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The role of artificial intelligence in supply chain management: mapping the territory

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ABSTRACT

The study aims to identify the current trends, gaps, and research opportunities in research pertaining to the disruptive field of artificial intelligence (AI) applications in supply chain management (SCM). Since SCM represents managerial innovation due to its new way of integrated system thinking, SCM has emerged as one of the most fruitful business disciplines for AI applications. The study utilises bibliometric review in tracing the evolution of AI research in SCM and further synthesises decades of past AI research efforts to develop viable solutions for various supply chain problems and then proposes promising future research themes that would enrich supply chain decision-aid tools. The study identified five main research clusters through scholarly network and content analysis. The identified themes were: (a) supply chain network design (SCND), (b) supplier selection, (c) inventory planning, (d) demand planning, and (e) green supply chain management. As the role of AI in SCM continues to grow, there is a growing need for exploiting AI as a way to add value to supply chain process. The study proposes a research framework which will help academicians and practitioners in identifying current research patterns of AI in SCM.

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KEYWORDS
Artificial intelligence; supply chain management; bibliometric analysis; citation analysis; trend analysis

1. Introduction

In the era of the fourth industrial revolution characterised by a fusion of disruptive technologies such as artificial intelligence (AI) and robotics, a traditional boundary between man and machine becomes blurred. As the role of humans in supply chain operations changes, management paradigm shifts has accelerated for the last decade. For example, conventional manufacturing has been transformed into smart, data-driven cyber manufacturing with the aid of cyber physical systems (CPS) and the internet of things (IoT) (Lee, Azamfar, and Singh 2019, 2018, 2015; Rüßmann et al. 2015). This kind of transformation not only improves the operational efficiency and productivity of the supply chain management (SCM), but also enhances supply chain visibility throughout the end-to-end supply chain processes (Ben-Daya, Hassini, and Bahroun 2019). One of the emerging catalysts for supply chain transformation is artificial intelligence due to its interoperability, data storage, and business analytics capabilities (Baryannis, Dani, and Antoniou 2019a; Spanaki, Karafili, and Despoudi 2019). Generally, AI is referred to as the use of computers for reasoning, recognising patterns, learning, or understanding certain behaviours from experience, acquiring, and retaining knowledge, and developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce (Min 2010). In a nutshell, AI provides a machine with the capability to carry out any cognitive functions that human used to handle through its self-awareness and self-learning. AI aims to design computer systems that can mimic human behavioural patterns and create knowledge relevant to problem-solving (Min 2010). Thus, AI is essential for automation and digitalization of supply chain activities and the subsequent improvement of supply chain productivity (Dolgui and Ivanov 2021). In particular, the use of AI in SCM can fundamentally metamorphose current business practices and managerial tasks. Gartner's 2018 report has touted AI as the number one strategic technology and expected that global investments on AI based applications would surpass USD 50.2 billion by 2021

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(IDC 2018). As such, the worldwide revenues from the AI market are expected to reach USD 2.59 trillion by 2021 (Statista 2018). AI is shaping, reinventing, and transforming the next generation business models and ecosystems such as digital twins, continuous adaptive security, and event-thinking (Gartner 2017).

AI was introduced in the early 1970s to create intelligent thinking machines capable of learning, aiding, and eventually, replacing human intelligence (Pomerol 1997). Despite the widespread popularity and enormous potentials of AI as a decision-making tool, AI has not been fully exploited in SCM (Min 2010). In the recent past, however, this trend seems to be slowly changing with the growing body of literature on AI applications to SCM. This paper intends to capture such trend shifts and assess the potential impact of AI on SCM through a bibliometric analysis. This paper also synthesises which themes of SCM have been studied and what has been learned from AI applications to SCM by reviewing a pool of more than 3500 published articles and filtering this collection to include significant works and investigators. This review uncovers important roles of AI in SCM. Using rigorous bibliometric tools aided by a comprehensive network analysis (e.g. citation and co-citation analyses), we identified five major clusters of research areas. These algorithmically identified clusters set the stage for topical classification of the published models and further investigation of the evolution of these clusters over the years. From these clusters, we gained detailed insights into research streams and common research interests, while pinpointing potential directions for future research. The bibliometric analysis reveals that there is a dearth of research dealing with analytical models and empirical studies.

Although AI is deployed by thousands of organizations around the world, the business potential of AI still remains untapped (Brynjolfsson and Mcafee 2017). As AI emerges from theoretical backgrounds to become the frontier of game-changing technologies, there is an urgent need for systematic development and implementation of AI to see its real impact in the next generation of data-driven supply chains (Kamble and Gunasekaran 2020; Lee et al. 2018). Therefore, in order to address the identified research gaps, the following research questions (RQs) will be answered:

RQ1: What is the extent of research pertaining to AI in SCM?

RQ2: What is the future outlook of AI applications to SCM?

The remainder of the paper is organised as follows: Section 2 describes the genesis of AI research. Section 3 highlights the review methodology used for the study. Bibliometric results and analysis are highlighted in Section 4. Section 5 presents the conceptualised proposed framework. Finally, research gaps, implications from the study, and future research directions are discussed.

2. Genesis of AI research

Artificial Intelligence (AI) was first coined by a team of Prof. John McCarthy and scientists in the year 1955 (Brynjolfsson and Mcafee 2017). Put simply, AI allows the machines to mimic human intelligence and helps them to recognise, analyse, and do things in ways like humans do (Pan 2016). Its abilities in executing the tasks are acquired through machine learning and deep learning algorithms. In a broad sense, Table 1 highlights the various applications and domains of AI in fields such as industrial systems and engineering, data science, societal impacts of AI, supply chain risk management, and industry 4.0 based manufacturing systems.

Practitioners often classify AI into two broad areas viz. artificial general intelligence (AGI) and artificial narrow intelligence (ANI). AGI can perform tasks that match or surpass human intelligence and ANI performs specific tasks (Bawack, Fosso Wamba, and Carillo 2019). AI has brought biggest advancements in data science through perception and cognition, which are the distinguished features of AI. The application areas of AI include machine learning, deep learning, computer vision, robotic process automation, speech and voice recognition, and neural networks as depicted in Figure 1. The recent COVID-19 pandemic has highlighted how fragile global supply chains are (with longer physical flows and dependency on multiple tier suppliers across geographies). Thereby, the demand for resiliency, agility, and flexibility from the stakeholders has drastically increased and this calls in for AI enabled solutions for SCM. Almost all application areas of AI find their use across one supply chain decision-making area or the other (for example, predicting supply chain risks using machine learning (Baryannis et al. 2019b); trend forecasting in the fashion supply chain using logistic regression (Chakraborty, Hoque, and Kabir 2020); prediction of backorder scenarios in the supply chain using gradient boosting machine learning techniques (Islam and Amin 2020); forecasting (Nguyen et al. 2021); and machine failure mode analysis (Okabe and Otsuka 2021)). The wide adoption of AI in SCM is because of AIs ability to improve the decision-making capabilities, reduce cycle-times, and improve the overall operational efficiency. As the supply chains are becoming global, the level of complexity and uncertainty increases therefore, organizations worldwide are investing in autonomous AI enabled systems for improving their supply chain processes (Kohtamäki et al. 2019). The advantages of AI in SCM are powerful

Table 1. Application areas and domains of AI.

Domain	Application area	Author(s)
Industrial Systems and Engineering	Machine fault diagnosis	Liu et al. (2018)
Data Science	Explainable AI	Adadi and Berrada (2018)
Societal impacts of AI	AI applications across different sectors	Makridakis (2018)
Developmental history of AI	AI perspective	Pan (2016)
Industry 4.0 based manufacturing systems	AI ecosystem design in smart manufacturing	Lee et al. (2018)
Supply chain	Risk management	Baryannis, Dani, and Antoniou (2019a)

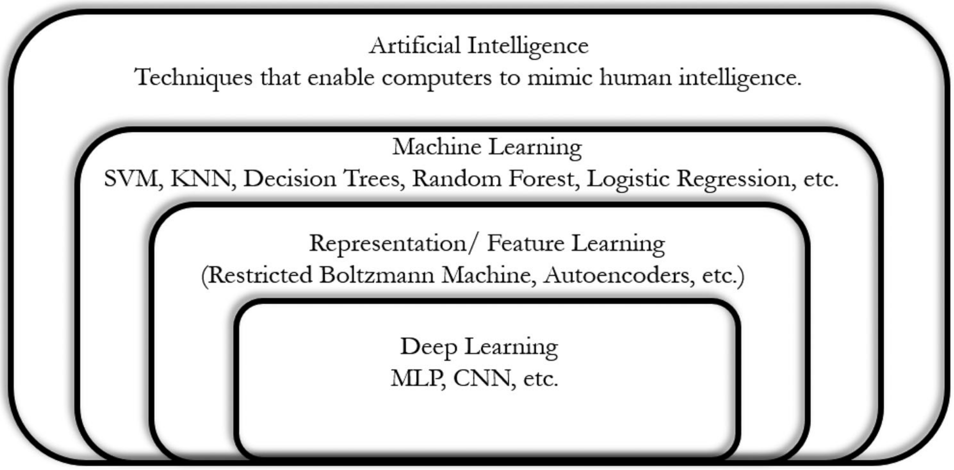


Figure 1. AI categories.

optimization capabilities, accurate forecasting capabilities, improved quality, lower supply chain costs, and safe working conditions. Studies in the recent past (see Toorajipour et al. 2021) have highlighted that AI in SCM can lend unprecedented value and competitiveness through effective forecasting and efficient risk management techniques.

