Journal of Business Research 122 (2021) 502–517

Contents lists available at ScienceDirect

Journal of Business Research

journal homepage: www.elsevier.com/locate/jbusres

Artificial intelligence in supply chain management: A systematic literature review

Reza Toorajipour [a], Vahid Sohrabpour [b,c], Ali Nazarpour [d], Pejvak Oghazi [e,*], Maria Fischl [f]

[a] School of Innovation, Design and Engineering, Mälardalen University, Box 325, 631 05 Eskilstuna, Sweden
[b] Department of Operations Management, Copenhagen Business School, Copenhagen, Denmark
[c] SAVEGGY AB, Ideon Innovation, Ideon Science Park, Lund, Sweden
[d] School of Business, Maynooth University, Maynooth, Co. Kildare, Ireland
[e] School of Social Sciences, Sodertorn University, Alfred Nobels allé 7, Stockholm, Sweden
[f] Siemens Gas and Power GmbH & Co. KG, Siemens Energy, Berlin, Germany

ARTICLE INFO

Keywords:
Artificial intelligence
Supply chain management
Systematic literature review

ABSTRACT

This paper seeks to identify the contributions of artificial intelligence (AI) to supply chain management (SCM) through a systematic review of the existing literature. To address the current scientific gap of AI in SCM, this study aimed to determine the current and potential AI techniques that can enhance both the study and practice of SCM. Gaps in the literature that need to be addressed through scientific research were also identified. More specifically, the following four aspects were covered: (1) the most prevalent AI techniques in SCM; (2) the potential AI techniques for employment in SCM; (3) the current AI-improved SCM subfields; and (4) the subfields that have high potential to be enhanced by AI. A specific set of inclusion and exclusion criteria are used to identify and examine papers from four SCM fields: logistics, marketing, supply chain and production. This paper provides insights through systematic analysis and synthesis.

1. Introduction

The world has been moving towards a digital future over the years, and Industry 4.0 technologies are considered to be the way of the future (Kumar et al., 2020). One of the most prominent of these technologies (including blockchain, IoT, cloud computing, etc.) is artificial intelligence (AI) (Dirican, 2015), defined as the capability of machines to communicate with, and imitate the capabilities of, humans (Schutzer, 1990). Using AI leads to problem solving with higher accuracy, higher speed and a larger amount of inputs. AI is neither a new subject nor a new academic field of study (Huin et al., 2003); however, only recently have technological developments shown that AI has a vast set of applications (Min, 2010), making headlines by adapting processes in numerous diverse areas (Martínez-López and Casillas, 2013; Jarrahi, 2018), including supply chain management (SCM). While some areas of information technology are being reduced to a position of competitive necessity, AI technology is emerging as a competitive advantage (Thow-Yick and Huu-Phuong, 1990). In this regard, many companies are shifting from remote monitoring to control, optimization, and finally, advanced autonomous AI-based systems to improve their functionality (Kohtamäki et al., 2019).

Along with its rising importance in industry, AI shows an increasing and broader presence in the scholarly discourse, and this presence has affected many fields, such as business research, which has picked up on the topic, and AI is now researched from a more holistic perspective (e.g. Canhoto and Clear, 2020; Dirican, 2015; Soni et al., 2020), with SCM being recognised as one of the fields most likely to profit from AI applications. Although interest from practitioners and researchers is thus high (as demonstrated by the large number of studies regarding AI, e.g. Jarrahi, 2018; Kaplan and Haenlein, 2020; Nishant et al., 2020; Ransbotham et al., 2017), there is a need to explore the contribution of AI to the field of SCM. Several studies have mentioned this need (e.g. Dubey et al., 2020; Min, 2010; Vargas Florez et al., 2015). This gap is addressed by the current study through a systematic review and by answering the following research question (main RQ): *how does AI contribute to SCM studies?*

In order to conduct an inclusive yet practical literature review, we focus on related subfields based on the work of Stock and Boyer (2009),

* Corresponding author.
E-mail addresses: vahid@saveggy.com (V. Sohrabpour), ali.nazarpour@mu.ie (A. Nazarpour), Pejvak.oghazi@sh.se (P. Oghazi), maria.fischl@siemens.com (M. Fischl).

https://doi.org/10.1016/j.jbusres.2020.09.009
Received 5 May 2020; Received in revised form 4 September 2020; Accepted 6 September 2020
Available online 25 September 2020

who cover the main aspects and fundamental keywords in their definition of SCM:

> *The management of a network of relationships within a firm and between interdependent organizations and business units consisting of material suppliers, purchasing, production facilities, logistics, marketing, and related systems that facilitate the forward and reverse flow of materials, services, finances and information from the original producer to final customer with the benefits of adding value, maximizing profitability through efficiencies, and achieving customer satisfaction.*

From the above theoretical definition, four key words are extracted for the search strings, including marketing, logistics, production and SCM (material supplier and purchasing are included in the latter). This study is structured as follows. The next section outlines the methodology of the research, with details about how the review was conducted. Then, the analysis and synthesis section breaks down individual studies into constituent parts and describes the relationships between them. The paper concludes by discussing and summarising the findings of the research (Denyer and Tranfield, 2009).

2. Methodology

To overcome the recognised weaknesses of a narrative review (Tranfield et al., 2003) or an expert review with ad hoc literature selection (Kitchenham et al., 2009), this study adopted an evidence-informed, systematic literature review approach. We followed the five-step process outlined by Denyer and Tranfield (2009), including a pilot search in the first phase to gain a deeper understanding of the current literature, construct the criteria for literature selection and derive the research question and the subsequent steps. Consequently, the systematic review that we employed has five phases, as depicted in Fig. 1.

2.1. Pilot search and research question

2.1.1. Pilot search

As outlined above, we conducted a pilot search as part of the first phase in order to better our understanding of the examined field and the existing literature. We located the sources of literature by checking the results of a defined search string in different publishers' electronic databases (refer to Table 1). In addition, we used the pilot search to identify criteria for the inclusion and exclusion of literature following the suggestion of Denyer and Tranfield (2009), which is fully explained in Section 2.3.

2.1.2. The research question

A proper systematic literature review is based on a well-formulated, answerable question that guides the study (Counsell, 1997). Formulating a research question is the most crucial and probably the most difficult part of the research design, and devising a research question leads to selecting research strategies and methods; in other words, research is conducted on the foundation of research questions (Bryman,

Table 1
Search protocol for selected literature sources.

Database	Article parts searched	Fields searched	Search string	Time span
Science direct	Title, abstract, keywords	All fields	"artificial intelligence" AND "keyword"	2008–2018
Emerald insight	Title, abstract, keywords	All fields	"artificial intelligence" AND "keyword"	
JSTOR	Title, abstract, caption	Business, Public Policy & Administration, Management & Organisational Behavior, Marketing & Advertising, Finance	"artificial intelligence" AND "keyword 1" NOT "keyword 2" NOT "keyword 3" NOT "keyword 4"	
Wiley online library	Title, abstract, keywords	All fields	"artificial intelligence" AND "keyword 1" NOT "keyword 2" NOT "keyword 3" NOT "keyword 4"	
Taylor & Francis	Title, keywords	All fields	"artificial intelligence" AND "keyword"	

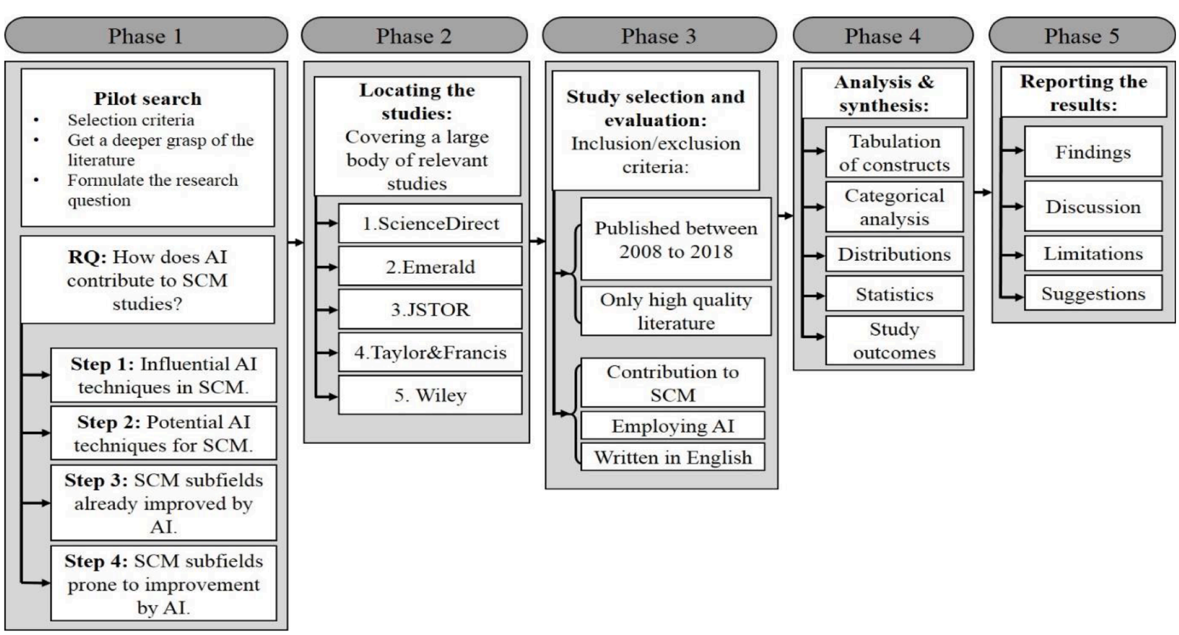

Fig. 1. Research process of systematic literature review.

