning problem for a complex supply chain using a stochastic nonlinear programming model (i.e. robust optimization) that minimizes costs of production, labor, inventory, and workforce under uncertainty. The model finds the optimal solution that is less sensitive to uncertain and noisy data. You et al. (2009) investigate risk management for mid-term planning of a multinational and multi-product chemical supply chain with uncertain freight rate and demand. You et al. (2009) use a two-step stochastic linear programming to develop a multi-period planning model considering customer service, production, and inventory levels as well as transportation modes and times of shipments. The model is compared with a rolling horizon simulation framework, concluding that the stochastic model produces at least 5 % more saving compared to the deterministic model. In another example, Nickel et al. (2012) investigate financial decisions, such as return on investment, to address a multi-period supply chain network design problem. Demand and interest rates are considered uncertain and scenario tree is constructed for the planning horizon. Nickel et al. (2012) formulate the problem as a multi-stage stochastic mixed-integer linear programming problem aiming to maximize the total profit. The primary methodological framework adopted in Cluster 7 is stochastic programming (linear and nonlinear). No prominent theoretical framework was found for the articles included in this cluster. Most articles in this cluster are published before 2010.

Looking into decision-making Clusters 0-1-7 in tandem (and informed by our taxonomy), the aforementioned AI decision-making methods were frequently used in studies surrounding supply chain design, planning, forecasting, scheduling, and problem solving. Despite this, most of the articles in these three clusters date back to 2010 and prior, which makes us speculate that the application of AI decision-making methods in SCM is quite saturated and matured over many years.

4.2. Learning clusters

4.2.1. Cluster 3: time-series analysis

Among the seminal articles in this cluster, Gardner (2006) develops a statistical rationale for exponential smoothing, and introduces a new adaptive method for simple smoothing to determine reliable forecast accuracy improvement over fixed-parameter smoothing. Fildes et al. (2009) argue that demand forecasting is a decisive part of planning in SCM, but the most common approaches involve computerized forecasting systems and substantial management effort, time, and judgmental adjustments. Through examining a database of 60,000 forecasts collected from four SC companies, Fildes et al. (2009) explore the extent of forecasts' accuracy improvement by adjustments. The results reveal that larger adjustments lead to greater accuracy but smaller adjustments damage accuracy. They also find that positive adjustments are less likely to improve accuracy than the negative adjustments. Hyndman et al. (2011) propose a new method to hierarchical forecasting providing optimal forecasts that are more accurate compared to both top-down and bottom-up hierarchical time series approaches. The primary methodological framework in Cluster 3 is time series analysis. We found no dominant underlying theory in these studies.

4.2.2. Clusters 6 and 12: Big data analytics

While Cluster 6 captures a broader representation of big data applications across multiple fields of study, Cluster 12 reflects on a narrower scope and is more related to the context of this paper. For instance, Cluster 6 includes articles that investigate the application of big data in human resources (Shah et al., 2017), retailing (Bradlow et al., 2017), information security (Bharathi, 2017), and high frequency trading (Seddon and Currie, 2017), to name a few. On the other hand, Cluster 12 is more tailored toward supply chain context as highlighted in the most frequent journals of this cluster. Overall, in contrast with the decision-making clusters, the sources included in Clusters 6 and 12 are more recent, reinforcing the rapidly growing nature of big data and analytics-related research, especially in a supply chain context. Few examples of the latter in these two clusters include the application of big data and data analytics for supplier selection (Cavalcante et al., 2019), supply chain risk management (Ivanov et al., 2019), and production planning and control in supply chains (Ivanov and Sokolov, 2013; Dolgui et al., 2019).

We provide some representative examples of publications in these two clusters. Tan et al. (2015) argue the need for more sophisticated methods and analytics that can assist supply chains to gain competitive advantage through capturing data-driven innovations. They proposed an approach based on a deduction graph technique as an analytical infrastructure to assess supply chain competencies. The approach was tested through case studies to investigate how big data innovations could boost supply chain competitiveness.