AI in SCM will enable end-to-end visibility and transparency leading to quick and responsive decision-making (Pournader et al. 2021; Riahi et al. 2021; Belhadi et al. 2021; Dora et al. 2021; Rodríguez-Espíndola et al. 2020). By implementing AI in their SCM systems, organizations can effectively predict bottlenecks for streamlining production planning, smart maintenance, smart service operations, smart manufacturing, and scheduling (Helo and Hao 2021; Wang, Skeete, and Owusu 2021). Based on the real-time information, manufacturers can predict seasonal fluctuations and reduce the bullwhip effects through improved resource planning and demand-driven manufacturing. In case of inventory optimization, drawing upon from the supply-demand data, AI based systems help in accurate planning which leads to reduced wastage and costs (Oroojlooyjadid et al. 2021; Pillai et al. 2021). In case of procurement and supplier selection, spend analytics plays a critical role as it helps in analysing the procurement data which is then used to track procurement and supplier performance. Majority of the organizations deploy AI-enabled SCM optimization software/ enterprise platforms (such as ELI by Throughput Inc.; Luminate by Blue Yonder; NEXXE by GEP; BEO by NebulARC; llama.ai by LLamasoft to name a few) which deliver analytical insights based on cognitive predictions. The insights (based on cost, time, and revenue data) delivered by these software help in improving the overall supply chain performance.

A brief overview of AI algorithms and their applications in SCM are highlighted in the Appendix 1.

3. Review methodology

A literature review lays the foundation for any research. It helps deliver useful insights into main research streams, emerging fields, and new knowledge guiding future research initiatives (Fahimnia, Sarkis, and Davarzani 2015; Govindan et al. 2015b). Subsequently, a complete analysis and thorough assessment of the relevant literature was done, for identifying research gaps which need to be filled for charting future research directions (Tranfield, Denyer, and Smart 2003). The present study adopted the review procedure as highlighted by Saunders, Lewis, and Thornhill (2016). The literature review is achieved using the three phases as proposed by Tranfield, Denyer, and Smart (2003) comprised of planning the review, review execution, and finally, reporting the review. To ensure a wide scope of article selection for the most updated and comprehensive review, we searched all

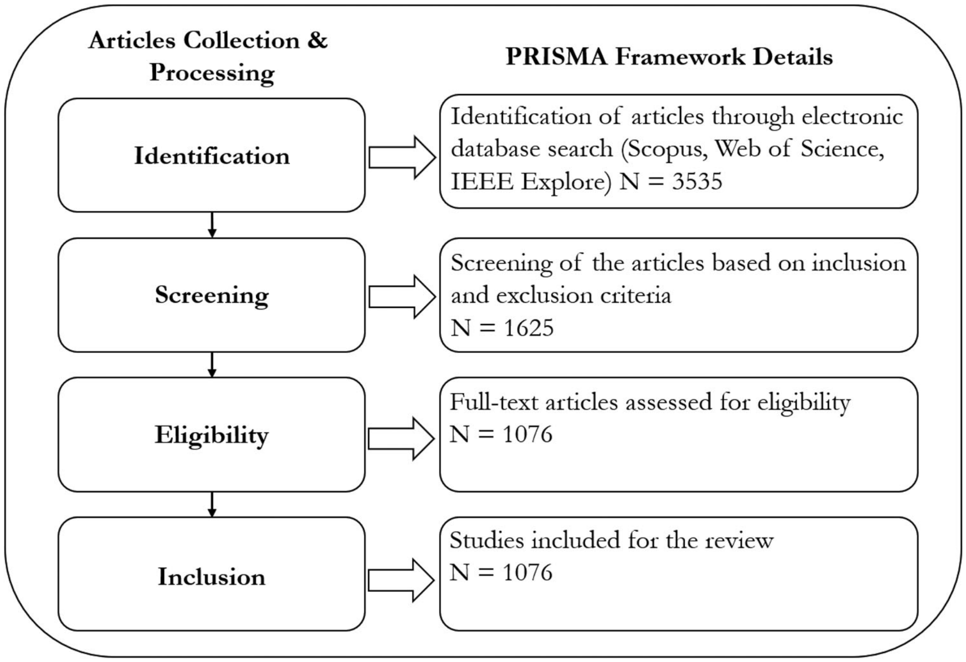


Figure 2. Bibliometric review methodology.

electronic databases such as Web of Science and Scopus. In particular, we chose Scopus database for referring and searching the published articles since it has the largest collections[1] of refereed literature (Geraldi, Maylor, and Williams 2011). The bibliometric review methodology in this research followed the PRISMA framework (see Figure 2) (Moher et al. 2009).

3.1. Keyword selection

For establishing a comprehensive, unbiased, and a reproducible article search procedure in this current bibliometric review, we cited only the most significant and widely cited articles relevant to the field of AI in SCM (AI-SCM). To check the relevancy, we used the following keyword search queries (see Table 2):

The use of aforementioned keywords also set the tone for the bibliometric analysis in this paper.

3.2. Collection and filtering of articles

The time period involved for the literature review covers the studies published during 1994–2021. The initial search returned 3535 research papers (search was carried in January '21). This search excluded academic sources editorial notes, book chapters, working papers, conference proceedings, unpublished reports, and doctoral dissertations, since they often represent preliminary research work or unverified practical viewpoints (Lamba and Singh 2017; Ramos-Rodríguez and Ruíz-Navarro 2004). A further refinement based on the above exclusion criteria led to a drop in the number of articles to 1625. Among these articles, we segregated the

Table 2. Keywords.

Search String	OR	Search String	AND	Search String
'artificial intelligence/ AI'		'LDA'		'supply chain management'
'deep learning'		'unsupervised clustering'		
'artificial neural network/ ANN'		'k-means clustering'		
'random forest'		'word embedding'		
'decision tree'		'topic model'		
'intelligent automation'		'reinforcement learning'		
'support vector machine/ SVM'		'dynamic Bayesian network'		
'machine learning/ ML'		'granular computing'		
'intelligent agents'		'neural net'		
'artificial immune system'		'genetic algorithm'		
'fuzzy set'		'semantic rules'		
'supervised learning'		'evolutionary algorithm'		

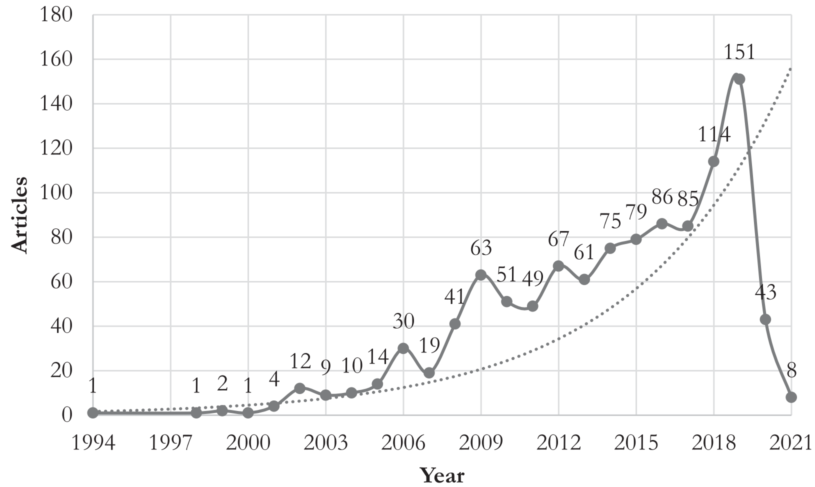


Figure 3. The annual number of publication of AI-SCM articles.

shortlisted articles into articles from top 25 SCM journals (based on impact factor). The final list of articles selected for this bibliometric analysis was 1076. Figure 3 highlights a yearly breakdown of these articles, and their publication counts and shows a dramatic surge of AI-SCM publications for the last 15 years. Its exponential growth started in 2012, a year after the Industry 4.0 was introduced by Germany as the next wave of industrial revolution that theorises the AI thinking of man-machine interfaces.

3.3. Data analysis

The structural dimensions of the citation analysis that allowed us to categorise the past literature could be carried out inductively or deductively. For a citation analysis, we began with an inductive approach (Fahimnia, Sarkis, and Davarzani 2015). To carry out the literature analysis, we also took deductive approach prior to actual data analysis. Herein, an inductive citation analysis helped us to determine the structural dimensions and categories of the published literature through generalization, while a deductive citation analysis helped us categorise the past articles prior to their selection and inclusion for our literature review (Mayring 2003). In addition, we conducted the data analysis using a bibliometric analysis and a network analysis. Particularly, the bibliometric analysis was carried out using R which is helpful in the analysis of a dynamic field of study such as bibliometrics (Aria and Cuccurullo 2017). For network analysis part, we utilised VOS Viewer (Van Eck and Waltman 2009). Both software programs are open source and are able to work on large datasets with a wide range of visualization, innovative analysis, and investigation options.

4. Analysis and results

As a structured methodology to classify and categorise existing AI-SCM literature, we performed bibliometric analysis and network analysis to be described in detail in the following subsections.

4.1. Bibliometric analysis

According to Feng, Zhu, and Lai (2017), a bibliometric analysis provides the following advantages over the other traditional methods such as the content analysis. First, bibliometric analysis can efficiently handle many articles. Second, it enables us to analyse the relationships among articles, keywords, citations, and co-citations and thus provide comprehensive information about the research area. Additionally, bibliometric analysis helps visualise research streams and thus easily identify the future research avenues in the field. The top publishing outlets are highlighted in Appendix 2.