2007). Conducting a pilot search led us to the question that this research is centred around: *how does AI contribute to SCM studies?*

To provide a clear answer to this question, we anatomised it into the following four sub-research questions (SRQs): (SRQ 1) Identify the most prevalent techniques of AI that are applied in SCM studies. (SRQ 2) Identify the potential AI techniques that can be employed in SCM research. (SRQ 3) Identify the subfields and tasks in SCM that have already been improved using AI. (SRQ 4) Identify the subfields and tasks that have high potential to be improved by AI. The aim of SRQs 1 and 3 is to analyse the existing literature and provide deep insight into the current state of knowledge for both researchers and practitoners. The aim of SRQs 2 and 4 is to identify potential gaps and opportunities for research and practical improvement and devise a guideline for future studies.

2.2. Locating the studies

In order to locate the relevant studies, we selected the search engine (s) and the search strings. Bearing in mind that we required databases providing broad access to a multitude of relevant literature over a specific period of time, we opted for five databases with large coverage of the peer-reviewed literature related to our research question; namely, Wiley Online Library, ScienceDirect, Emerald Insight, Taylor & Francis and JSTOR. These databases were explored using search strings specifically seeking contributions relevant to the topic (see Table 1).

As suggested by Rowley and Slack (2004), it is necessary to be very specific regarding the search strings. For this study, the search strings included “artificial intelligence” AND “keyword”. The keywords used were “supply chain”, “production”, “marketing” and “logistics”, which were extracted from the comprehensive definition of SCM by Boyer and Stock (2009). While the search protocols used to explore the individual databases were fundamentally the same, minor modifications were applied for each search engine to account for the search mechanisms of these databases. For ScienceDirect and Emerald Insight searches, for instance, the search string was applied to the title, abstract and keywords sections, while for Taylor & Francis, the search string did not include the abstract section. In order to obtain results for Wiley Online Library and JSTOR, we had to modify the search string to “artificial intelligence” AND “keyword 1” NOT “keyword 2” NOT “keyword 3” NOT “keyword 4”.

2.3. Study selection and evaluation

The primary search strings used were relatively broad to ensure that papers adopting different taxonomies were identified. Considering the inclusion and exclusion criteria from the pilot search, we identified 758 articles. The first criterion targets the time span of the literature, which is between 2008 and 2018, since the majority of the papers and a large number of new trends and applications contributing to this topic have emerged during this period. The second criterion focuses on relevance and quality: only peer-reviewed journal and conference papers were considered for the review, meaning book reviews, chapters, case reports, discussions and news articles are not included; in addition, each paper was read by two authors to ensure that the paper has the required quality. We applied a second set of criteria to exclude irrelevant papers. To avoid overlooking highly relevant articles and to mitigate the possibility of forming opinions that biased the relevance we attached to certain articles (Orwin et al., 1994), we defined a bespoke article inclusion protocol for reviewing titles, keywords and abstracts of studies. This additional set of selection criteria stipulate the following: (1) the article is written in English, (2) it employs AI as the main tool/perspective/focus, and (3) it contributes to the field of SCM.

To achieve an acceptable level of accuracy in applying the selection criteria, we reviewed an initial sample of 50 abstracts by two reviewers, checking the inter-code reliability throughout the process. The selection of articles was checked against the criteria, the results were compared and discussed, and issues were resolved in case of disagreement (Miles and Huberman, 1994). Application of these criteria reduced the number of selected articles for analysis and synthesis to 64. This process is highlighted in Table 2; numbers without parentheses show the initial results after the database search and the application of the inclusion/exclusion criteria from the pilot search, while numbers in parentheses are the selected papers after applying the second set of criteria.

2.4. Analysis and synthesis

In order to analyse the 64 articles, we broke them down into constituent parts based on a specific set of characteristics feeding back to our research question. These characteristics are as follows: the SCM field of the study (i.e. supply chain, production, marketing and logistics); the respective subfield(s) of the study; the AI technique(s) used; the outcomes and findings; and the industry that the study aims to improve. For synthesis, we strove to identify and describe the associations of the different characteristics.

2.5. Reporting the results

Targeting an academic audience, the results of this study are presented in the form of tabulations, statistics and discussions. Following the suggestion of Denyer and Tranfield (2009), the findings and discussion section encompasses a summary of the reviewed literature in terms of extracted data, highlighting what is known and what is unknown about the research question.

3. Analysis and synthesis

After gathering the appropriate collection of relevant papers, the data analysis and synthesis begins. Whereas the aim of the analysis is to breakdown each study into its constituent parts and describe the overall relationships and connections, the aim of synthesis is identify the associations between parts of different studies (Tranfield et al., 2003). Analysis and synthesis of this study are represented through the following subsections.

3.1. Distribution and statistics

Article type and date. Out of the 64 articles identified for review, 14 contribute to marketing, 6 to logistics, 23 to production and 21 to the general field of supply chain. As depicted in Fig. 2, the time span of this review was 2008 to 2018, with the literature being sourced from peer-reviewed journals and conference proceedings through a database search. 25% of the literature came from conference proceedings, and 75% were journal papers (Fig. 3).

3.2. Categorical analysis of the literature

Table 3 assigns the different articles to the SCM fields of marketing,

Table 2
Search results.

Subfileds	Science direct	Emerald insight	JSTOR	Wiley	Taylor & Francis	Total
	Artificial Intelligence					
Marketing	16 (10)	22 (1)	75 (1)	44 (1)	3 (2)	160 (15)
Logistics	44 (3)	5 (2)	41 (0)	13 (0)	2 (1)	105 (6)
Supply Chain	25 (15)	5 (2)	15 (1)	1 (0)	4 (2)	50 (20)
Production	209 (14)	23 (6)	94 (1)	112 (0)	5 (2)	443 (23)
Total	294 (42)	55 (11)	225 (3)	170 (1)	14 (7)	758 (64)

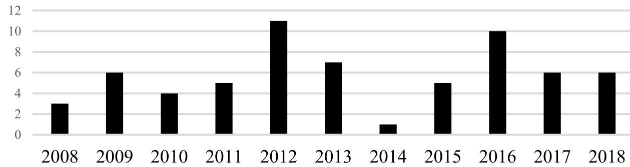

Fig. 2. Time distribution.

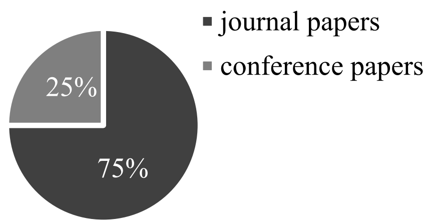

Fig. 3. Paper type distribution.

logistics, production and supply chain. We will now summarise the subfields and contents of each category.

A total of 14 articles can be assigned to the field of marketing. Three articles independently refer to sales: Lee et al. (2012) propose a system based on an artificial neural network (ANN) to forecast sales in the convenience store industry, Ketter et al. (2012) propose a real-time model for sales management using agent-based systems (ABSs), and O'Donnell et al. (2009) use a genetic algorithm (GA) to present an online system that helps sales promotion. Two articles address pricing: Shakya et al. (2010) use various AI techniques to propose a pricing system for diverse products and services, and Peterson and Flanagan (2009) use an ANN to suggest a pricing model with lower errors and greater precision. Two articles focus on segmentation: Casabayó et al. (2015) combine cluster analyses and fuzzy models to propose an approach for market segmentation, and Sarvari et al. (2016) use an ANN and k-means clustering for customer segmentation. Bae and Kim (2010) and Martínez-López and Casillas (2009) focus on consumer behaviour; the former use association rule and tree-based models to suggest an integrative consumer behaviour prediction model, whereas the latter use a genetic fuzzy system to propose a methodology for knowledge discovery in databases that supports consumers' decision behaviours. Stalidis et al. (2015) also use an ANN when proposing a marketing decision support framework. Rekha et al. (2016) explore the use of support vector data description to facilitate the selection of contacts. Martínez-López and Casillas (2013) carry out a historical literature review of AI-based systems applied to marketing. Kwong et al. (2016) propose a methodology of integrating affective design, engineering and marketing to define the design specifications of new products using a GA and fuzzy models. And, finally Taratukhin and Yadgarova (2018) suggest an approach for product life-cycle management (PLM) with multi-agent systems (MASs).

Seven articles belong to the logistics field. Two refer to container terminal operations and management: Salido et al. (2012) employ heuristics through a decision support system (DSS) to calculate the number of reshuffles needed to assign containers to the appropriate places, whereas Cardoso et al. (2013) use automated planning to propose a system for container-loading problems. Wang et al. (2012) propose an intelligent system for industrial robotics in the logistics field. Knoll et al. (2016) adopt a predictive inbound logistics planning approach, whereas Klumpp (2018) develops a multi-dimensional conceptual framework to distinguish between better- and worse-performing human–artificial collaboration systems in logistics. Eslikizi et al. (2015) address inter-organisational lot-sizing problems by implementing a set of self-interested and autonomous agents. Finally, Lee et al. (2011) examine how AI techniques and radio-frequency identification (RFID) can enhance the responsiveness of the logistics workflow.

Table 3
Summary of the categorisation of the literature.