In another study, Chae (2015b) proposes a framework to analyze

Table 3
Summary of cluster analysis.

Cluster	Theme	Selective Operations Management and SCM Articles	Informing Theoretical Articles	Informing Methodological Articles	Most Publishing Journals
0 (DMC[1])	Supply Chain Simulation Supply Chain System Dynamics	Holweg et al. (2005) Van Der Zee and Van Der Vorst (2005) Olhager and Persson (2006) Umeda and Zhang (2006) der Zee (2011) Venkateswaran and Son (2005) Greasley (2005) Reiner (2005) Villegas and Smith (2006) Tako and Robinson (2010)	***Systems theory:*** Richardson (1991)	***Simulation:*** Goel et al. (2002) Ding et al. (2005) Rathore et al. (2005) ***System Dynamics:*** Angerhofer and Angelides (2000) Georgiadis et al. (2005) ***Discrete-Event simulation and System Dynamics (integration):*** Crespo Marquez and Blanchar (2004) Helal et al. (2007) ***Case Study Research:*** Gnoni et al. (2003) Byrne and Heavey (2006) Georgiadis et al. (2006)	International Journal of Production Economics (23) International Journal of Production Research (17) European Journal of Operational Research (11) Production and Operations management (5) Production Planning and Control (5)
1 (DMC)	Genetic Algorithm Agent-Based Approach	Malmborg (1996) Min et al. (2006) Ko et al. (2007) Yeh and Chuang (2011) Pasandideh et al. (2011) Swaminathan et al. (1998) Gjerdrum et al. (2001) Turowski (2002) Xue et al. (2005) Lima et al. (2006) Liang and Huang (2006)	***Agent Theory:*** Logan Mary (2000)	***Genetic Algorithm:*** Bortfeldt and Gehring (2001) Min et al. (2006) Pasandideh et al. (2011) Yeh and Chuang (2011) ***Agent-Based Approach (single and multi-agent):*** Swaminathan et al. (1998) Gjerdrum et al. (2001) Xue et al. (2005)	European Journal of Operational Research (10) Computers and Industrial Engineering (7) Expert Systems with Applications (6) Journal of Intelligent manufacturing (5) International Journal of Production Economics (5)
2 (HC)	Sustainable/Green Supplier Selection and Evaluation	Lee et al. (2009) Aydın Keskin et al. (2010) Amindoust et al. (2012) Kannan et al. (2013) Govindan et al. (2015)	***Rough Set Theory:*** Bai and Sarkis (2010b) ***Grey System Theory:*** Bali et al. (2013)	***Fuzzy Approach:*** Tseng et al. (2011) Mavi et al. (2013) Kannan et al. (2013) Chaharsooghi and Ashrafi (2014) Kusi-Sarpong et al. (2015) Akman (2015) ***Grey Relational Analysis:*** Sun and Ye (2009) Bai and Sarkis (2010c) Bai and Sarkis (2011) Dou et al. (2014)	Journal of Cleaner Production (19) International Journal of Production Research (15) International Journal of Production Economics (13) European Journal of Operational Research (12) Supply Chain Management: An International Journal (8)
3 (LC[2])	Supply Chain Forecasting	Gardner (2006) Fildes et al. (2009) Boylan and Syntetos (2010) Hyndman et al. (2011) Syntetos et al. (2016)	***N/A***	***Time Series Analysis (Forecasting):*** Gilbert (2005) Hyndman et al. (2011) Luna and Ballini (2011) Kourentzes et al. (2014) Hyndman et al. (2016)	International Journal of Forecasting (19) Journal of the Operational Research Society (16) Foresight (10) International Journal of Production Economics (9) Ima Journal of Management Mathematics (9)
4 (HC)	Sustainable/Green Supplier Selection and Evaluation	Chen et al. (2006) Kuo et al. (2010) Bai and Sarkis (2010a) Yeh and Chuang (2011) Chai et al. (2013) Kannan et al. (2014)	***Stakeholder Theory:*** Freeman (1994) Donaldson and Preston (1995) ***Rough Set Theory:*** Bai and Sarkis (2010a)	***Fuzzy Approach:*** Sarkar and Mohapatra (2006) Keskin et al. (2010) Ma et al. (2011) Kannan et al. (2013) ***Rough set:*** Bai and Sarkis (2010b) ***Grey approach:*** Baskaran et al. (2012) ***Neural Network:*** Kuo et al. (2010)	Journal of Clean Production (26) International Journal of Production Economics (15) Expert Systems with Applications (13) International Journal of Production Research (12) Journal of Supply Chain Management (11)
6 (LC)	Big Data Analytics	Raghupathi and Raghupathi (2014) Hazen et al. (2014) Tan et al. (2015) Akter et al. (2016) Bradlow et al. (2017)	***N/A***	***Big Data Analytics:*** Chae (2015b) Zhou et al. (2016) Zhang et al. (2016) ***Case Study:*** Li (2010) Dutta and Bose (2015)	Journal of Business Research (9) Technological Forecasting and Social Change (9) Global Journal of Flexible Systems Management (9) Decision Support Systems (8) International Journal of Production Economics (7)
7 (DMC)	Stochastic programming for Planning	Yu and Li (2000) Leung et al. (2007) You et al. (2009) Sodhi and Tang (2009) Nickel et al. (2012)	***N/A***	***Stochastic programming:*** Yu and Li (2000) Di Domenica et al. (2007) Huang and Ahmed (2009) Nickel et al. (2012)	International Journal of Production Economics (12) European Journal of Operational Research (11) Management Science (7)