4.1.1. Descriptive analysis

The preliminary data analysis helps capture the basic information of the literature. Table 3 recapitulates the generic descriptions of the AI-SCM literature reviewed for the preliminary data analysis. Figure 3 shows the publication trend starting from 1994 during which the first AI-SCM article was published in the scholarly journal. A number of published articles in the AI-SCM field was scarce until the year 1999. In fact, there were a total of mere nine AI-SCM articles during the period of 1994 through 2001. The domain started to gain traction from the year 2002 with 12 articles in that year to 151 articles in the year 2019. Interestingly, research outputs published for the last five years (2015–2020) add up to nearly 45% of the total articles published in this field. This growing

Table 3. Descriptive statistics of bibliographic collection.

Description	Results
Refereed articles	1076
Sources (Journal articles only)	25
Author's keywords	2717
Time-period	1994–2021
Average citations per article	34.49
Authors	2384
Authors (single-authored articles)	58
Authors (multi-authored articles)	2326
Co-authors per article	3.12
Collaboration index*	2.34

*Note: Collaboration index refers to the average number of authors for a collaborated article. It is calculated using the following formula.

trend is expected to continue into the foreseeable future. This trend reflects the growing scholarly recognition and the subsequent popularity of the AI-SCM field.

$$CI = \frac{\text{Total number of authors}}{\text{Total number of collaborated articles}}$$

4.1.2. Author influence

Table 4 highlights the most prolific authors based on the number of articles published. M K Tiwari, with 30 articles followed by F T S Chan with 22 articles, turned out to be two most prolific authors.

4.1.3. Keyword analysis

As He (1999) argues that keyword analysis is a scientific approach for discovering the linkages among sub-fields of a particular research field. Table 5 summarises a list of the top 20 keywords based on the frequency of their usage by the authors in their articles. 'Supply chain management' with 1036 occurrences is the most frequent keyword within the reviewed articles. Other frequently used keywords include 'supply chains', 'decision making', 'genetic algorithms', and so forth.

Figure 4 depicts the trends of various emerging keywords (research focuses) across the timeline of literature. The keywords reflecting most frequently studied subjects have emerged during the period 2012–2018. AI-SCM research started with subjects tied to 'intelligent agents' and 'inventory control'. In the recent past, such research covered latest topics such as 'sustainability', 'sustainable development', 'sustainable supply chains', and so forth. It can also be observed that topics such as sustainable supplier selection, green supply chain, green supplier selection, and supply chain finance in combination with AI/ML techniques are garnering a lot of attention from the practitioners and academia.

Table 4. Author contribution to the AI literature.

Authors	Articles
Tiwari M K	30
Chan F T S	22
Niaki S T A	15
Gen M	12
Tseng M L	11
Govindan K	10
Mousavi S M	10
Tavakkoli-Moghaddam R	10
Gunasekaran A	10
Chung S H	9

4.2. Scholarly network and content analysis

Rapid recent advancement in AI theory and its application to SCM produced an enormous amount of digital scholarly data on AI-SCM. These data contained various forms of publications such as journal articles, books, reports, and proceeding papers. Among these, journal articles themselves allowed us to compile and analyse scholarly source of information using scholarly network analysis (SNA). Generally, SNA is designed to provide deep insights into the interaction of research aggregates such as citation, co-citation, co-authorship, and bibliographic coupling through the data-driven, network-based bibliometric analysis (Yan and Ding 2012). SNA helps us discover the scholarly collaboration between authors and depict how individual scientific ideas of authors can generate meaningful scientific findings through collaborative research. It also helps us find relationships between cited papers and a set of papers which cited those papers. This proves useful for a detection of academic communities working in the related area. Furthermore, it allows us to discover the current research areas as well as their evolution over time, not to

Table 5. Frequency of keyword occurrences.

Keywords	Occurrences	Keywords	Occurrences
Supply chains	632	manufacture	115
Supply chain management	488	sales	109
Genetic algorithms	380	algorithms	93
Decision making	314	problem solving	93
Optimization	204	multiple objective techniques	89
Fuzzy sets	201	scheduling	84
Artificial intelligence	188	inventory control	80
Decision support systems	148	supplier selection	79
Integer programming	147	competition	78
Costs	137	sustainable development	76

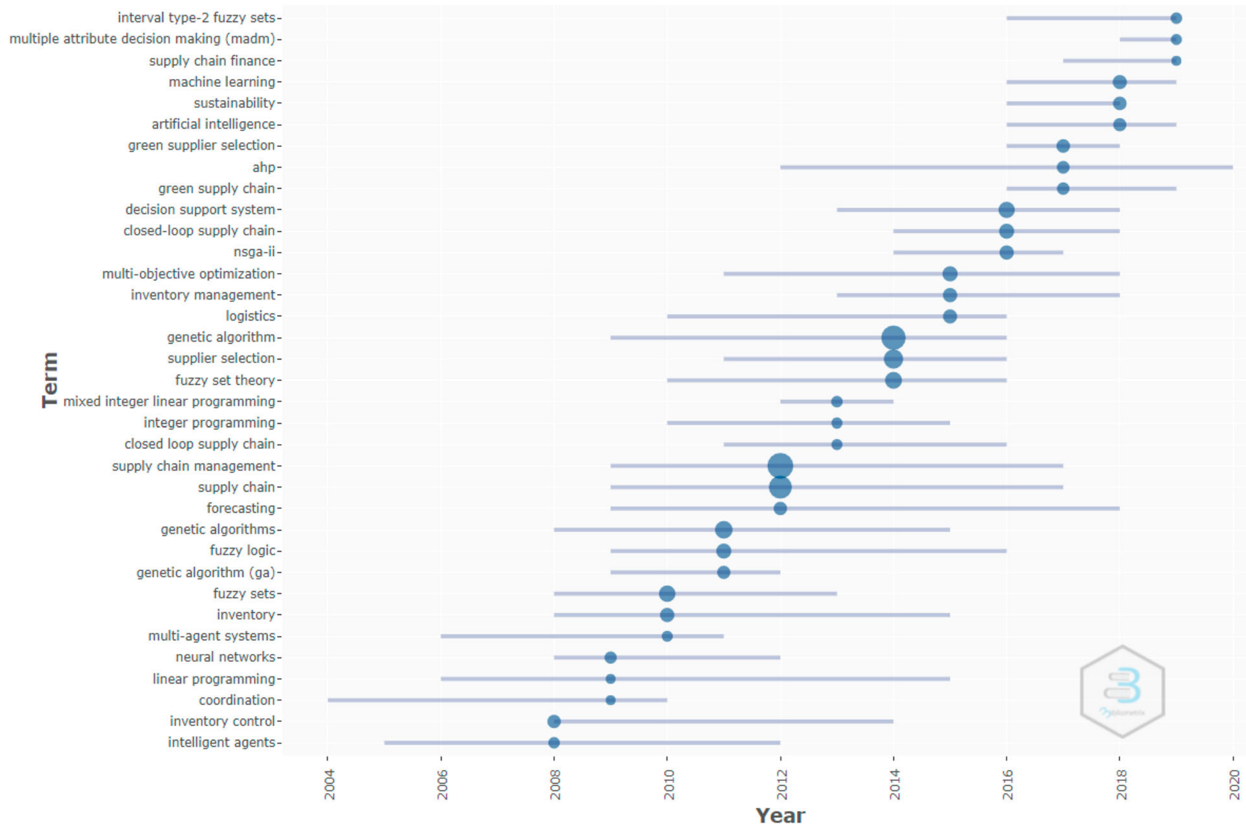


Figure 4. Emerging keywords (or focus areas) of the AI applications in SCM (Source: R).

mention the identification of the relationships between topics in the specific research field through finding the co-occurrence of keywords. Recognising the aforementioned usefulness of the SNA, we conducted SNA for the AI-SCM literature (see Figure 5). As a complementary tool, we used a content analysis.

The content analysis basically serves to record and identify intersubjective and objective characteristics from the selected studies (Maditati et al. 2018; Fahimnia, Sarkis, and Davarzani 2015). Thus, the results derived from a content analysis are credible and consistent if multiple researchers are engaged in the similar process (Duriau, Reger, and Pfarrer 2007). We systematically reviewed the contents of 44 selected articles written by researchers who conformed the underlying sub-themes of AI-SCM. These 44 articles had at least 150 citations for citation mapping after examining competing maps with at 145 citations and at least 155 citations, since these many citations reflected the criticality and vitality of their contributions to the literature of a particular topic (i.e. AI-SCM). To facilitate the content analysis, a concept matrix was formulated based on the study by Salipante, Notz, and Bigelow (1982) which consists of the following attributes: title of the article, author(s), publication year, keywords, research question(s), methodology used, theories used, main themes, sub-themes, and important findings of the selected 44 articles. The five major AI in SCM research clusters were considered as potential themes for each of the articles in the concept matrix. However, as the analysis progressed, article themes and sub-themes were defined through an iterative analysis of the contents of the selected 44 articles. Table 6 summarises five different clusters of 44 most frequently cited articles and their authors. Figure 5 depicts a number of clusters that were generated by using the VosViewer software.

As a result, five key research streams of AI applications in SCM were identified: (a) supply chain network design (SCND), (b) supplier selection, (c) inventory planning, (d) demand planning, and (e) green supply chain management. Figure 6 shows that supplier selection is the most popular theme of AI applications with 128 frequencies; genetic algorithms are most dominant AI tools for solving SC problems with a frequency of 397 articles.

In the following sub-sections, the key theories, methods, and findings of the selected articles are discussed briefly in the context of their respective research streams and sub-streams.