Field	Subfield		Study
Marketing	Sales	forecasting	Lee et al. (2012)
		management	Ketter et al. (2012)
		promotion	O'Donnell et al. (2009)
	Pricing		Shakya, Chin, and Owusu (2010); Peterson and Flanagan (2009)
	Segmentation	Market	Casabayó, Agell and Sánchez-Hernández (2015)
		Customer	Sarvari, Ustundag and Takci (2016)
	Consumer behaviour		Bae and Kim (2010); Martínez-López and Casillas (2009)
	Marketing decision support		Stalidis, Karapistolis and Vafeiadis (2015)
	Direct marketing		Rekha, Abdulla and Asharaf (2016)
	Industrial marketing		Martínez-López and Casillas (2013)
	New products specification design		Kwong et al. (2016)
	Product life-cycle management		Taratukhin and Yadgarova (2018)
Logistics	Container terminal operations and management		Salido et al. (2012); Cardoso et al. (2013)
	General		Wang et al. (2012)
	Inbound Logistics Processes		Knoll, Prüglmeier and Reinhart (2016)
	Logistics systems automation		Klumpp (2018)
	Lot-sizing		Eslikizi et al. (2015)
	Logistics workflow		Lee et al. (2011)
Production	Assembly	lines	Kucukkoc and Zhang (2015)
		automation	Sanders and Gegov (2013)
	Production	monitoring	Olsson and Funk (2009)
		forecasting	Li, Chan and Nguyen (2013); Gligor, Dumitru and Grif (2018); Sheremetov et al. (2013)
		systems	Küfner et al. (2018); Ennen et al. (2016)
		planning and scheduling	Ławrynowicz (2008); Sousa and Tavares (2013)
		data	Quiñónez-Gámez and Camacho-Velázquez (2011)
	Integrated production management		Bravo et al. (2011)
	General		Mayr et al. (2018)
	Manufacturing	systems	Martinez-Barbera and Herrero-Perez (2010); Heger et al. (2016)
		decision support	Kasie et al. (2017)
		problem-solving	Camarillo, Ríos and Althoff (2018)
	Quality	control and improvement	Taylan and Darrab (2012)
		monitoring	Brandenburger et al. (2016)
	Product line optimisation		Tsafarakis et al. (2013)
	Workflow		Ma, Leung and Zanon (2018)
	Product-driven control		Trentesaux and Thomas (2012)
	Low-volume production		Munguia, Bernard and Erdal (2011)
Supply chain	Demand forecasting		Küfner et al. (2018); Amirkolaii et al. (2017); Bala (2012); García, Villalba and Portela (2012); Geem and Roper (2009); Mobarakeh et al. (2017);
	Facility location		Vargas Florez et al. (2015)
	Supplier selection		Ferreira and Borenstein (2012); Vahdani et al. (2012);
	Supply chain network design		Zhang et al. (2017)
	Supply chain risk management		Tsang et al. (2018)
	Inventory replenishment		Sinha, Zhang and Tiwari (2012)

(continued on next page)

Table 3 (*continued*)

Field	Subfield	Study
	Crisis management	Zgaya et al. (2009)
	Global value chains	Dias et al. (2009)
	Supply chain process management	Pino et al. (2010);
	General	Min (2010)
	Supply chain integration	Chong and Bai (2014)
	Supply chain planning	Ferreira and Borenstein (2011)
	Maintenance systems	Regal and Pereira (2018)
	Sustainability	Merlino and Sproġe (2017)

A total of 23 articles pertain to production. Kucukkoc and Zhang (2015) offer a GA-based model for parallel two-sided assembly line balancing problems, whereas Sanders and Gegov (2013) review some of the applications and examples of AI tools for assembly automation. Olsson and Funk (2009) present a CBR-based system for production monitoring. Three articles concentrate on production forecasting and all of them employ ANNs. For example, Li et al. (2013) evaluate the applicability of neural decision tree (NDT) for modelling petroleum production data in addition to comparison of the NDT and ANN approaches for prediction of petroleum production. Gligor et al. (2018) propose an ANN-based solution for forecasting the electricity production of a photovoltaic power plant, and Sheremetov et al. (2013) focus on different models, such as a feedforward neural network model and a Gamma classifier for forecasting in the time series context of petroleum engineering. In production systems, Küfner, Uhlemann, and Ziegler (2018) utilise decentralised data analysis for decentralised data reduction and information extraction; their model can also detect production faults and reduces machine maintenance costs. Ennen et al. (2016) implement a self-learning production ramp-up system. In production planning and scheduling, Sousa and Tavares (2013) present a study of different planning approaches, while Ławrynowicz (2008) proposes an AI-based methodology. Quiñónez-Gámez and Camacho-Velázquez (2011) offer an AI-based classification methodology for validation of production based on ANN, GA and data mining. Bravo et al. (2011) implement a distributed AI architecture to approach the problems of integrated production management. Mayr et al. (2018) identify and introduce exemplary application scenarios for knowledge-based systems. Martinez-Barbera and Herrero-Perez (2010) and Heger et al. (2016) address manufacturing systems using fuzzy logic (FL) and Gaussian models. Kasie, Bright, & Walker (2017) approach manufacturing decision support using case-based reasoning (CBR) and rule-based reasoning (RBR). Camarillo et al. (2018) address manufacturing problem-solving using CBR and a production-oriented approach In quality control and improvement, Taylan and Darrab (2012) demonstrate the use of AI techniques to propose an approach for the design of fuzzy control charts. In quality monitoring, Brandenburger et al. (2016) suggest a system for quality monitoring and data representation. The rest of the articles target various subfields of production: Tsafarakis et al. (2013) propose a hybrid particle swarm optimisation approach for product line optimisation; Ma et al. (2018) propose an AI-based workflow framework for steam-assisted gravity drainage (SAGD) reservoirs; Trentesaux and Thomas (2012) present the concept of product-driven control; and Munguia et al. (2011) propose a tool for the assessment and selection of rapid prototyping/manufacturing systems for low-volume production using ANN and FL.

20 articles relate to the supply chain. A significant portion of the articles in this field are concerned with forecasting. Five articles are devoted to demand forecasting. Efendigil et al. (2009) propose an AI forecasting mechanism modelled using ANNs and adaptive network-based fuzzy inference system techniques to manage the fuzzy demand with incomplete information. Amirkolaii et al. (2017) present a survey on forecasting methods used in supply chains to select the best-performing AI methods. Bala (2012) develop an AI forecasting model for retailers based on customer segmentation to improve the performance of inventory. García et al. (2012) propose an intelligent system for time series classification using support vector machines. Geem and Roper (2009) propose an artificial neural network model to efficiently estimate the energy demand. Mobarakeh et al. (2017) investigate forecasting methods, their variants and artificial intelligence (AI) methods to propose best method variant that is capable of accurate demand forecasting. Vargas Florez et al. (2015) propose an AI-based humanitarian facility location DSS that is able to adequately manage the response to a disaster despite failures or inadequacies of infrastructure and potential resources. Two articles focus on supplier selection: Ferreira and Borenstein (2012) suggest a fuzzy-bayesian supplier selection model, whereas Vahdani et al. (2012) suggest a neuro-fuzzy supplier selection model for the cosmetic industry. By means of ABSs and MASs, Ferreira and Borenstein (2011) present a simulation framework for supply chain planning, Zgaya et al. (2009) suggest a negotiation model, and several studies examine and elaborate the use of RFID technology integrated into an ICT framework (Dias et al., 2009; Parida et al., 2016; Oghazi et al., 2018). In a study, Zhang et al. (2017) propose an efficient bio-inspired algorithm for designing optimal supply chain networks in a competitive oligopolistic market. Tsang et al. (2018) propose an Internet of Things (IoT)-based risk monitoring system (RMS) specifically created with AI techniques in mind. Sinha et al. (2012) suggest an algorithm to solve the problem of inventory replenishment in the relationship between distributed plant, warehouse and retailer. Two articles concentrate on the SCM process: Pino et al. (2010) focus on a multi-agent supply chain system, and Merlino and Sproġe (2017) explore the main technological changes and the most advanced cases of augmented supply chains. A literature review by Min (2010) explores different subfields of AI that are suitable for solving practical problems relevant to SCM. Chong and Bai (2014) examine the predictors of open inter-organisational system adoption, using RosettaNet as a case study. Finally, Regal and Pereira (2018) conceptually model intelligent maintenance systems and spare-parts supply chain integration as a means to benefit areas such as AI, reasoning and context-aware systems.

3.3. AI techniques

Another characteristic we analysed was the AI technique that the articles used or revolved around. By "AI techniques", we mean algorithms, architectures, data or knowledge formalisms, and methodological techniques, that can be described in a precise, clean manner (Bundy, 1997). To conduct the analysis, we first identified the scientific sources that report a comprehensive list of AI techniques in practice and scientific literature. Studies by Chen et al. (2008) and Min (2010) introduce a group of AI techniques and their application. More comprehensively, Bundy (1997) presents a thorough catalogue of AI techniques as a reference work available for different purposes. Other references are mentioned independently of the source in which they are being cited. Table 4 presents the AI techniques used in every field of the literature, and Table 5 presents all the AI techniques used, along with their frequencies.