(*continued on next page*)

Table 3 (*continued*)

Cluster	Theme	Selective Operations Management and SCM Articles	Informing Theoretical Articles	Informing Methodological Articles	Most Publishing Journals
					Operations Research (7) Decision Support Systems (7)
8 (LC)	Neural Network and Support Vector Machine	Yu and Xi (2009) Mahadevan and Shah (2009) Ge et al. (2011) Cheng et al. (2011) Yan et al. (2014)	***N/A***	***Support Vector Machine:*** Sun and Tsung (2003) Kumar et al. (2006) Ge et al. (2011) Ning and Tsung (2013) ***Neural Network:*** Yu and Xi (2009) Wu and Yu (2010) Cheng and Cheng (2011)	Journal of Quality Technology (15) Quality and Reliability Engineering International (9) International Journal of Production Research (7) Expert Systems with Applications (5)
9 (HC)	Supply Chain Risk Management	Swaminathan et al. (1998) Galindo and Tamayo (2000) Paul (2015) Garvey et al. (2015) Mani et al. (2017)	***Bayesian Theory:*** Badurdeen et al. (2014)	***Bayesian Approach:*** Garvey et al. (2015) Abolghasemi et al. (2015) Shang et al. (2017) Ojha et al. (2018) ***Agent-Based:*** Giannakis and Louis (2011) ***Big Data Analytics:*** Mani et al. (2017) Shang et al. (2017) ***Fuzzy Approach:*** Paul (2015) ***Stochastic approach:*** Hahn and Kuhn (2012) ***Genetic Algorithm:*** Tang et al. (2008) ***Support Vector Machine:*** Ye et al. (2015) ***Simulation:*** Wu and Olson (2008)	International Journal of Production Research (15) International Journal of Production Economics (9) European Journal of Operational Research (6) The International Journal of Logistics Management (6) International Journal of Advanced Manufacturing Technology (6)
10 (HC)	Sustainable/Green Supplier Selection and Evaluation	Wu (2009) Boran et al. (2009) Deng and Chan (2011) Zouggari and Benyoucef (2012) Hosseini and Barker (2016)	***Fuzzy Sets:*** Zadeh (1965a); Zadeh (1965b)	***Fuzzy Approach:*** Boran et al. (2009) Zeydan et al. (2011) Kannan et al. (2013) Chen (2014) ***Rough Set:*** Bai and Sarkis (2010b) ***Neural Network***: Lee and Ou-Yang (2009) Azadnia et al. (2012) ***Bayesian Approach:*** Hosseini and Barker (2016) ***Support Vector Machine:*** Guo et al. (2009) ***Genetic Algorithm:*** Wang et al. (2015) ***Grey Approach:*** Golmohammadi and Mellat-Parast (2012) ***Ant Colony Optimization:*** Zhao et al. (2016)	International Journal of Production Research (30) Expert Systems with Applications (21) International Journal of Production Economics (8) European Journal of Operational Research (7) Mathematical Problems in Engineering (7)
12 (LC)[4]	Big Data Analytics Capabilities	Waller and Fawcett (2013) Giannakis and Louis (2016) Shah et al. (2017) Duan et al. (2019) Albergaria and Jabbour (2020)	***Resource-based View:*** Barratt and Oke (2007) Wu (2010) Gunasekaran et al. (2017) Dubey et al. (2019) ***Dynamic Capabilities View:*** Mikalef et al. (2019a) Wamba et al. (2017)	***Big Data Analytics:*** Chen et al. (2015) Ji-fan Ren et al. (2017) Albergaria and Jabbour (2020)	International Journal of Production Economics (14) Journal of Business Research (14) International Journal of Production Research (10) International Journal of Information Management (7) Journal of Operations Management (5)