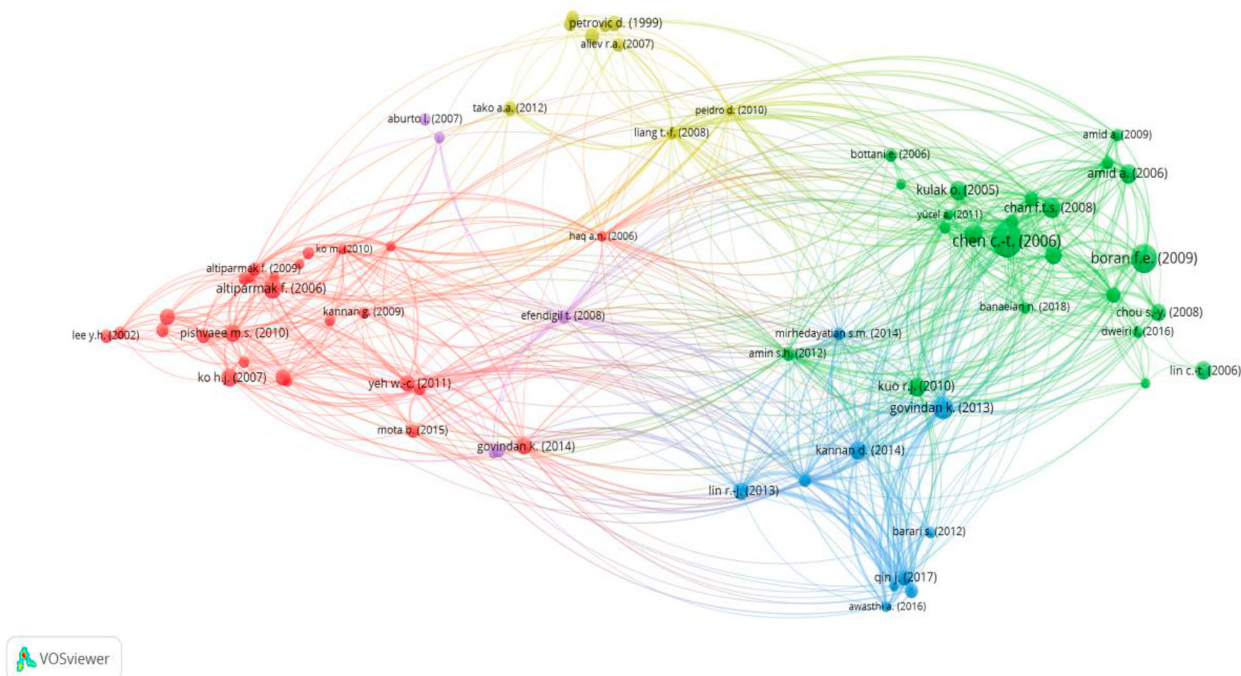


Figure 5. Scholarly network and content analysis of the AI-SCM literature.

Table 6. Clusters of most frequently cited AI-SCM research work.

Cluster I		Cluster II	
Author(s)	Citations	Author(s)	Citations
Altiparmak et al. (2006)	388	Chen, Lin, and Huang (2006)	1003
Ko and Evans (2007)	314	Boran et al. (2009)	759
Pishvaee, Farahani, and Dullaert (2010)	286	Chan et al. (2008)	374
Govindan et al. (2014)	254	Kumar, Vrat, and Shankar (2004)	343
Yeh and Chuang (2011)	248	Amid, Ghodsypour, and O'Brien (2006)	341
Kannan, Sasikumar, and Devika (2010)	241	Kuo, Wang, and Tien (2010)	330
Syarif, Yun, and Gen (2002)	237	Kulak and Kahraman (2005)	325
Wang and Hsu (2010)	186	Sanayei, Mousavi, and Yazdankhah (2010)	319
Altiparmak et al. (2006)	170	Lin, Chiu, and Chu (2006)	292
Lee et al. (2002)	165	Chou, Chang, and Shen (2008)	270
Cluster III		**ClusterIV**	
Govindan, Khodaverdi, and Jafarian (2013)	431	Petrovic, Roy, and Petrovic (1999)	230
Kannan, de Sousa Jabbour, and Jabbour (2014)	296	Petrovic, Roy, and Petrovic (1998)	229
Lin (2013)	288	Tako and Robinson (2012)	207
Qin, Liu, and Pedrycz (2017)	208	Aliev et al. (2007)	174
Tseng and Chiu (2013)	200	Carbonneau, Laframboise, and Vahidov (2008)	167
Govindan et al. (2015)	162	Giannoccaro, Pontrandolfo, and Scozzi (2003)	160
Mirhedayatian, Azadi, and Saen (2014)	140	Liang (2008)	142
Barari et al. (2012)	123	Petrovic (2001)	130
Tseng (2011)	110	Peidro et al. (2010)	108
Awasthi and Kannan (2016)	104		
Cluster V			
Efendigil, Önüt, and Kahraman (2009)	178		
Lieckens and Vandaele (2007)	170		
Aburto and Weber (2007)	150		
Efendigil, Önüt, and Kahraman (2009)	125		
Quariguasi Frota et al. (2010)	113		

4.3. AI taxonomy by the application area

To have a general panorama of prior AI studies and their key research themes, the present study highlights a taxonomy depicting two broad classifications viz. (1) application area as a basis for identifying particular fields of SCM problems for which AI is most suitable; (2) the methodology as a basis for assessing the theoretical progress and development in AI-SCM studies. Figure 7

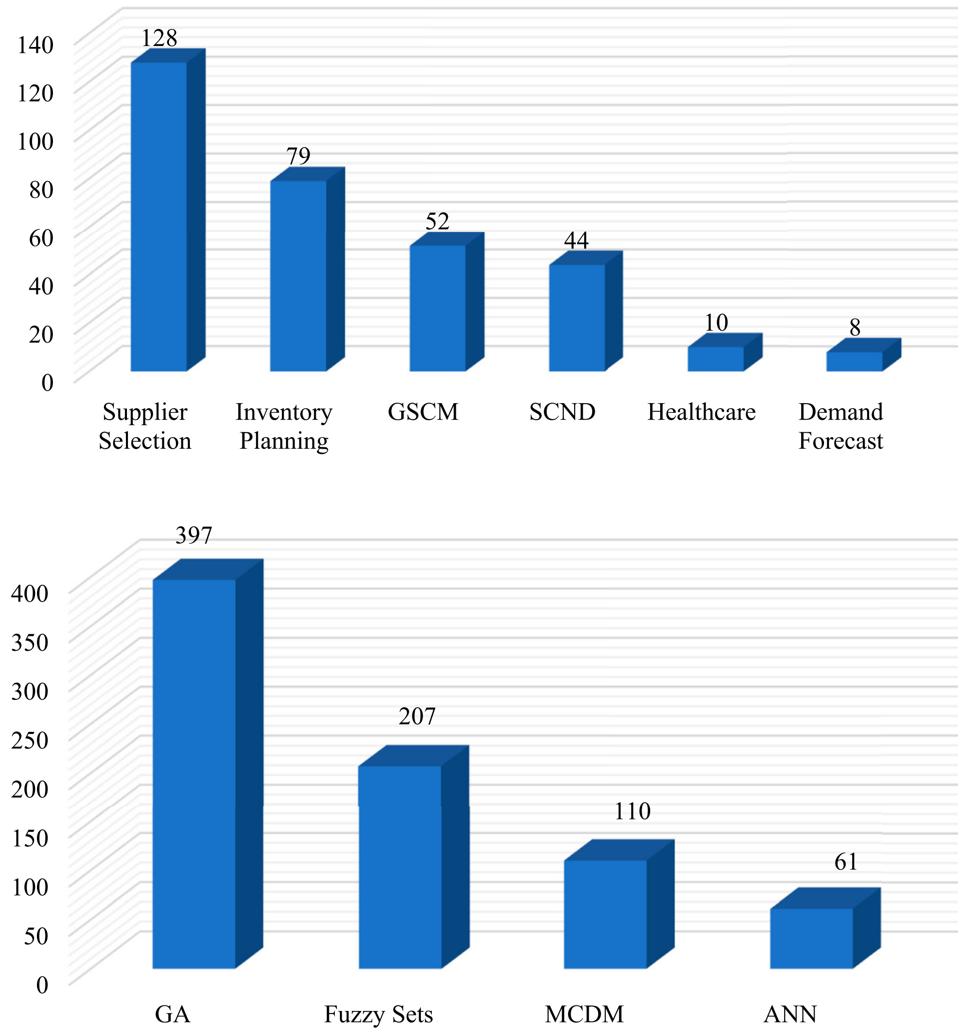


Figure 6. Popular focused areas and research tools of AI-SCM articles.

shows the yearly trends of published AI-SCM studies with respect to their application areas for the last two decades. The following subsections will summarise and synthesise selected (noteworthy) AI studies that applied various AI tools to a spectrum of challenging SCM problems.