Most of the variety in terms of AI techniques can be seen in the field of production. Aside from the higher number of articles, this is primarily due to the practical nature of the literature in this field, which typically encompasses experimental research, case studies and real-life problem-solving studies. ANNs, GA and ABSs are the most frequently used techniques in production. With 12 techniques used, marketing is second in terms of variety, with the most frequent techniques being ANNs and GA, with four appearances each. The third-most-diverse field is supply chain, with 21 articles and 11 AI techniques. ANNs, fuzzy models and GA are more frequent in this field. Finally, logistics has the least variety, with eight techniques from seven articles.

Table 5 presents the total frequency of AI techniques through the entire literature. Since some articles employed more than one AI technique, the total frequency of AI techniques is greater than the number of articles. More precisely, 41 articles (64.1%) have a single-technique approach, 13 (20.4%) have a double-technique approach, three (4.6%)

Table 4
Categorisation of AI techniques based on fields.

Field	AI technique
Marketing	1.Artificial neural networks (4) 2. Genetic algorithm (4) 3. FL/modelling (3) 4. Agent-based/multi-agent systems (2) 5. Swarm intelligence (1) 6. Simulated annealing (1) 7.Association rule (1) 8.Tree-based models (1) 9.Support vector machines (1) 10.General forms of AI (1) 11.k-means clustering (1) 12. Hill climbing (1)
Logistics	1.Artificial neural networks (1) 2.Agent-based/multi-agent systems (1) 3.Data mining (1) 4.Simulated annealing (1) 5.Automated planning (1) 6. Robot programming (1) 7. General forms of AI (1) 8. Heuristics (1)
Production	1.Artificial neural networks (8) 2.FL/modelling (5) 3. Case-based reasoning (4) 4. Genetic algorithm (3) 5.Agent-based/multi-agent systems (2) 6. Data mining (2) 7.Decision trees (2) 8.General forms of AI (1) 9. Gaussian (1) 10. Rule-based reasoning (1) 11. Automated planning (1) 12.Swarm intelligence (1) 13.Expert systems (1)
Supply chain	1.Artificial neural networks (5) 2.FL/modelling (4) 3. Agent-based/multi-agent systems (4) 4. General forms of AI (4) 5.Physarum model (1) 6. Bayesian networks (1) 7.Swarm intelligence (1) 8.Data mining (1) 9.Support vector machines (1) 10. Stochastic simulation (1)

Table 5
Total frequency of AI techniques used.

AI techniques	Amount
Artificial neural networks	18
Fuzzy logic and models	12
Multi-agent and agent-based systems	9
Genetic algorithm	7
General forms of AI	7
Data mining	4
Case-based reasoning	4
Swarm intelligence	3
Support vector machines	2
Simulated annealing	2
Automated planning	2
Decision trees	2
Association rule	1
Tree-based models	1
Hill climbing	1
k-means clustering	1
Expert systems	1
Heuristics	1
Robot programming	1
Stochastic simulation	1
Bayesian networks	1
Physarum model	1
Rule-based reasoning	1
Gaussian models	1

have a multi-technique approach, and seven (10.9%) articles adopt a more generalised view on AI. It is noteworthy that studies used double or multiple AI techniques in two manners: by combining them and making a hybrid and by employing them in a sequential manner.

The most popular AI technique is ANN (used 15 times), which can be seen across all the fields. The second-most-frequent technique is FL/modelling (12 times), a technique capable of extending the simple Boolean operators as a means to express implications Bundy (1997). Intelligent agents, in the form of MASs and ABSs, are in third place (nine times), perhaps due to the wide range of their applications. GA is the next most popular technique (seven times), followed by data mining and CBR (four times each), swarm intelligence and support vector machine (SVM) (three times each), and simulated annealing and automated planning (two times each). The rest of the techniques – association rule, tree-based models, hill climbing, k-means clustering, expert systems, heuristics, robot programming, stochastic simulation, Bayesian networks, RBR, decision trees and Gaussian models – are used once.

3.4. Distribution of outcomes

Another factor on which the analysed literature is based is the outcome of the research. Like any scholastic methodology or purpose, every study has a unique outcome (an algorithm, a system, a methodology, etc.). Table 6 presents the studies' outcomes, which have been categorised by field.

Experimental/practical studies usually produce models, systems, frameworks, approaches, algorithms, methods and methodologies, whereas conceptual/philosophical studies deliver literature reviews, examples, concepts, ontologies, comparisons, forecasts and explorations. In line with this, we conclude that the selected marketing literature has an experimental/practical orientation, since the majority of results adopt forms similar to those just outlined. For the same reason, logistics is considered to have an experimental/practical orientation. Furthermore, whereas approximately 25% of the production literature

Table 6
Distribution of outcomes.

Field	Outcome	Amount	%
Marketing	Model	4	28.5
	Approach	3	21.4
	System	2	14.2
	Methodology	2	14.2
	Framework	1	7.1
	Method	1	7.1
	Literature review	1	7.1
Logistics	System	4	57.1
	Approach	2	28.5
	Framework	1	14.2
Production	Approach	6	26
	System	4	17.3
	Methodology	2	8.6
	Framework	2	8.6
	Application and comparison	1	4.3
	Application scenario	1	4.3
	Applications and examples	1	4.3
	Architecture	1	4.3
	Model	1	4.3
	Concept	1	4.3
	Concept and applications	1	4.3
	Assessment tool	1	4.3
	Comparative study	1	4.3
Supply chain	Model	6	28.5
	System	4	19
	Method	3	14.2
	Algorithm	2	9
	Forecast	1	4.7
	Ontology	1	4.7
	Literature review	1	4.7
	Exploration	1	4.7
	Framework	1	4.7

produced conceptual/philosophical outcomes, the bulk of the results in this field are experimental/practical. Finally, SCM – with fewer than 25% of conceptual/philosophical outcomes – is considered experimental/practical.

4. Discussion

To answer the main RQ, the following four SRQs are devised to provide a clearer and more comprehensive answer. In this part, we strive to provide responses to each of these steps.

SRQ 1: What are the most prevalent AI techniques applied in SCM studies?

Although many AI techniques can be applied to SCM, the results of our study show that some are used more than others. The most prevalent and influential is ANNs, an information-processing technique that can be used to find patterns, knowledge or models from an extensive amount of data (Aleksendrić and Carlone, 2015). ANNs are normally based on mathematical regression to correlate input and output streams from and to process units. Such models predominantly depend on a large number of experimental data (Yang and Chen, 2015). ANNs are typically used as the main technique in computational intelligence due to their impressive versatility (Kasabov, 2019). In SCM, such applications range from sales forecasting, marketing DSSs, pricing and customer segmentation to production forecasting, supplier selection, demand management and consumption forecasting. Li (1994) argues that ANNs are increasingly popular in today's business fields. This is mainly due to their capability of solving data-intensive problems in which the rules or algorithms for solving the problem are unknown or difficult to express (Chen et al., 2008).

The second technique is FL/modelling, which represents the border between AI and non-AI techniques (Bundy, 1997). While it has been approximately 40 years since Zadeh (1965) first introduced the FL theory, it has only recently become a prominent technique for developing complicated models and systems. The reason for this rapid development, as well as for its growing popularity, is that such an approach addresses qualitative information perfectly in that it resembles the manner in which humans make inferences and decisions (Keramitsoglou et al., 2006).

Another group of techniques that are frequently used in SCM studies is that of ABSs and MASs. An agent-based model is a type of computational model that simulates the actions and interactions of autonomous agents, either collectively or individually, while considering the assessment of their influences on the system in general. This technique merges elements from complex systems, game theory, computational sociology and evolutionary programming (Grimm and Railsback, 2005). In other words, agents are entities capable of perceiving the surrounding environment and can act autonomously and proactively to solve specific problems. When agents interact with one another to achieve goals, they form MASs, i.e. a network of agents (Lesser, 1995), Functioning as a piece of software containing code and data (Parrott et al., 2003), they are capable of modelling, designing and implementing complex systems. It is for this reason that since the mid-1990s, agents have been widely employed in SCM and other fields to solve several types of problems. Examples of applications include distributed supply chain planning (Frayret et al., 2007), design and simulation of supply chain systems (Barbuceanu et al., 1997), analysis of the complex behaviour of supply chains (Avci and Selim, 2017; Wang et al., 2012) and negotiation-based collaborative modelling (Jiao et al., 2006).

Results show that one of the most influential AI techniques in the SCM literature is Gas, a search technique mimicking natural selection (Kraft et al., 1997), in which the algorithm evolves to the point at which it has adequately solved the problem. Introduced in the 1970s, GAs are a group of computational models inspired by evolution. These algorithms encode a potential solution to a particular problem using a data structure similar to chromosomes. They apply recombination operators to these structures in such a manner as to preserve crucial information. GAs are often regarded as function optimisers, and the range of problems to which GAs have been applied is quite extensive (Whitley, 1994). As an AI technique, GAs address various categories of combinatorial decision problems. These problems encompass complicated managerial challenges regarding supply chain activities of selling, sourcing, making and delivering goods or services. GAs have increased their role in developing managerial decision-making processes, improving supply chain efficiency as a result (Min, 2015). GAs have become a popular technique in many SCM studies due to their wide range of applications, including multi-objective optimisation of supply chain networks (Altiparmak et al., 2006), partner selection in green supply chain problems (Yeh and Chuang, 2011), multi-product supply chain networks (Altiparmak et al., 2009) and the problem-solving approach to closed-loop supply chains (Kannan et al., 2010).