Note: [1] DMC: Decision-Making Cluster.
[2] LC: Learning Cluster.
[3] HC: Hybrid Cluster.
[4] Clusters 5, 11, and 13 are not included.

supply chain tweets, highlighting the impact of social media – especially Twitter – on SCM practices and research. The proposed framework integrates three big data analytics methodologies including descriptive analytics, network analytics (based on network visualization and metrics to pull out intelligence from #supplychain tweets), and content analytics combining sentiment analysis and text mining. The findings show that different groups of SC professionals and organizations use SC tweets to share information, hire professionals, and connect with stakeholders.

Akter et al. (2016) raises the issue of big data implementation being only partially successful in supply chains. They propose a big data analytics capability model which is based on resource-based theory and socio-materialism's entanglement. Their study provides a big data analytics capability as a hierarchical model consisting of three primary dimensions and 11 subdimensions. The findings of online surveys and two Delphi studies of business analysts confirm the value of the proposed entanglement conceptualization model.

Giannakis and Louis (2016) integrate big data analytics into a multiple agent-based SCM system that is capable of applying autonomous corrective control activities. They develop the architecture of this system based on a sequential approach in which they identify three fundamental aspects of supply chain agility (i.e., speed, flexibility, and responsiveness), define agents' roles, and model their interactions. Their study shows the effectiveness of the proposed model in addressing supply chain agility and its effectiveness to instigate improvements across all agility dimensions. The primary methodological frameworks in both clusters are big data analytics and case studies. Resource-based and dynamic capabilities views are the predominant theories of Cluster 12.

4.2.3. Cluster 8: neural network and support vector machine

The primary aim of these articles is to resolve issues pertaining to statistical process control through the application of support vector machines and neural networks. Yu and Xi (2009) argue that, in multivariate process control, although quality control charts can detect out-of-control signals effectively, they are unable to overcome the need for pinpointing source(s) of those signals that locate the assignable causes of out-of-control situations. They develop a selective neural network ensemble approach to monitor, investigate, and diagnose out-of-control signals in a bivariate procedure. The results of their analysis show that the proposed model surpasses the traditional multivariate control system in terms of assessing out-of-control signal classification and the average run length. In another example, Mahadevan and Shah (2009) propose a novel approach based on one-class support vector machines for fault detection and diagnosis. The approach is based on a nonlinear distance metric measured in a feature space and develop proper distance metrics for fault detection. Using the support vector machines recursive feature elimination, authors perform fault diagnosis and demonstrate the efficacy of their approach by the model's application to Tennessee Eastman problem and a real-time process dataset.