4.3.1. Supply chain network design

Supply chain network design (SCND) is one of the most critical area of strategic decision-making in SCM. SCND is primarily concerned with determining the optimum location and size of facilities (e.g. plants and warehouses) and the flow of products through the facilities. Due to its criticality, SCND has one of the popular subjects of scientific inquiries within the AI framework. For example, one of the earliest AI-SCM research efforts includes Syarif, Yun, and Gen (2002) who developed a spanning tree-based genetic algorithm (GA) built upon Prüfer number representation to solve SCND problems. Min, Ko, and Ko (2006a, 2006b) proposed a nonlinear integer program and utilised GA for solving the multi-echelon SCND problem involving product returns and freight consolidation across geographical areas and holding time. Altiparmak et al. (2006) developed steady-state GA combined with a multiple-objective programing technique (MOPT) to find a set of Pareto-optimal solutions for the multi-product SCND problem. In their study, the proposed GA was complemented by simulated annealing and Lagrangian relaxation heuristics. Ko and Evans (2007) presented a mixed integer nonlinear programming model for designing a distribution network that integrated both forward and reverse product flows. Similarly, Pishvaee, Farahani, and Dullaert (2010) proposed MOPT for solving SCND problems in such a way that they avoided a sub-optimality caused by a separate, sequential design of forward and reverse logistics networks. Govindan et al. (2014) introduced a MOPT model that took into account sustainability for designing a perishable food distribution network. They developed

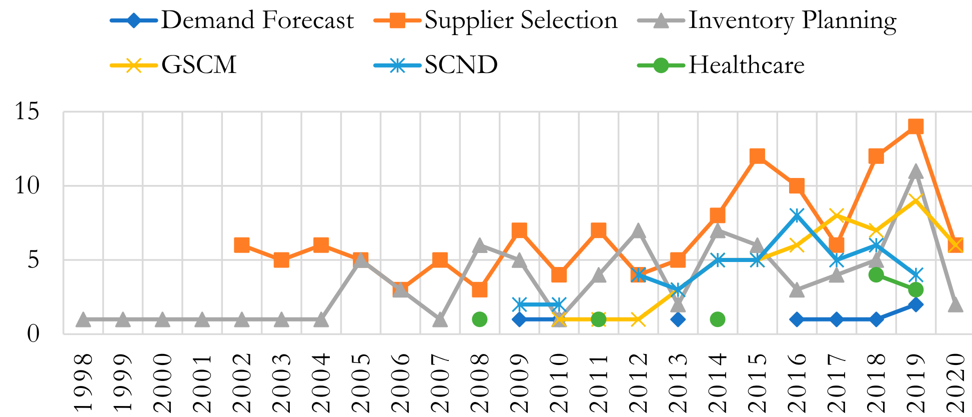


Figure 7. Yearly trends of AI-SCM articles and their application areas.

an AI-based meta-heuristics to solve the MOPT problems within a two-echelon, distribution network framework. Other noteworthy AI-SCM studies that used similar solution procedures such as GA for tacking variants of SCND problems include Kannan, Sasikumar, and Devika (2010), Wang and Hsu (2010), and Yeh and Chuang (2011).

4.3.2. Supplier selection

One of the critical steps of sourcing in the SCM is to find right sources of supply by evaluating and selecting the right supplier(s) (Min 2015b). Due to its importance to the upper stream of SCM, it garnered interest from many researchers and has become the popular subject of quantitative analysis including AI methodologies. Another aspect of AI in SCM related to procurement and supplier selection is spend analytics wherein procurement data is collected, processed, and analysed. Organizations then use insights from spend analytics for managing their suppliers, tracking procurement and supplier performance, and optimising costs. As such, there exist the abundant AI-SCM literature focusing on supplier selection problems (Weber, Current, and Benton 1991; Pal, Gupta, and Garg 2013). All the AI-SCM studies in this cluster utilised a combination of fuzzy sets theory and multi-criteria decision-making (MCDM) models for supplier selection due to the vagueness of supplier attribute information and conflicting goals of identifying low-cost and reliable suppliers. For instance, Kumar, Vrat, and Shankar (2004) developed a fuzzy, mixed-integer, goal programming model for supplier selection problem with conflicting goals of minimising the net cost, minimising the net rejections, and minimising the net late deliveries subject to constraints of the buyer's demand, the supplier's capacity, the supplier's quota flexibility, purchased value of items, and budget allocation to individual supplier. Chen, Lin, and Huang (2006) utilised the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method and fuzzy set theory for dealing with the supplier selection problems. Chan et al. (2008) discussed the fuzzy based Analytic Hierarchy Process (fuzzy-AHP) for efficiently tackling both quantitative and qualitative decision factors involved in global supplier selection. Boran et al. (2009) proposed a TOPSIS method combined with intuitionistic fuzzy sets for selecting the right supplier in a group decision-making environment. They utilised the intuitionistic fuzzy weighted averaging (IFWA) operator for aggregating individual opinions of decision makers for rating the importance of supplier selection criteria. Other AI-SCM studies similar to the aforementioned studies included Amid, Ghodsypour, and O'Brien (2006), Lin, Chiu, and Chu (2006), Chou, Chang, and Shen (2008), and Sanayei, Mousavi, and Yazdankhah (2010) utilised the variations of fuzzy set theory in the MCDM environments to select the most desirable supplier. Unlike these studies, Kuo, Wang, and Tien (2010) developed an artificial neural network (ANN) combined with data envelopment analysis (DEA) and analytic network process (ANP) to select green (most environment-friendly) supplier while making tradeoffs among the multiple criteria of cost, time, damage/loss, flexibility, and documentation ability of potential suppliers.

4.3.3. Green SCM

With the increased awareness of sustainability and mounting environmental pressures across the world, green SCM drew considerable interest from many academic communities (Min and Kim 2012; Kannan, de Sousa Jabbour, and Jabbour 2014). Recognising the emergence of green SCM, Govindan, Khodaverdi, and Jafarian (2013) presented a fuzzy MCDM model to green sourcing problem with sustainable supply chain initiatives based on the Triple Bottom Line (TBL). Similarly, Kannan, de Sousa Jabbour, and Jabbour (2014) proposed a fuzzy TOPSIS model for tackling green sourcing problem encountered by a Brazilian electronics company. Other notable AI-SCM studies that used variants of fuzzy set theory for green SCM included Tseng (2011), Barari et al. (2012), Lin (2013), Tseng and Chiu (2013), Govindan et al. (2015), Awasthi and Kannan (2016), and Qin, Liu, and Pedrycz (2017).

4.3.4. Inventory planning

Inventory planning and control systems are implemented by firms for controlling demand variability, reducing costs throughout the SC processes, maintaining sufficient inventory levels, and meeting adequate customer service levels. To tackle inventory planning problems, Petrovic, Roy, and Petrovic (1999) proposed a hybrid fuzzy sets and simulation model in an uncertain decision environment. Following suit, Giannoccaro, Pontrandolfo, and Scozzi (2003) exploited fuzzy set theory to define a multi-echelon inventory planning problem. Liang (2008) developed a fuzzy multi-objective linear programming (FMOLP) model with a piecewise linear membership function to solve multi-period, multi-product inventory planning problems with vague objectives. Similarly, Peidro et al. (2010) developed a fuzzy linear programming model for solving an inventory planning problem in a multi-echelon, multi-product, multi-period supply chain network. Rather than using the fuzzy set theory, Carbonneau, Laframboise, and Vahidov (2008) applied advanced machine learning techniques such as neural networks, recurrent neural networks, and support vector machines to forecast the distorted inventory demand caused by bullwhip effect.

4.3.5. Demand planning

Demand planning sets the tone for supply chain activities since it has a trickle-down effect on the upper stream supply chain activities involving logistics, manufacturing, and sourcing. Effective demand planning enhances labour productivity, speeds up product flows, and increases profits and revenues (Quariguasi Frota et al. 2010). In addition, accurate demand planning helps mitigate supply chain risks. Recognising such importance of demand planning, Yu, Graham, and Min (2002) developed an agent-based demand forecasting technique that combined human expertise and data mining techniques to predict the aggregate demand for new products. Their experiments indicated that the dynamic pattern matching procedure built on AI outperformed exponential smoothing techniques with respect to forecasting accuracy. Liang and Huang (2006) proposed a multi-agent system and employed genetic algorithm to control inventory and minimise the total supply chain cost by creating forecasting knowledge obtained from multiple agents. Aburto and Weber (2007) presented a hybrid intelligent system combining Autoregressive Integrated Moving Average (ARIMA) models with neural networks for a volatile demand forecasting problem. Efendigil, Önüt, and Kahraman (2009) proposed artificial neural networks and adaptive network-based fuzzy inference system techniques to manage uncertain demand with incomplete demand information.

4.3.6. AI in healthcare SCM

To cope with the mounting health care cost resultant from recent healthcare crisis such as the ongoing COVOID-19 pandemic, a growing number of healthcare service providers made conscious efforts to improve their healthcare productivity. One of the best ways to improve such productivity is technical innovation. Examples of technical innovation that have wide-application potentials for healthcare SCM include robotics and expert systems. For instance, robotics can help healthcare professionals monitor the patient's medical condition and recovery progress by managing his/her medical charts and vital signs without human intervention. An expert system can also diagnose the patient's symptoms by using the pre-developed If–Then rules (Min 2014). With the aid of wearable technology, the medical doctor can generate such diagnosis and alert the patient about his/her health concerns in real time. In addition, AI can be useful for developing plans of smart delivery of medical supplies and pharmaceuticals essential for patient care.

Cognizant of the AI's usefulness for healthcare SCM, a growing number of recent studies reported the successful applications of AI to healthcare supply chain settings (Min 2017; Mathur et al. 2018). For example, Sabegh, Mohammadi, and Naderi (2017) developed the artificial neural network and hybrid genetic algorithm to respond to natural disasters in such a way that a pharmaceutical company could minimise costs of poor product quality and transportation in the pharmaceutical supply chain. Rath, Rajaram, and Mahajan (2017) proposed a two-stage, mixed-integer stochastic dynamic programming model with recourse for solving the problems of staffing and scheduling at one of the largest medical centres in the U.S. Fan et al. (2018) investigated how receptive medical professionals are of artificial intelligence-based medical diagnosis decision support systems (AIMDSS) for disease treatments in the Chinese hospitals in terms of trustworthiness. Zahiri, Jula, and Tavakkoli-Moghaddam (2018) presented a novel robust possibilistic optimization model to minimise the total costs and maximum unmet demand of perishable drugs in a uncertain pharmaceutical SC network. Aswani, Shen, and Siddiq (2019) designed a principal-agent problem highlighting the interaction between Medicare Shared Savings Program (MSPP) and Medicare provider. In their study, the MSPP sets the financial benchmark for each Medicare provider, and each Medicare provider decides what investment to make in order to reduce costs.