Data mining is a new discipline that has arisen by combining several other disciplines, stimulated mainly by the growth of gigantic databases (Hand, 2013). The primary motivating stimulus behind data mining is that these big databases contain information that is valuable to the database owners in that it provides insight into decision-making and other processes. In SCM, data mining could be used in several manners, such as controlling and monitoring warehouses, food supply chains and sustainability in supply chains (Ting et al., 2014; Wang and Yue, 2017), improving knowledge management and marketing (Shaw et al., 2001), and enhancing supply chain innovation capabilities (Tan et al., 2015).

Several studies employ CBR, a technique based on the cognitive psychological notion that humans find their knowledge through solving multiple problems (Clifton and Frohnsdorff, 2001). Functioning as a paradigm of cognitive science and AI, in which the reasoning procedure is modelled as primarily memory-based, CBR solves new problems by retrieving gathered and saved "cases" of analogous problem-solving episodes and by adapting the solutions to match new needs (Leake, 2001). CBR has been used in SCM studies in a number of manners, such as designing mechanisms for supply chains under demand uncertainties (Kwon et al., 2007), supply chain risk management (Giannakis and Louis, 2011), supplier performance evaluations (Humphreys et al., 2003), agile SCM (Lou et al., 2004), and supply chain negotiations (Fang and Wong, 2010).

Forming part of collective intelligence, swarm intelligence studies the behaviour of social insects by determining their efficiency at solving complicated problems, such as finding the shortest route between their nest and food source or organising their nests (Saka et al., 2013). Over the past 20 years, such a technique has attracted considerable attention in almost every area of engineering, science and industry (Yang and Karamanoglu, 2013). In SCM studies, it is usually utilised for the designing of systems for pricing, product line optimisation (Tsafarakis et al., 2013), inventory replenishment (Sinha et al., 2012), supply chain network architecture optimisation (Kadadevaramath et al., 2012), and minimisation of supply chain costs (Kumar et al., 2010) and the designing of agile supply chain networks (Bachlaus et al., 2008).

Another technique employed in the AI-SCM literature is SVMs, an approach that uses a linear classifier to classify data (Peter et al., 2019) that is capable of deciphering subtle patterns in noisy and complex data sets (Hongmao, 2016). SVMs were introduced in the 1990s and have been widely used in numerous applications (Gholami and Fakhari, 2017). In terms of SCM, they have been used in numerous studies and for different purposes, such as supply chain demand forecasting (Carbonneau et al., 2008), time-series classification in supply chains (García et al., 2012), supplier selection (Guosheng and Guohong, 2008), and the designing of systems for supply chain networks (Surana et al., 2005).

In addition to the leading AI techniques discussed thus far, there are various other techniques that are applied to SCM studies, including simulated annealing, automated planning, association rule, tree-based models, hill climbing, k-means clustering, expert systems, heuristics, robot programming, stochastic simulation, Bayesian networks, the Physarum model, RBR, decision trees and Gaussian models.

SRQ 2: What are the potential AI techniques that can be employed in

SCM research?

There are many AI techniques that have received less or even no attention from SCM researchers, despite their appropriateness for inclusion in future SCM studies. One of the most promising of these is natural language processing (NLP): the study of computer programs that take human (natural) language as input. Applications of NLP deal with tasks ranging from the low level (such as assigning parts of speech to words) to the high level (such as providing specific answers for questions) (Cohen, 2014). In other words, NLP is the use of computers to understand and then process human language in the form of text or speech (Geman and Johnson, 2001). Machine translation (the automatic translation of text or speech from one language to another) began with the very earliest computers (Kay et al., 1994) and is now being widely used in many tasks in different businesses. NLP interfaces also permit computers to interact with humans using natural language, such as to query databases (Geman and Johnson, 2001). This feature allows NLP to be an important facilitator in SCM, mainly due to its potential to enhance and simplify human–machine interactions. Text mining is an example of NLP at its most practical: finding information in prose of various types (Cohen, 2014) to aid production, manufacturing and logistics. Such a process can also accelerate industrial procedures and improve the process of data generation and collection as a result of simplified interactions between humans and machines. Most NLP systems are based on formal grammar; that is, a description of the language. Such systems usually identify the language from the sentences and provide descriptions by defining, for instance, the phrases of the sentence, their interrelationships and certain aspects of their meanings (Geman and Johnson, 2001). The advanced use of this process is evident in chatting robots or "chatbots", which are being used increasingly in today's world. Chatbots on social networking platforms and websites represent a new innovation in computer-based marketing communication (Van den Broeck et al., 2019). The use of NLP in the form of chatbots has great potential in marketing campaigns, online advertisement, brand management, customer relationship management and data collection. As a means for improved relationships with customers (Letheren and Glavas, 2017), chatbots present a commercially savvy tactic, having been introduced to Facebook messenger in 2016 as a means for companies to accelerate and facilitate their customer service processes (Van den Broeck et al., 2019).

Tabu search (TS) is a neighbourhood search method that avoids local minimum traps by accepting worse (or even infeasible) solutions and by limiting the current solution neighbourhood to the solutions' search history (Pióro and Medhi, 2004); in other words, TS is a local search algorithm that restricts the feasible neighbourhood by using excluded neighbours (Edelkamp and Schrödl, 2012). Since the search history is stored as a Tabu or in a forbidden list, the attribute-based Tabu memory helps to diversify the search by avoiding short-term cycles or sequences of similar solutions (Pióro and Medhi, 2004). The main idea of this technique is to prevent the search from becoming stuck in local minima by preventing backward moves (Dechter, 2003). Similar to simulated annealing, TS is not foreign to SCM, having been employed to solve the problem of closed-loop supply chain networks (Easwaran and Üster, 2009), as well as to redesign multi-echelon supply chain networks (Melo et al., 2012). However, this technique has potential for wider and deeper use in SCM. Lately, metaheuristic techniques, such as simulated annealing, GAs and TS, have been proposed to solve certain optimisation problems (Glover and Marti, 2006), with the evidence suggesting that TS is often overlooked in favour of these.

In the area of robotics, a robot is defined as a system of rigid bodies or links connected by joints. Bundy (1997) names robot dynamics and robot programming as specific AI techniques. These systems have been in use for a long time, and every now and then, a new application is developed. While robot dynamics concentrates on the problems of calculating the acceleration of a robot for simulation and control, robot programming tells a robot (a mechanical device in conjunction with an electronic system) what to do. Moreover, the need for a more agile supply chain is now deemed necessary by consumers that want faster and error-free deliveries.

A Markov decision process (MDP) is often defined as a framework with which to model decision-making, whereby the outcome is partially based on the input of the decision maker and partially random. Littman (2001) argues that MDPs make models in sequential, stochastic environments; the nature of the model is that an agent or decision maker inhabits an environment that changes state randomly in response to action choices made by the decision maker. The environment influences the instant reward obtained by the agent, in addition to the probabilities of future state transitions. The agent's goal is to select actions that maximise the long-term pay-off of the reward. MDP can also be used for planning optimisation, allowing the decision maker to determine at what states specific actions should be taken.

Another AI technique that has not been used to its full potential in SCM is that of expert systems; while our review shows some degree of utilisation, this technique has a lot to offer. Expert systems are predominantly used in the fields of reasoning and decision-making in that they emulate the decision-making abilities of humans. This technique can be employed in DSSs, particularly in terms of lot-sizing and supplier/buyer selection.

SRQ 3: What are the subfields and tasks in SCM that have already been improved using AI?

To elaborate on the contributions of AI on SCM subfields in more detail, we need to take a closer look at the outcomes of the studies and the influences of AI on the literature. In the subfield of marketing, ANNs have a strong impact, both when used solely or in combination with others. In terms of the latter, a combination of self-organisation map neural networks and radial basis function neural networks has been used to create an "Enhanced Cluster and Forecast Model", which, in comparison to other similar models, is easier to build, has higher accuracy and is suitable as a forecasting system in real-world sales campaigns. ANNs are also used to improve marketing DSSs by increasing accuracy, with an ANN-based marketing support framework being devised to provide automatic classification of unknown cases, done not by performing a new data analysis but rather by generalising the knowledge derived from already-analysed examples. Furthermore, ANNs are used to develop customer segmentation – an approach that is vital in marketing campaigns – and improve customer segmentation. Fuzzy models are the second-most-prevalent technique in the literature, having been used to make an innovative segmentation approach that combines cluster analyses and fuzzy learning techniques to produce higher accuracy. Pricing, one of the components of the marketing mix, is enhanced by a multi-level ANN-based model, which generates significantly lower pricing errors, has greater pricing precision out-of-sample and extrapolates better from more volatile pricing environments compared to hedonic models (which typically utilise large numbers of dummy variables). Another pricing system, which employs a combination of a GA, swarm intelligence, simulated annealing and hill-climbing techniques, has been developed for a range of products and services to optimise price and production policies. A particular advantage of such a system is the significant reduction in the cost of implementing, and the increased expressiveness of, the revenue management model.

Consumer behaviour has been extensively studied in the management science and operations management community (Wei and Zhang, 2018), with AI being a particular influence. On a related note, it is worth acknowledging that current AI approaches are developed by combining various AI techniques, rather than by employing a singular AI technique. Target marketing strategies often combine the association rule and tree-based models within an integrated model to predict whether a customer buys a specific product, with the results demonstrating good performance compared to other models. Moreover, GA and fuzzy models have been combined to devise a brand-new complete methodology for knowledge discovery in databases, to be applied in marketing causal modelling and with utilities to be used as a marketing management decision support tool for consumer behaviour. Development of technologies can result in effective and efficient sales management (Madhavaram and McDonald, 2010), and the current digitisation shift will have profound implications for personal selling and sales management functions (Syam and Sharma, 2018).