In a similar study, Cheng et al. (2011) point out to the weakness of the existing control chart techniques in predicting the magnitude of change resulting from out-of-control signals. They propose a support vector regression model to predict process mean changes, which employs a cumulative sum chart to spot process mean changes. Once the cumulative sum chart signals a shift, the proposed support vector regression model estimates the shift's magnitude. The performance of the proposed model is evaluated using simulation and its predictive ability is assessed through comparison with neural networks and statistical methods. The proposed model was shown to outperform both methods. Naturally, the primary methodological framework adopted in Cluster 8 is support vector machine and neural network methods. A common underlying theory could not be identified for the studies of this cluster.

4.3. Hybrid clusters

4.3.1. Cluster 2, 4, 5 and 10: AI methods for sustainable SCM

Articles in these clusters employ analytical network process (not part of our AI taxonomy) to tackle *supplier selection* decisions. Clusters 2, 4 and 10 have identical AI methods and supply chain context (i.e., green/sustainable SCM and supplier selection). We may wonder why different clusters are formed when the methods and contexts are identical in these articles. Our speculation is that the graph analysis for the co-citation study differentiates articles in different clusters based on their comparative co-citation. There may be reasons beyond the scope of our review why papers are cited together (e.g., people in certain research groups/communities/institutions/research areas citing each other).

Cluster 2 includes the study of Lee et al. (2009), which propose a model for evaluating green suppliers. A Delphi method is applied to differentiate various criteria from which a hierarchy is constructed to help evaluate the importance of the selected criteria and the performance of the selected suppliers. Keskin et al. (2010) argue that supplier selection has become more difficult and riskier because of human judgment requirement in several phases. In their study, fuzzy adaptive resonance theory is incorporated as a new feature into supplier selection/evaluation to generate a new tool. The proposed method demonstrate ability to select the most suitable suppliers and group the vendors according to preferred criteria. Amindoust et al. (2012) argue that sustainable supplier selection is a central component in sustainable SCM. The authors propose criteria and sub-criteria for sustainable supplier selection and develop a methodology to evaluate and rank a given set of suppliers using a fuzzy approach to address the subjectivity of decision makers' evaluations. Similarly, Kannan et al. (2013) integrate fuzzy multi attribute utility theory and multi-objective programming to rate and select the best performing suppliers given a set of criteria. The approach allocates optimum order quantities to different suppliers given the criteria.

In the same fashion, many articles in Cluster 4 focus on fuzzy decision-making approaches to tackle supplier selection problems. Chen et al. (2006) use linguistic values to evaluate the ratings and weights of quantitative and qualitative factors of a suitable supplier and propose a hierarchical multi-criteria decision-making model based on fuzzy-sets theory. The proposed model calculates the distances to both fuzzy positive and negative ideal solutions concurrently to define a closeness coefficient. The suppliers are ranked according to the calculated closeness coefficient. Kuo et al. (2010) integrate artificial neural network and two multi-attribute decision analysis methods, including data envelopment analysis and analytic network process, to develop a green supplier selection model. They argue that the proposed approach overcomes the limitations of traditional data envelopment analysis. Yeh and Chuang (2011) develop an optimal scheduling model that incorporates green appraisal score, product quality, time and cost. Two multi-objective GAs are employed to find the set of Pareto-optimal solutions using a weighted sum approach.