More recently, Kargar, Paydar, and Safaei (2020) proposed a multi-item multi-objective linear programming model under uncertainty for designing a medical waste reverse supply chain. Their proposed model had three objective functions viz. minimising total costs, utilization of best medical waste treatment technology, and minimising the total stored medical waste. Abbassi et al. (2020) addressed a two-echelon location-distribution problem of non-medical products in healthcare supply chain logistics using multi-objective particle swarm optimization and genetic algorithm and develop a multi-objective mathematical model for minimising distribution cost and distribution time. Sadjadi, Ziaei, and Pishvaee (2019) designed a vaccine supply chain using the mixed integer programming model considering strategic decisions for each echelon and tactical decisions among the echelons of the vaccine supply chain. Dehghani, Abbasi, and Oliveira (2021) employed a two-stage stochastic programming model along with the Quasi-Monte Carlo sampling approach to manage inventories of perishable blood in uncertain demand environments. They also tested the performance of their proposed model in proactive transshipment from the central flood bank to a network of hospitals in Australia.

4.4. AI classification by methodology

As discussed in earlier section 4.3, a multitude of AI tools was utilised to solve various SCM problems. These tools include genetic algorithm, fuzzy set theory (or logic), TOPSIS, AHP/ANP, artificial neural network as shown in Figure 8. Though AI tools are still evolving, and their application potentials are growing, we noticed that some of them had been frequently adopted to solve SCM problems. Figure 9 shows the yearly trend of published AI-SCM articles with respect to their particular AI-tools during the period of 1998 through 2020. With that in mind, the following subsections recapitulate a list of most popular AI tools relevant to SCM.

4.4.1. Genetic algorithm

The roots of genetic algorithm (GA) can be traced back to the theory of evolution. The rules of natural selection processes found in the nature to create the best-fit organisms are impersonated in GA to solve challenging combinatorial optimization problems (Min 2015a). Combinatorial optimization problems, which possess the possibility of building a function which evaluates the fitness of a given solution to a given problem, have often been solved by using GAs. GA translates the potential solutions of the problem into numerical strings known as chromosomes. Through multiple iterations on chromosomes using genetic operators (viz. crossover, mutation, and selection) to the whole population, GA provides solutions that are not necessarily optimal, but satisfice the fitness criteria to the optimization problem. GAs find their application to a variety of challenging supply chain network design and inventory management problems (Min 2015a). These problems include but are not limited to: vehicle routing and scheduling (Wang et al. 2016; Biesinger, Hu, and Raidl 2018), minimum spanning tree (Contreras-Bolton et al. 2016; Contreras-Bolton et al. 2016; Shi et al. 2016; Singh and Sundar 2020); delivery and pickup (Al Chami et al. 2017; Jia, Jing, and Hong 2019; Rüther and Rieck 2020); and location – allocation problems (Zhou, Min, and Gen 2002; Min, Ko, and Ko 2006a); and inventory planning and control problems (Disney, Naim, and Towill 2000; Pasandideh, Niaki, and Nia 2011; Petering, Chen, and Hsieh 2019).

4.4.2. Artificial neural networks

Artificial neural networks (ANN) are theoretically designed to function like the brain cells of a living organ and are classified as a subset of deep learning. The deep learning neural network uses interconnected network of computer memories to learn from experience, recognise different features and patterns, and even process ambiguous or abstract information using weights, data inputs, and bias. The deep neural networks comprise interconnected nodes forming multiple layers. Some of the complex deep learning neural networks are convolutional neural networks (CNN) which find applications in computer vision; and recurrent neural networks (RNN) which find applications in speech recognition and natural language processing. Although ANNs are of wide variety and type, feed-forward error back-propagation type neural nets are mostly deployed in SCM. In SCM, ANN was successfully utilised for developing hierarchical SC planning that determined the time/capacity needed for setups, estimated optimal lot-size between successive SC processes, and linked inventory and scheduling decisions at the lower level to demand and production planning decisions at the higher level (Rohde 2004). As illustrated in section 4.3, ANN was one of the AI tools that were proven to be effective for handling various SC problems including demand forecasting (Aburto and Weber 2007).

Özkan and İnal (2014) proposed the Adaptive Neuro-Fuzzy Inference System (ANFIS) for solving multi-criteria decision-making problems involving supplier evaluation and selection. ANFIS was a feed-forward,

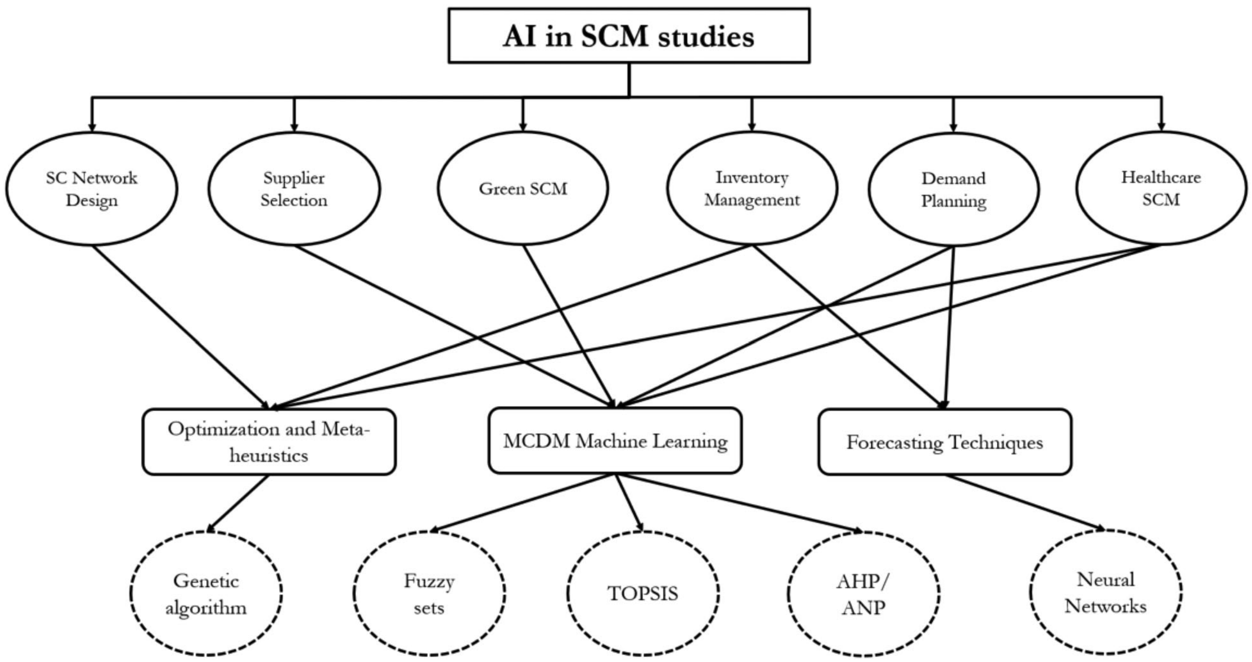


Figure 8. Research focus of AI studies in SCM.

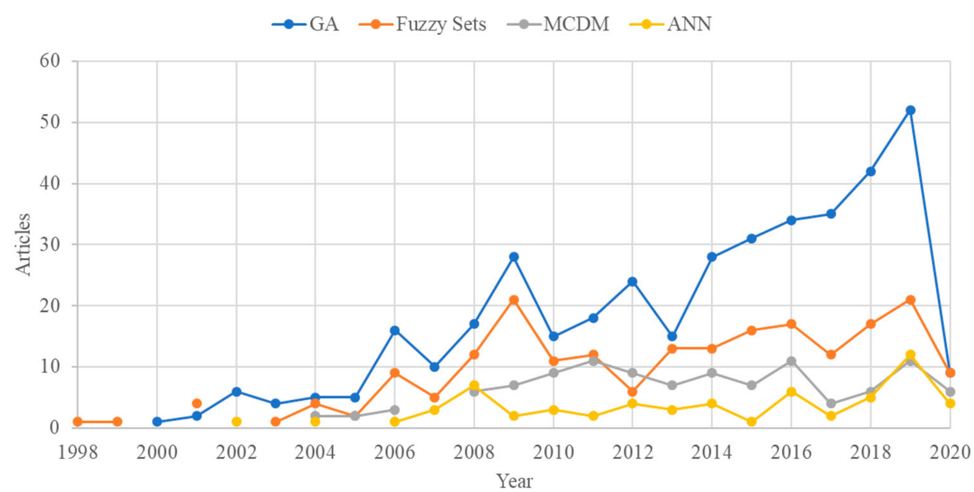


Figure 9. Yearly trends of AI-SCM articles and their methodology.

hybrid learning ANN where each layer is a neuro-fuzzy system component and tended to perform better for clustering and pattern recognition than the standalone ANN did based on the comparative experiments. Similarly, Tavana et al. (2016) developed a hybrid ANFIS–ANN model for evaluating and ranking potential suppliers based on their past performances. Liu et al. (2019) also exploited the ANFIS-ANN model to identify factors significantly affecting price fluctuations in a steel supply chain in China. Lima-Junior and Carpinetti (2019) proposed a SC performance prediction system based on ANNs (multilayer perceptron neural networks) and SCOR model. Their proposed AI-based methodology was useful for evaluating and comparing historical SC performance data. Carrera, Mayorga, and Peng (2020) utilised ANNs for developing a hybrid neuro-fuzzy analytical network (NFANP) approach that was intended to solve group decision-making problems. The NFANP approach was applied for selecting a right supplier with respect to ongoing supplier performance, supplier characteristics, and project management capabilities. When it came to supplier selection, there were several Neuro-Fuzzy applications in an AI domain. Nezamoddini, Gholami, and Aqlan (2020) proposed a risk-based optimization framework using ANNs and genetic algorithms which could aid SC professionals in making SC decisions at all decision hierarchies (i.e. strategic, tactical, and operational levels).