In sales, GAs have been used to devise an online system for reducing the bullwhip effect along supply chains, from which an optimal ordering policy for each member of the supply chain can be determined, which in turn reduces both costs and the bullwhip effect. Moreover, ABSs have been employed to create a real-time sales management model with the ability to predict future economic conditions to make tactical sales decisions. This AI-based model outperforms more traditional short- and long-term predictive modelling approaches. The concept of direct marketing has gained popularity in recent years (Ładyżyński et al., 2019), allowing producers to customise their product properties for individual customers in a unique manner, thus increasing campaign efficiency and reducing costs (Hossein Javaheri et al., 2014). To improve the process of direct marketing, SVMs have been used to develop a method that is able to predict with higher accuracy compared to existing methods.

The field of industrial marketing has evolved profoundly since it was first introduced in 1971, with part of this evolution being the inclusion of research in SCM (Ellram and Ueltschy Murfield, 2019). As a revolutionary factor of Industry 4.0, AI-based systems applied to industrial marketing have been an influential and important part of the current literature. Another field that has been improved by AI is PLM. A multi-agent approach for PLM, which integrates business and engineering knowledge during the whole product life cycle, has yielded improved performance. Finally, GA and fuzzy models have been merged to develop a methodology in which affective design, engineering and marketing are integrated simultaneously as a means to define the design specifications of new products.

According to the literature, the focus in logistics is predominantly on two subfields: first, container terminal operations and management and second, lot-sizing. Within these subfields, it is common to see DSSs used to assist terminal operators in finding the most appropriate solution in each particular case. To this end, a heuristic planner (that calculates the number of reshuffles needed to assign the containers to the appropriate places) and a greedy randomized adaptive search procedure (that generates an optimised order of vessels to be served according to existing berth constraints) are combined to solve the berth allocation problem and the quay crane assignment problem. Metaheuristics are general high-level processes that coordinate simple rules and heuristics to find appropriate or optimal approximate solutions to computationally difficult combinatorial optimisation problems (Aiex et al., 2002). GRASP (Feo and Resende, 1995) is a multi-start or iterative metaheuristic in which every iteration comprises two phases: construction and local search. The former creates a solution; if it is not feasible, then a repair procedure should be applied.

Automated planning is an AI technique that studies a deliberation process that chooses and organises actions by anticipating their expected outcomes computationally (Ghallab et al., 2004). It is often employed to create a fully automated system, capable of carrying out the entire loading process through the information relating to the products, the industrial plant and the transporting devices. In lot-sizing, ABSs are used to develop a simulation framework for supply chain planning, which is able to capture all aspects of the sample supply chain and to model the regulations not only by highlighting their simple external constraints but also by incorporating them in the decision-making process of each agent. As such, the agents can quickly respond to norms and adapt their behaviour to find more adequate strategies with which to plan the operation of the supply chain. In addition to ABSs, simulated annealing has been utilised to respond to an inter-organisational lot-sizing problem in a more efficient, cost-effective manner. The inbound logistics process is another related subfield that has been improved by using an approach based on data-mining techniques. AI has been used to develop a multi-dimensional conceptual framework that aids in the planning of human–artificial collaboration systems in logistics systems automation by distinguishing between the performances of such systems ex ante for investment decision purposes. Finally, robot programming is used to improve real-life strategies in the form of an intelligent system for industrial robotics in logistics.

In the field of production, 18 subfields have been addressed using AI techniques. Assembly lines and automation are addressed by GAs, fuzzy models, ANNs, and CBR, which has led to more sufficient algorithms and improved performances. Production forecasting has received focus from several studies employing decision trees and ANNs to devise models and approaches that are more efficient and demonstrate competitive performance. The three subfields of manufacturing – systems, decision support, and problem-solving – are influenced by Gaussian models and FL, CBR and RBR, and CBR, respectively. This has led to an improved dynamic approach for parameter adjustment of dispatching rules, an enhanced automated guided vehicle system, a less complex decision support framework and a novel approach for solving manufacturing problems. Quality monitoring, control and improvement has been addressed by data mining and FL, leading to the creation of a precise system for quality monitoring and data representation and a systematic approach for designing fuzzy quality control tools. Production planning and scheduling are influenced by expert systems, GA and automated planning, which has led to improved methodologies and approaches. Production monitoring, systems and data are addressed by CBR, ANNs, and data mining, ANNs and FL, respectively. This has resulted in high-performing monitoring systems, a decentralised data analysis integration concept with higher accuracy and an adaptable AI-based classification methodology for validation of production data. MASs and ABSs are utilised to enhance subfields of integrated production management and production systems, leading to highly effective architecture and a more stable self-learning production ramp-up system. Swarm intelligence – the collective behaviour of decentralised, self-organised systems (Beni, 2009) – has been utilised to address product line optimisation by constructing an approach for optimal industrial product lines. The concept and applications of product-driven control are addressed by MASs, with the expected advantages and the related problems also being discussed. Being the most prevalent AI technique in the literature, ANNs have been employed to enhance production workflow by creating a workflow framework that identifies associated shale heterogeneities in SAGD reservoirs based on features extracted from production time-series data. ANNs, in combination with FL, have been used to build a more effective tool for assessing and selecting rapid prototyping/manufacturing systems for low-volume production.

Supply chain demand forecasting and management has remained the centre of focus for SCM, with ANNs, fuzzy models, data mining and SVMs leading to forecasting methods with higher accuracy, improved performances and more effective approaches. Supplier selection is another important topic that has attracted attention from researchers. In this subfield, Bayesian networks, ANNs and FL are utilised, resulting in supplier selection models with greater effectiveness and performance. In supply chain, MASs have been employed to simulate a SCM process management network and propose a standard one. In other subfields, the use of stochastic simulation has led to the creation of a new humanitarian facility location DSS, Physarum models being used to increase the efficiency and practicality of supply chain network designs, and FL being utilised to enhance the effectiveness of risk management and monitoring systems. A co-evolutionary immuno-particle swarm optimisation algorithm has addressed the problem of inventory replenishment in distributed plants, warehouses and retailers by using an algorithm that is superior to conventional ones in terms of cost-effectiveness. For supply chain planning, ABSs have been employed to design a framework that quickly reacts to norms and adapts to find better strategies. Crisis management has become an important issue due to globalisation and outsourcing, and supply chains have become more exposed to disruptive external incidents (Ponis and Ntalla, 2016). AI researchers have addressed this issue using MASs and have developed an architecture characterised by independent agent zones sharing information that focuses on provision balancing in order to avoid stock-out conditions and effective resource balancing to reduce risk and the bullwhip effect. As a growing engineering discipline, intelligent maintenance relates to the analysis of multivariate data from multiple sources and provides users with information about systems, products and machines (Lapira et al., 2013), from which a conceptual model of intelligent maintenance systems and spare-parts supply chain integration has been devised. Consumption forecasting is addressed through SVMs and ANNs, which have been used to develop an improved oil consumption forecasting model. Exploration of the main technological changes in sustainable supply chains has been performed from an AI perspective, ranging from material handling (Martinez-Barbera and Herrero-Perez, 2010) to production and distribution (Merlino and Sproģe, 2017). Global value chains and supply chain integration are addressed through the use of MASs and ANNs, respectively, which has led to improved models and forecasts.

It is noteworthy that the degree of focus on different topics varies, with some topics not receiving any attention at all, deemed here to be gaps in the literature. In general, in marketing, the subfields of sales and segmentation have received the most attention, while pricing, consumer behaviour, marketing decision support, direct marketing, industrial marketing and PLM have received less, despite all employing AI techniques. In logistics, container terminal operations and management received more attention than the other subfields of inbound logistics processes, logistics systems automation, lot-sizing and logistics workflow. In production, the subfields of assembly, quality, manufacturing and forecasting were more frequently cited compared to product line optimisation, workflow, product-driven control and low-volume production. In supply chain, the subfield of demand forecasting was the most commonly cited, while supply chain integration, supply chain planning, supplier selection, supply chain network design and supply chain risk management received less attention.

SRQ 4: What are the subfields and tasks that are likely to be improved by AI?

AI is an industry 4.0 technology that is capable of revolutionising many industries and fields (Kearney et al., 2018; Townsend and Hunt, 2019). As such, almost all the fields of SCM, as well as its subfields, are prone to being influenced by AI.

Discussing marketing mix, Kotler (1982) looks at price, place, promotion and product. Our results show that most marketing articles that focus on AI revolve around price, sales and segmentation, with less attention given to promotion, product and place. Overall, sales promotion, advertising, inventory, sales force, public relations and direct marketing are the subfields that can be improved dramatically through the use of AI.

Taking logistics as an example, distribution and transportation, logistics hub management, healthcare logistics and logistics risk management are likely to be improved with AI due to both their applicative potential and the lack of research in this field. In supply chain, the subfields of buyer selection, financial SCM, automated replenishment, smart warehousing and green supply chain are those in need of more attention from an AI perspective. Finally, in production, subfields such as mega-projects management and advanced project process management are important topics for consideration.