Representative articles of Cluster 10 include Wu (2009) and Deng and Chan (2011). By integrating data envelopment analysis, decision tree, and neural network, Wu (2009) present a hybrid model for supplier performance assessment. Based on efficiency scores and data envelopment analysis, suppliers are classified into efficient and inefficient. Supplier performance data is then used to train a decision tree and neural network model. The trained decision tree is applied to new suppliers. Deng and Chan (2011) develop a multifactorial decision-making approach to address supplier selection in an uncertain environment. The proposed approach integrates fuzzy set theory and Dempster Shafer theory of evidence based on a technique for order preference by similarity. They argue that their method is more flexible than traditional fuzzy methods because the basic probability assignments can be calculated without the transformation stage. In a more recent study, Hosseini and Barker (2016) propose a Bayesian network to quantify suppliers' suitability considering resilience, in addition to sustainability criteria. The proposed approach is able to handle expert evidence and performs sensitivity and propagation analyses. Most studies in these clusters investigate green SCM and supplier selection using hybrid frameworks integrating fuzzy methods with one or more of the following approaches: rough set, grey, and neural network, Bayesian, support vector machine, genetic algorithm, and ant colony optimization.

4.3.2. Cluster 9: AI methods for supply chain risk management

Most articles in cluster 9 employ AI methods to tackle problems related to supply chain risk management. In one of the earliest works, Galindo and Tamayo (2000) argue that accurate risk estimation is an essential component of efficient use of resources and risk models. They develop a comparative analysis of statistical and machine learning methods to investigate their advantages and limitations. Their results indicate that decision-tree models followed by neural networks and K-nearest neighbor algorithms provide best estimations surpassing the performance of standard Probit algorithms.

Paul (2015) develop a rule-based fuzzy inference model to choose the most suitable supplier considering multiple selection criteria (both quantitative and qualitative) for managing supply risks. Risk factors are incorporated in the proposed model through fuzzy parameters and suppliers are ranked based on their aggregated ranking index value. Numerical examples demonstrate the usefulness of the proposed model. Garvey et al. (2015) propose a risk propagation model using Bayesian Network. The proposed model considers the inter-dependency of different risks and supply chain network structure idiosyncrasies in generating specific risk measures. Finally, a simulation study illustrates the application of output risk measures in a supply chain setting.

Due to high diversity of articles in this cluster in terms of theory and methodology, there is hardly a single theory or methodology standing out. However, Bayesian theory is used more frequently compared to others. Agent-based, case-based reasoning, big data, stochastic programming, fuzzy approach, simulation, support vector machine, and genetic algorithm are the other approaches/methods used in this cluster.

4.4. Miscellaneous clusters 11 and 13

The focus of articles in these clusters is not directly relevant to AI methods and their application in SCM. Instead, they cover a variety of topics under the umbrella of *supply network relationship management*. These articles form the basis for studies surrounding buyer-supplier relationship, alliance and performance management in supply networks, and power and trust dynamics in supply chains. It is not our intention to thoroughly analyze studies in this cluster since discussions surrounding these topics are extensive and deserve a separate review paper.

5. Future research

The supply chain literature is quite matured in the area of AI applications in decision making. Instead, our intention in this section is to discuss potential research ideas surrounding (i) learning methods and (ii) sensing and interacting methods. We also provide a guiding discussion on behavioral and psychological factors associated with implementation of AI-driven systems in organizations.

5.1. Future studies on learning methods

Our review shows that learning methods have been primarily applied to supply chain forecasting and inventory management. However, the application of such methods can go well beyond what is examined so far. For instance, studies surrounding machine learning techniques for supply chain risk management can be a promising area of research, particularly studies surrounding risk identification and prioritization approaches. Baryannis et al. (2019b) use machine learning approaches to map the literature of supply chain risk management. They point out that the literature is at the early stages of truly embracing the predictive and learning capabilities of big data sets and machine learning methods. We reflected on the latter study to draw more attention to the risk identification and assessment phases, which is a critical first step for risk mitigation in SCM. While the supply chain risk management literature is indeed enriched with studies surrounding risk identification and assessment (Pournader et al., 2020a), it has yet to embrace sophisticated learning methods to build a more accurate profile of impact and likelihood of such risks.