4.4.3. Fuzzy logic/set theory

Fuzzy logic was introduced by Zadeh (1965) and is an extension of Boolean logic that was designed for handling the ambiguity, inaccuracy, and uncertainty of objects. It aids the decision-making process without having to set clear-cut boundaries. It helps make definite decisions based on imprecise and ambiguous data (Ordoobadi 2009). It is an extension of the classical set theory which is based on fuzzy sets and provides a medium for highlighting the vagueness, subjectivity, and ambiguity with the help of mathematical formulations. Earlier studies such as Patel, Shah, and Chhinkaniwala (2019) and Goularte et al. (2019) utilised fuzzy logics to integrate with expert systems and pattern recognition to handle SC problems with uncertainty and/or opaqueness (Castillo et al. 2016; Wang et al. 2016; Hamamoto et al. 2018; Baykasoğlu and Gölcük 2019; Chaturvedi et al. 2019; dos Santos, Godoy, and Campos 2019; Jain and Singh 2020). Fuzzy set theory has diverse SC application potentials and has been widely explored for SC decisions with uncertainty and imprecise information. As discussed earlier in Section 4.3, many AI-SCM studies applied fuzzy set theory as one of the popular AI tools for addressing various SCM issues.

4.4.4. MCDM techniques with machine learning capabilities

Though MCDM techniques are generally viewed as one of the O.R. tools, AI and MCDM shares the same traits such as interactivity, reasoning of decision alternatives, decision support orientation, and user involvement in decision making (Perny and Pomerol 1999; Doumpos and Grigoroudis 2013). In particular, most MCDM techniques were designed to make tradeoffs among multiple conflicting criteria by rules (Perny and Pomerol 1999). These rules can be learned by machines and then can be applied automatically by those machines. Thus, some popular MCDM techniques can be categorised as a subset of AI tools. Earlier AI-SCM studies utilised various MCDM techniques with machine learning capabilities such as linear weighted average methods (Timmerman 1986); cost-ration method (Dobler, Lee, and Burt 1990); vendor profile analysis (Thompson 1990); and dimensional analysis (Kools et al. 1996) for sourcing problems in the upstream SCM. Though an integral part of AI tools, these MCDM techniques posed challenges for assigning weights (or relative importance) to various attributes as the weights were purely based on personal judgments and intuitions of the decision-maker. To overcome such a shortcoming of the aforementioned techniques, researchers proposed alternative scoring methods such as analytical hierarchy process (AHP), analytic network process (ANP), ELECTRE, TOPSIS, to name a few. These techniques provide a systematic way for determining the weights of multiple attributes following a series of pairwise comparison of all attributes including qualitative attributes that are difficult to express mathematically. These MCDM techniques are widely used for solving various SCM problems including supplier selection (Sari 2017), production planning and control (Rasmi, Kazan, and Türkay 2019), reverse logistics (Gu et al. 2019), and SC performance evaluation (Khan, Chaabane, and Dweiri 2019). However, these MCDM techniques have been used primarily as a complementary technique for a popular AI tool such as fuzzy set theory rather than a stand-alone AI tool.

The previous sub-sections highlighted the review findings, and it can be observed that AI techniques find their applications across all phases of the SC. Today's turbulent business environment demands for tailor-made AI solutions that can drive the enterprise forward in terms of effective risk management (Baryannis et al. 2019b), overcoming operational challenges, sustainability related issues (Bechtsis et al. 2021), effective forecasting (Badakhshan et al. 2020), and consumer demand. The SC organizations will greatly benefit from the AI and other emerging technological advancements such as blockchain technology, additive manufacturing, and big data analytics (Olan et al. 2021).

Owing to the high amounts of data generation in production, operations, and supply chains, AI promises to drive the SC digitalization capabilities by delivering predictive insights which enhance organizational competitiveness (Dubey et al. 2020). Successful AI integration in the SC depends on the cultural SC enablers (such as processes, autonomy, information sharing) which help in improving SC performance (Cadden et al. 2021; Helo and Hao 2021). Overall, AI enabled SCs can create value and drastically improve organizational performance and competitiveness in this digital age.

The next sub-sections will discuss about the research and managerial implications followed by future research directions, and conclusion.

5. Implications, future research directions and conclusion

5.1. Research implications

The following sub-sections highlight the study implications.

5.1.1. Theoretical implications of this study

This paper makes a number of theoretical contribution to the existing body of SCM literature. First, it expands the knowledge bases of existing AI-SCM literature by reviewing and synthesising hundreds of AI-SCM articles published in the latest two decades and summarising notable trends that point specific research directions. These directions will boost research interest in the AI-SCM field. Second, unlike past literature survey articles that simply categorised past research efforts and developed taxonomies, this paper goes beyond the traditional literature survey approach by using science mapping techniques. Thirdly, it identifies research clusters that will help academicians better understand the dynamic relationship among past AI-SCM studies and visualise topical connections and level of collaboration among researchers. Fourthly, it provides substantial support to the argument on emerging technologies, operational performance, and competitiveness of organizations by highlighting various AI in SCM application areas. Coincidentally, the review highlights the importance of AI as an emerging technology in IT capability building and creating sustainable competitive advantage (Bhatt and Grover 2005). AI capabilities will strengthen the sensing and seizing capabilities which further enhance SC competitive advantage (Teece 2007; Pournader et al. 2021).

5.1.2. Practical implications of this study

This paper not only gave a birds' eye view of AI-SCM research outcomes, but also illustrated how AI has been applied to a number of actual SC problems successfully. Practitioners can learn from the past AI-SCM applications and develop their own best AI-SCM practices based on the summary of past AI-SCM application efforts. In particular, this paper identified the most popular SC application areas of AI and pinpointed the most fruitful (or rewarding) application areas of AI-SCM such as SC network design, supplier selection, demand planning, and inventory planning where AI played a significant role in boosting SC productivity. In novel areas of research such as supply chain financing, AI techniques will help practitioners by enabling focal industries and other value chain players to gain analytical advantage and thereby improve the decision-making processes (Olan et al. 2021). The AI tools can accurately forecast the consumer demands with minimal errors and thereby help in proactively reducing the SC risks and disruptions (Baryannis et al. 2019b). Adding further, practitioners can make use of AI enabled teleworking activities to improvise human resources in their organizations. As AI can be integrated with other emerging technologies, it can be used for improving the real-time production system performance and eliminate waste thereby paving the way for sustainable production systems. On the behavioural operations front, the real-time information sharing enabled by AI systems can improve SC relationships, SC integration, and coordination among the stakeholders (Helo and Hao 2021). Therefore, the practitioners should focus on the key cultural enablers for successful AI integration in the supply chains (Cadden et al. 2021). In production and operations management areas, AI techniques can be seen as an advantage on the socio-technical front. AI implementation will not only minimise errors and reduce setup times but will improve workers safety by improvising the human–robot interaction.

To summarise, this study finding can help practitioners make wise AI investments in the specific SC functions with the highest return-on-investment of emerging AI tools. In addition, this paper identified and proposed specific AI tools (e.g. artificial neural network, agent-based systems, MCDM-machine learning, meta-heuristics) that were most relevant to SC applications.

5.2. Future research directions

Despite the relative youth of supply chain disciplines, SCM fields have emerged as one of the most popular research themes due to their breadth of coverage encompassing any business activities of sourcing, making, delivering, and selling. As the SCM fields continue to mature, SCM research paradigm has shifted from asset management to knowledge management due to the importance of information exchange among various supply chain partners to SCM success (Min 2016). This paradigm shift sparked a widespread interest in the application of AI tools to SCM. Though still limited, AI applications to SCM begun to grow rapidly for the last decade (see Table 9). However, our current study indicates that AI has not been fully exploited to solve some challenging SC problems that are too complex or too 'ill-structured' (loosely defined) to solve. Indeed, our study has discovered a pattern that most AI applications in the SCM area remain confined to relatively well structured (or pre-defined or narrowly defined), tactical and operational SC problems such as SC network design, inventory planning, demand planning (esp. forecasting), and supplier selection problems. That is to say, a vast majority of existing AI-SCM studies proposed AI tools mainly as the better alternatives to conventional business analytics tools or operations research/statistics techniques for tackling SC problems. This may explain why well-defined, well-known supplier selection or inventory planning problems turned out to be the most studied AI-SCM subjects and continued to garner huge interest as evidenced by the explosive growth of publications focusing on those two subjects. The relative youth of the SCM discipline may have contributed to a lack of well-defined SC problems. Figure 10 shows a synthesis framework consolidating the drivers of AI in SCM which emphasises the growing need of using AI to