5. Conclusion

Recent breakthroughs in computing power have enabled the growth and complexity of AI applications. Building on this further, the aim of the current research was to clarify how AI contributes to SCM studies based on a systematic review of the literature. We examined 64 articles published that were identified through five phases. Our findings suggest that among several different AI techniques available, some have been employed in a wider range in comparison to others. Our results indicate that the most prevalent AI technique is ANNs, which are usually used to find complex patterns that humans cannot find. ANNs can be applied to several categories of problems, including pattern classification, approximation, optimisation, clustering, function, prediction, retrieval by content and process control. The second-most-commonly used technique is FL, which is a form of multiple-valued logic that handles the concept of partial truth. As Bundy (1997) argues, FL extends the simple Boolean operators by providing and presenting a series of implications. In contrast with conventional set theory, in which an object is either a member of a set or not, a fuzzy set takes any value between 0 and 1. As such, fuzzy models can describe vague statements through natural language (Chen et al., 2008). Results show that FL is widely used as a modelling tool and is also a popular technique for creating hybrid intelligent systems. The third technique is ABS/MAS, which has a broad application in SCM. This prevailing technique works by perceiving the surrounding environment, followed by acting autonomously and proactively to solve a specific problem. Agents have been extensively used in SCM to solve several types of problems in supply chain planning, design and simulation of supply chain systems, analysis of the complex behaviour of supply chains and negotiation-based collaborative modelling.

Other major techniques that can be considered prevalent in the literature are GAs, a type of search technique that mimics natural selection that is capable of tackling various categories of combinatorial decision problems; data mining, which can be employed to provide insights and make decisions from big data sets; CBR, a cognitive psychological-based technique that solves new problems by retrieving gathered and saved cases of analogous problem-solving episodes and adapting the solutions to match new requirements; swarm intelligence, which mimics behaviour of social insects to solve complicated problems; and SVMs, which use a linear classifier to classify data to decipher subtle patterns in chaotic data sets. Other less prevailing AI techniques used in SCM studies include simulated annealing, automated planning, association rule, tree-based models, hill climbing, k-means clustering, expert systems, heuristics, robot programming, stochastic simulation, Bayesian networks, the Physarum model, RBR, decision trees and Gaussian models. These techniques have been used in SCM studies but not as frequently as ANNs, FL, ABSs, GA, data mining, CBR, swarm intelligence or SVMs, which make for an interesting gap that should be addressed in future research. In addition, our findings reveal a number of AI techniques in need of further research and industrial adoption, such as NLP (machine–human interactions), TS (optimisation, robot dynamics, and programming that focuses on creating intelligent robots) and MDP (a framework for modelling the decision-making process).

Furthermore, we find that the network-based nature of SCM and logistics provides a natural framework with which to implement AI. A network of suppliers, for instance, generates large amounts of data and requires agile decision-making. As such, using AI tools for big data analysis and DSSs is highly recommended. In addition, SCM companies depend on physical and digital networks that must function harmoniously amidst large volumes, lean asset allocation, low margins and time-sensitive deadlines. AI facilitates optimisation and improving network orchestration in an efficient manner, which cannot be achieved by humans. Therefore, research on interactive decision-making systems promotes a deeper understanding of AI solutions and accordingly improves the capabilities of such solutions. Using such systems allows AI to help this industry redefine today's practices by transitioning operations from reactive to proactive, processes from manual to autonomous, services from standardised to personalised and production planning from forecasting to prediction. Improvements in computer chip technology are an essential part of the widespread use of AI. Since logistics is concerned with transportation, employing computer chips for tracking is a vital step. Since tracking generates large amounts of data that can be analysed and interpreted for many different purposes, research on such processes for the outcome of these technologies is necessary. As an important part of marketing, automation of customer interactions is a new yet promising area. Voice or chatbots represent a new generation of customer service, with high productivity levels and acceptable returns on investment. Since these virtual assistants are developed to allow more complex dialogues with customers, their use can be profoundly effective for automation of customer service enquiries.

6. Limitations and implications

Like any other study, this research has limitations. Conducting a literature review in order to identify the research gaps and evaluate the current knowledge in the field can lead to a broad perspective. Since we aimed to cover a wide-reaching body of knowledge with several subfields, we were unable to cover the details of every study. Therefore, a more focused and single-technique evaluation is highly recommended.

This study has both managerial and theoretical implications that can be applied to research and practice in SCM. First, this study contributes to theory by analysing and discussing the state-of-the-art of AI in SCM. In this regard, the most prevalent AI techniques applied in SCM studies are covered in order to provide a comprehensive perspective on the existing literature on the topic. Answering the second SRQ, the potential AI techniques that can be employed in SCM research are discussed. The aim here was to offer a wider range of less-popular techniques that might become more influential in future research. The third SRQ addressed the subfields and tasks in SCM that have already been improved using AI. The aim of this discussion was to analyse the existing literature that can be the foundation of future studies. Moreover, it allows researchers to identify what has been done already. Answering the final SRQ, the subfields and tasks that are likely to be improved by AI are discussed to provide insight for future studies in the field. In addition to these four parts, this study explains the existing gaps and future research opportunities that can improve the body of the literature. Not only can this pave the way for future researchers but also it can act as a structured guideline that prevents repetition and bias in conducting AI-SCM studies.

The results of our study have some implications for managers and practitioners as well. Here, we suggest the following notions and guidelines:

GAs have a vast set of applications that not only contribute to scientific research but also have increased its role in developing managerial decision-making processes and improving supply chain efficiency (Min, 2015). GAs have become a popular technique due to its applicability to multi-objective optimisation of supply chain networks (Altiparmak et al., 2006), partner selection in green supply chain problems (Yeh and Chuang, 2011), multi-product supply chain networks (Altiparmak et al., 2009) and the problem-solving approach towards closed-loop supply chains (Kannan et al., 2010). Hence, we suggest that managers employ GA-based solutions in the form of bespoke software to address the existing supply chain problems.

Another AI technique that has the potential to revolutionize the future of SCM is NLP. Various applications of this technique are already available; however, the full potential of NLP is yet to be discovered. Currently, NLP is employed in the form of chatbots used in marketing campaigns, online advertisement, brand management, customer relationship management and data collection.

Glover et al. (2008) highlight a wide range of applications for TS in terms of SCM, including workforce planning, machine scheduling, transport network design, network design for services, flexible manufacturing, just-in-time production, multi-item inventory planning, volume discount acquisition, project portfolio optimisation, vehicle routing and multi-mode routing. This paper therefore sees TS as another potential technique for further utilisation for supply chain researchers, managers and practitioners.

Robots have various applications, as seen in manufacturing and warehouse logistics (e.g. Amazon Robotics). While robot dynamics and robot programming are not new in SCM (particularly in terms of the practical aspects of manufacturing, production and warehousing), the vast potentials of these areas have not been fully utilised. Within the broad subfields of SCM, our study reveals limited use of these techniques, such as packaging and container terminal operations, which are likely to see further robotic influence going forward. Therefore, not only can researchers conduct exhaustive literature reviews or empirical studies on automatic robots but also managers can benefit from the vast applications of intelligent robots in logistics, warehousing, manufacturing and production.

Like other decision-making models, managers can utilize MDPs in SCM processes and tasks; although this technique has a limited use, it has robust potential for utilisation in SCM. MDP is mainly applicable to planning optimisation, allowing the decision maker to determine at what states specific actions should be taken.

Expert systems can assist SCM managers in the form of DSSs, particularly in dealing with lot-sizing and supplier/buyer selection issues. Furthermore, other planning-oriented techniques of AI, such as distributed problem-solving and hierarchical planning, are also useful for SCM managers. Due to the forward-looking nature of supply chain planning, such techniques are potentially applicable to this field as well.

7. Further research

Although some studies provided insights into the use of AI in SCM, there are still many scientific gaps. Scrutinising the collected literature, we identified several research suggestions that were either made by authors or elaborated on through the literature analysis and synthesis itself. For instance, we found that while supply chain integration has been addressed by AI researchers (Regal and Pereira, 2018), there is still a need for more research on this topic in order to uncover more detail and to improve the scientific evidence. Based on this aforementioned scientific gap, effort could be made in the form of using ABSs with advanced complexity management capabilities for solving problems in supply chain integration. Such ABSs could also be applied to supply chain risk or disaster management issues, both of which are recognised gaps (Min, 2010).

Real-time pricing (RTP) is an important demand-side management factor for adjusting the load curve to achieve peak load shifting, and as stated in the literature (e.g. Min, 2010), it has the potential to be covered on a deeper level using AI. It is also recognised that research on RTP is partially country-oriented, with the majority of studies focusing predominantly on China (Jiang et al., 2019; Sun et al., 2018; Wang et al., 2018). Hence, we suggest more studies with a focus on non-Chinese markets.

Reverse auctions, in which sellers bid for the prices at which they are willing to sell their products, as mentioned by Min (2010), are a major gap in the literature, particularly from an AI perspective. We suggest more research on reverse auctioning involving supply chain partners using AI techniques, such as heuristic pricing methods.

Answering the second SRQ (identifying the AI techniques that have the potential for employment in SCM studies), we suggest utilising the following AI techniques in future research to ameliorate the current knowledge gap. First, NLP is an interesting and promising field with potential to significantly affect the SCM literature and practice by merging with other Industry 4.0 technologies such as IoT and blockchain. Second, due to the optimisation algorithm that can control an embedded heuristic approach, we believe that TS deserves more scientific focus in SCM studies in the future. Third, due their great applicability in manufacturing, production, warehousing and logistics, robot dynamics and programming provide a profound scientific basis for future research. Finally, automated planning, which has significant roles ranging from controlling space vehicles to programming robots, requires further attention to make new opportunities for synergy between theory and practice.