Another less explored but promising area of study in SCM is the use of machine learning methods in *sustainable/green supply chain evaluation*. This is an emerging and fast evolving area of research. Studies in this domain are often presented under the umbrella of sustainability assessment where supervised and/or unsupervised learning methods are used to predict sustainability performance across the supply chain using a set of environmental, social and governance criteria (e.g., Abdella et al., 2020; Nilashi et al., 2019).

Machine learning methods can also be adopted to inform strategic decisions pertaining to design and configuration of supply chains. Examples of such studies include Singh et al. (2018) that use Twitter data and support vector machine technique to identify issues in food supply chains. Using this approach, they form clusters of words from customer feedbacks that help unveil issues in the food products. Another example is Dev et al. (2016) who adopt agent-based modelling and decision trees to facilitate inventory and supply chain reconfiguration issues of a mobile phone supply chain. Future research in utilizing machine learning methods for supply network design and reconfiguration can focus on enhancing the predictive capability of such methods in developing supply chain robustness and responsiveness. Uncertainties can originate from downstream supply chain (e.g., consumer and competitor behavior) or upstream supply chain (e.g., supplier performance and buyer-supplier relationship). Large historical data can be exploited using advanced learning methods to help managers better predict the sources and scale of supply chain disruptions and/or interruptions.

5.2. Future studies on sensing and interacting methods

Current state of the literature on sensing and interacting methods and their applications in SCM is scarce and almost non-existent. Sensing and interacting methods such as NLP and especially text mining methods have been studied in supply chain mapping (Wichmann et al., 2018) and supply chain monitoring (Chae, 2015a; Wichmann et al., 2020). Such applications could go beyond this rather narrow lens. Combined with machine learning, NLP can be adopted to analyze publicly available data (e.g., social media, blog posts, news) to provide insights into *supply chain operational challenges, sustainability risks, market and competitor performance, customer preferences and demand*, and *future market trends*. Speech and image recognition capabilities can help provide a user-friendly interface for monitoring and controlling supply chain operations – more like adopting Amazon Alexa or Google Home features for supply chain operations. A trending topic in procurement management is the application of chatbots for digitizing interactions, conversations and beyond (Cui et al., 2020).

5.3. Behavioral considerations of AI application in supply chains

The broader area of Management Information Systems (MIS) initially brought forward the importance of behavioral considerations in adopting advanced technologies. These behavioral considerations encompass a wide array of topics pertaining to pre-and post-adoption behavioral issues (e.g., Karahanna et al., 1999; Venkatesh et al., 2003), intention, attitude, subjective norm, and perceived behavioral control (Pavlou and Fygenson, 2006), to name a few. A recent review by Ain et al. (2019) provides an summary of such attempts.

Looking at the literature of human behavior in operations and supply chain decision making (Fahimnia et al., 2019), behavioral studies on technology adoption are slowly building a momentum among supply chain scholars. An example of such attempts is Loch (2017) suggesting that the role of behavioral factors is even more important in technology adoption (i.e., AI applications) than in the management of established processes and operations. Carter et al. (2017) highlights the role of intuition and its effectiveness in situations when people are under time pressure or in the face of information uncertainty. A study conducted by PWC (2016) revealed that two-third of executives believe that their organization's decision-making is only 'somewhat' or 'rarely' data-driven. The reliance on intuition questions the degree to which AI could automate supply chain decisions.

In addition to the growing body of knowledge surrounding behavioral issues in MIS and technology adoption, there are unique characteristics in supply chains that make it even more interesting to explore human behavior in SCM. Most behavioral studies in technology adoption have considered organizations as silos without incorporating their links with upstream, mid-stream and downstream corporate partners. Technology adoption is often most effective when embraced across the supply chain. For instance, applying an end-to-end predictive and prescriptive supply chain risk management platform requires data from all tiers of a supply chain. Not only data across various internal and external operations are required, but implementation of technology adoption projects at the supply chain level also requires close inter-organizational collaborations. Interorganizational collaborations introduce a variety of behavioral issues such as bilateral/multilateral trust in sharing information, trust in using new systems, and cultural barriers in accepting and implementing new technologies. The pre- and post-adoption behavioral considerations already enumerated in the MIS literature should be customized to feature the unique interorganizational properties of supply chains. The latter puts more emphasis on introducing social psychology concepts/frameworks and group dynamics models to these studies (see Bendoly et al., 2010).