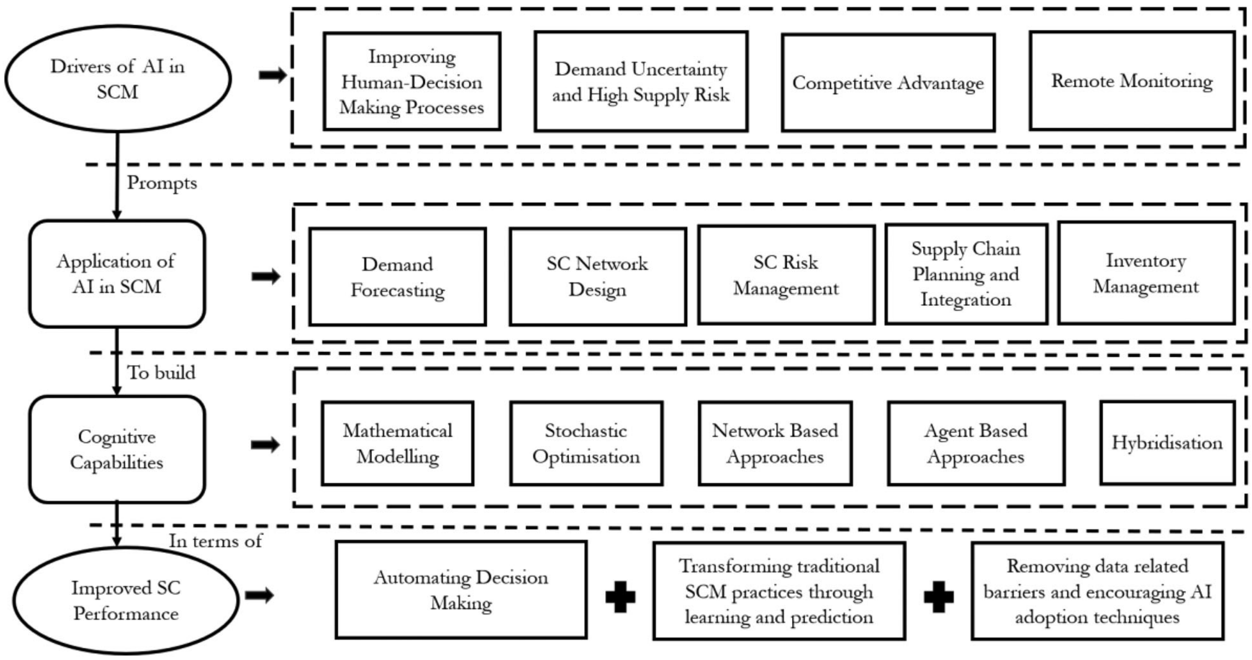


Figure 10. Synthesis Framework.

address the SC problems. It also indicates the application of AI tools being implemented to build capabilities and realising the potential of AI in improved SC performance.

Although this pattern has not been fully reversed at this moment, some recent AI studies such as Choy, Fan, and Lo (2003) and Mazumdar and Mishra (2010) have shown the great potential of AI tools (especially agent-based systems and data mining techniques) for addressing a variety of soft but strategic issues involving customer relationship management (CRM), supplier relationships, consumer behaviours, social marketing, and contract negotiation that have often been overlooked by more traditional analytical models. Another finding is that the genetic algorithm has emerged as one of the most dominant AI tools for tackling various aspects of well-defined SC problems, while the popularity of other promising AI tools such as ANN have not grown significantly as compared to GA and MCDM techniques (see Figure 10). Another noticeable trend that we observed is the combined use of multiple AI tools such as the hybrid MCDM and genetic algorithm and the hybrid MCDM and fuzzy set theory. Once the AI tools began to advance faster and a variety of new AI tools can be invented, we expect that the trend of integrating multiple AI tools would continue. Despite the increased popularity of AI tools for solving SCM problems, we should be aware of some challenges of using AI. These inherent challenges of AI applications to SCM include:

The effectiveness of AI tools relies heavily on the effectiveness and accuracy of AI computer software. Thus, the indiscreet use of AI tools for SCM may lead to wrong SC decisions, if it is programmed incorrectly.

AI solutions may not be easy to implement because they are so esoteric and relatively new. Thus, it may be hard for decision-makers with limited technical skills to comprehend and exploit.

Despite these challenges, as AI-SCM will continue to draw more attention from both practitioners and academicians alike. As the AI-SCM research has begun to take off as a subfield of main-stream supply chain studies, we should not lose sight of major drivers of AI-SCM: the incorporation of Industry 4.0 principles (e.g. man-machine interfaces) into value chains, links among sourcing, making, and delivering activities, and information/communication networks coordinating and synchronising those activities.

5.3. Conclusion and limitations

Despite the numerous contributions of this paper, it is subject to a number of limitations that can be addressed by future research. The bibliometric data that we collected are primarily confined to the database of scholarly journals in business disciplines. Thus, this paper cannot capture some past studies published in non-business journals mainly covering health-care, geography, and social science fields. Considering current research limitations, the continued investigation of the aforementioned AI-SCM drivers is worth pursuing as the promising future research agenda since it would help the AI-SCM research field mature and refresh. In particular, we would like to suggest the following lines of research for the subjects of further scientific inquiries.

- As the world gets closer with improved transportation means, infectious diseases can spread out more quickly and widely all across the world (Min 2014). Especially, developing countries with a rapid population growth but limited medical resources are highly susceptible to deadly disease outbreaks. Although some ground works have been established by a few pioneering researchers, more AI-SCM research from a health care perspective is needed to tackle public health care issues associated with infectious disease outbreaks such as the COVID-19 pandemic. The example of such research includes tracing of disease hot-spots and adequate, timely distribution of medical equipment and supplies to the hospitals.
- The diverse applications of AI can be seen along vertical sectors such as food processing and manufacturing industry where AI can be used for investigating the food safety, quality parameters, and product recalls.
- The AI/ ML techniques can be used for exploring legal aspects and research applications in fintech and banking operations (such as credit card frauds, loan defaults, etc.).
- AI applications can be explored in marketing operations wherein AI based robots (chatbots) can help in providing creative customer engagement.
- AI applications can have their potential impact on sustainable operations for new startups.
- Despite the enormous benefits and potentials of AI, factory automation powered by AI may increase anxiety among workers for their job security and then face strong organizational resistance. Since such resistance can derail AI success in the SC operations, empirical studies that can assess the extent of organizational resistance against AI-SCM would be needed.

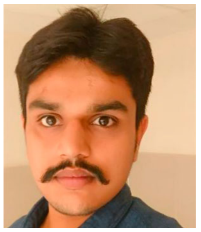
Note

1. The Scopus database encompass research articles from reputable publishers, such as Emerald, Elsevier, IEEE, Indersciences, Springer, Taylor and Francis, and Wiley (Mongeon and Paul-Hus 2016).

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors



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Data availability statement

Data will be made available upon request.

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Appendices

Appendix 1

Overview of AI algorithms and their applications in SCM

Supply Chain Activities	AI algorithm
Supply Chain Planning	Neural Networks
Demand Forecasting/ Sales Forecasting	ANN; GA
Customer Management	SVM; K-means Clustering; Clustering
Supplier Selection	ANN; GA; SVM; Decision Trees; FL
Supplier Risk Management	SVM; Decision Trees; ANN; Bayesian Networks
Manufacturing/ Operations/ Production	Bayesian Network; GA; Clustering
Inventory Management	GA; Clustering; Regression
Quality Management	ANN
Maintenance Management	ANN
Transportation	GA; ANN; AIS
Stores/ Warehouse	GA; Regression
Waste Reduction	ANN; FL
Reverse Logistics	ANN; GA
Cost Prediction	SVM; ANN; Regression
Scheduling	ANN; GA

Appendix 2

Top publishing outlets

Journal	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	Σ
IJPR	1	0	0	0	0	0	0	1	2	2	1	4	3	2	16
CIE	0	0	0	0	0	0	0	0	7	0	1	0	5	1	14
ESWA	0	0	0	0	0	0	0	0	1	1	0	3	1	0	6
IJPE	0	0	0	0	0	1	1	1	2	2	0	0	8	0	15
IJAMT	0	0	0	0	0	0	0	0	0	0	2	1	2	1	6
JCP	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
EJOR	0	0	0	0	1	0	0	1	0	2	0	1	4	3	12
ASCJ	0	0	0	0	0	0	0	0	0	0	2	0	0	2	4
JIM	0	0	0	0	0	1	0	1	0	0	0	0	2	0	4
IJLSM	0	0	0	0	0	0	0	0	0	0	0	0	3	1	4
	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	Σ
IJPR	7	5	5	8	11	8	7	8	8	11	9	18	6	7	118
CIE	3	10	4	1	3	5	3	10	14	12	11	24	9	0	109
ESWA	8	20	8	15	14	3	11	5	6	7	5	4	0	1	107
IJPE	4	8	6	3	4	2	6	6	4	7	4	9	1	3	67
IJAMT	2	6	3	3	6	11	14	1	2	3	3	1	0	0	55
JCP	0	0	1	0	0	5	0	2	10	6	15	16	4	0	59
EJOR	4	7	8	2	3	6	3	3	2	1	1	3	1	0	44
ASCJ	1	0	1	2	0	2	1	6	7	2	6	4	4	0	36
JIM	1	1	0	0	5	3	2	1	2	6	6	5	0	0	32
IJLSM	1	1	2	4	2	0	3	5	2	6	3	1	1	0	31

Notes: Where, IJPR (International Journal of Production Research), CIE (Computers and Industrial Engineering), ESWA (Expert Systems with Applications), IJPE (International Journal of Production Economics), IJAMT (International Journal of Advanced Manufacturing Technology), JCP (Journal of Cleaner Production), EJOR (European Journal of Operational Research), ASCJ (Applied Soft Computing Journal), JIM (Journal of Intelligent Manufacturing), IJLSM (International Journal of Logistics Systems and Management).