5.4. AI to create supply chain capability and competitive advantage

Our analysis revealed that organizations employ AI tools for various supply chain operations, mainly to facilitate better decision making. In particular, with the advancements in supply chain software development over the past two decades, AI methods have been extensively utilized for inventory management, demand forecasting, risk management, and sustainable SCM. While studies have predominantly pointed to isolated use of AI methods in these domains, there is little understanding pertaining to how AI could lead to capability building at the supply chain level. Recent studies show that despite the promise of AI to transform business models, many organizations and their supply chains have failed to truly comprehend its full potential and many have faced numerous barriers in leveraging the related technologies (Davenport and Ronanki, 2018). More importantly, there is ample evidence suggesting that organizations often conduct AI projects in ad-hoc pilots or in isolation from the broader organizational processes (Fountaine et al., 2019).

Studies investigating the role of new technology for performance implications emphasize the need for capability building and resource orchestration at the organizational level (Powell and Dent-Micallef, 1997; Tian et al., 2010). The availability of quality data and the ability to integrate data from different organizational silos is regarded as foundation for AI capability building (Mikalef et al., 2019b). From a supply chain perspective, firms must recognize the role of supply chain partners and cross-organizational processes when developing AI-oriented strategies for competitive advantage.

Coincidentally, our taxonomy that is informed by the existing literature and latest expert opinions has conceptual overlaps with Teece's dynamic capability view (Teece, 2007). The taxonomy proposed in this paper considers three functional areas of sensing, learning and decision making for AI application in SCM. These functional areas could be effortlessly associated to Teece's sensing, reconfiguring, and seizing, respectively. This conceptualization allows us to think of AI capability as a dynamic capability, which could undoubtedly contribute to the supply chain competitive advantage. Acknowledging the developing nature of AI research in SCM, we call the academic community for further investigation of motivations and facilitating mechanisms by which organizations could adopt and implement AI as a source of competitive advantage and supply chain capability. Specifically, understanding how AI could facilitate building dynamic capabilities across the supply chain is of practical and scientific significance.

6. Conclusion

This review was an attempt to capture the scope and boundaries of AI research in SCM. We adopted a multi-method approach to systematically review the existing literature. Our bibliometric and text/clustering analyses were informed by an AI taxonomy which classified AI studies into three research categories of sensing and interacting, learning, and decision making. Our review provided a big picture of the state of knowledge in AI research in SCM followed by thorough discussions related to each research category.

We identified the matured areas of research. Decision-making models and their applications in SCM are broadly investigated. We also identified and discussed the emerging areas of study which consist of learning and sensing/interacting categories. A caveat of our review is that it does not provide an in-depth analysis of AI methods and technicalities of their adoption in SCM. Furthermore, we only provide a high order review of future studies, that only scratch the surface of future scholarly attempts in this domain. Our AI taxonomy is not without limitations either. The challenge is that the field of AI is extremely fragmented. Hence, attempts to compartmentalize AI methodologies are inevitably imperfect. However, to capture the inherent value of AI for SCM research, the proposed taxonomy was essential to identify the lagging areas and opportunities for future research.

The practical implications of AI in SCM research are abundant. Particularly, we would like to draw more attention to the latest developments with respect to supply chain disruptions caused by COVID-19. The significant disruptions caused by the pandemic have initiated a debate globally on reversing outsourcing in supply chains and investing more on in-house manufacturing. A major roadblock here is the complexity and interconnectivity of supply chains making it difficult to map and replicate end to end supply chains (see Shih, 2020). Certainly, AI can offer a promising future to alleviate concerns of this type by increasing supply chain visibility and agility.

Online Appendices. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.actaastro.2021.07.043.

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