Rule-based expert systems, which are primarily based on sets of "if-then" statements, can be developed in the form of an assistant in logistics for outsourcing or manufacturing contract decisions, and such a process (Min, 2010) warrants further research.

While studies on transportation and mobility are not limited (e.g.

Dimitrakopoulos et al., 2020; Franklin and Paez, 2018; Redding and Turner, 2015), our literature review implies a gap in terms of the use of AI techniques in this area. Such a gap could be remedied by devising, for example, a hybrid meta-heuristic to integrate the AI traits of GAs with those of ant colony or other similar optimisation techniques.

Logistics and supply chain optimisation are new topics, but their use of AI techniques is considered important if the knowledge base of the field is to be enhanced. Another topic, arguably even more important, is supply chain and logistics cost management and optimisation (Min, 2010). Moreover, although some work has been done on facility location (e.g. Vargas Florez et al., 2015), this topic can be profoundly enhanced by applying novel AI techniques. Based on our results, we suggest the use of the FL approach integrated with GAs or ANNs to address this issue. Other AI techniques that are potentially apt for further research in SCM include expert systems and the Markov decision process.

Regarding the application of AI techniques in various industries, our research shows that the majority (76.5%) of the literature does not target or address a specific industry. Of those that do, the focus is predominantly on industries of convenience stores, the energy market, tourism, real estate, container terminals, oil production, electric drives, carpet, cosmetics and aircraft spare parts. While not being industry-specific results in a general perspective that can be applied to several industries, specific AI-SCM studies that focus on particular industries are also needed in order to create a more specialised and profound scientific background. More specifically, the literature exhibits a need for expert systems to be used to improve airline revenue management (Min, 2015). Other industries, such as heavy vehicles, drones and flying robots, the postal service, manufacturing, automobile and tourism, are potential avenues for more academic research. Moreover, due to the synergy and the complementary nature of hybrid AI techniques, it is more likely that future research trends will move towards these methods.

The results also show that many studies focus on creating and developing models, frameworks, approaches, solutions, etc., with few studies testing their usability, application or generalisability. This gap could be addressed through the use of real-world practical data to test the proposed items. Moreover, using AI for complex problems/scenarios, multiple case study designs and empirical comparison of studies on the same topic holds the potential to enhance the existing literature. In general, AI offers the ability to optimise and improve network orchestration with a level of efficiency that cannot be achieved with human thinking alone. Hence, we encourage research on the interactive decision-making systems to promote a deeper understanding, and thus improve the capabilities, of AI tools.

As a result of the discussions and following the recent trends in research (e.g. Byun et al., 2020; Kotler et al., 2019; Mahroof, 2019; Verma and Gustafsson, 2020), this study further recommends the following research propositions to be explored in future research. Each proposition corresponds to one or more relevant SRQs:

Proposition 1:. *ANNs, FL and ABS/MAS are the most prevailing AI techniques in SCM, and they have affected this field the most.* (*SRQ* 1)

Proposition 2:. *ANNs, FL and ABS/MAS are studied the most in the SCM literature; therefore, they have affected SCM practice more than other AI techniques.* (*SRQ* 1)

Proposition 3:. *The employment of an AI technique in both research and practice is dependent on the availability of relevant software/applications regarding that technique.* (*SRQ* 1,2)

Proposition 4:. *Using AI in the field of SCM happens through using appropriate AI-based software* (*on the AI side*) *and well-defined SCM problems that can make use of such software* (*on the SCM side*). *Therefore, to enhance the use of AI in SCM, both researchers and practitioners require purposefully designed software and well-structured problems.* (*SRQ* 1,3)

Proposition 5:. *The empirical studies that produce AI-based models, systems and frameworks have positive and direct impacts on practical use of AI.* (*SRQ* 1,3,4)

Proposition 6:. *Improvement of less-prevailing AI techniques and discovery of their novel applications can enhance the SCM subfields that have received less attention from researchers.* (*SRQ* 2,4)

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

A. Feo, T., Resende, M., 1995. Greedy Randomized Adaptive Search Procedures. Journal of Global Optimization 6, 109–133. https://doi.org/10.1007/BF01096763.

Aiex, R. M., Ribeiro, Celso C., & Resende, Mauricio G. C. (2002). Probability distribution of solution time in GRASP: An experimental investigation. *Journal of Heuristics, 8*, 343–373. https://doi.org/10.1023/A:1015061802659

Aleksendrić, D., & Carlone, P. (2015). Soft computing techniques. In D. Aleksendrić, & P. Carlone (Eds.), *Soft Computing in the Design and Manufacturing of Composite Materials, 4* pp. 39–60). Oxford: Woodhead Publishing. https://doi.org/10.1533/9781782421801.39.

Altiparmak, F., Gen, M., Lin, L., & Karaoglan, I. (2009). A steady-state genetic algorithm for multi-product supply chain network design. *Computers & Industrial Engineering, 56*, 521–537.

Altiparmak, F., Gen, M., Lin, L., & Paksoy, T. (2006). A genetic algorithm approach for multi-objective optimization of supply chain networks. *Computers & Industrial Engineering, 51*, 196–215.

Amirkolaii, K. N., Baboli, A., Shahzad, M. K., & Tonadre, R. (2017). Demand forecasting for irregular demands in business aircraft spare parts supply chains by using artificial intelligence (AI). *IFAC-Pap., 50*, 15221–15226. https://doi.org/10.1016/j.ifacol.2017.08.2371

Avci, M. G., & Selim, H. (2017). A Multi-objective, simulation-based optimization framework for supply chains with premium freights. *Expert Systems with Applications, 67*, 95–106.

Bachlaus, M., Pandey, M. K., Mahajan, C., Shankar, R., & Tiwari, M. K. (2008). Designing an integrated multi-echelon agile supply chain network: A hybrid taguchi-particle swarm optimization approach. *Journal of Intelligent Manufacturing, 19*, 747.

Bae, J. K., & Kim, J. (2010). Integration of heterogeneous models to predict consumer behavior. *Expert Systems with Applications, 37*, 1821–1826. https://doi.org/10.1016/j.eswa.2009.07.012

Bala, P. K. (2012). Improving inventory performance with clustering based demand forecasts. *Journal Model Management, 7*, 23–37. https://doi.org/10.1108/17465661211208794

Barbuceanu, M., Teigen, R., & Fox, M. S. (1997). Agent based design and simulation of supply chain systems, in. In *Proceedings of IEEE 6th Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises. IEEE* (pp. 36–41).

Beni, G. (2009). Swarm Intelligence. In R. A. Meyers (Ed.), *Encyclopedia of Complexity and Systems Science* (pp. 1–32). New York, New York, NY: Springer. https://doi.org/10.1007/978-3-642-27737-5_530-4.

Boyer, S. L., & Stock, J. R. (2009). Developing a consensus definition of supply chain management: A qualitative study. *International Journal of Physical Distribution & Logistics, 39*, 690–711. https://doi.org/10.1108/09600030910996323

Brandenburger, J., Colla, V., Nastasi, G., Ferro, F., Schirm, C., & Melcher, J. (2016). Big data solution for quality monitoring and improvement on flat steel production**The research leading to these results has received funding from the European Community's Research Fund for Coal and Steel (RFCS) under grant agreement n° RFSR-CT-2012-00040. *IFAC-Pap., 49*, 55–60. https://doi.org/10.1016/j.ifacol.2016.10.096

Bravo, C., Castro, J. A., Saputelli, L., Ríos, A., Aguilar-Martin, J., & Rivas, F. (2011). An implementation of a distributed artificial intelligence architecture to the integrated production management. *Journal of Natural Gas Science and Engineering, 3*, 735–747. https://doi.org/10.1016/j.jngse.2011.08.002

Bryman, A. (2007). The Research Question in Social Research: What is its Role? *International Journal of Social Research Methodology, 10*, 5–20. https://doi.org/10.1080/13645570600655282

Bundy, A. (Ed.). (1997). *Artificial Intelligence Techniques: A Comprehensive Catalogue* (4th ed.). Berlin Heidelberg: Springer-Verlag.

Byun, S.-E., Han, S., Kim, H., & Centrallo, C. (2020). US small retail businesses' perception of competition: Looking through a lens of fear, confidence, or cooperation. *Journal of Retailing and Consumer Services, 52*, Article 101925. https://doi.org/10.1016/j.jretconser.2019.101925

Camarillo, A., Ríos, J., & Althoff, K.-D. (2018). Knowledge-based multi-agent system for manufacturing problem solving process in production plants. *Journal of Manufacturing Systems, 47*, 115–127. https://doi.org/10.1016/j.jmsy.2018.04.002

Canhoto, A. I., & Clear, F. (2020). Artificial intelligence and machine learning as business tools: A framework for diagnosing value destruction potential. Bus. Horiz. *Artificial Intelligence and Machine Learning, 63*, 183–193. https://doi.org/10.1016/j.bushor.2019.11.003

Carbonneau, R., Laframboise, K., & Vahidov, R. (2008). Application of machine learning techniques for supply chain demand forecasting. *European Journal of Operational Research, 184*, 1140–1154.

Cardoso, R. N., Pereira, B. L., Fonseca, J. P. S., Ferreira, M. V. M., & Tavares, J. J. P. Z. S. (2013). Automated planning integrated with linear programming applied in the container loading problem. *IFAC Proceedings, 46*, 153–158. https://doi.org/10.3182/20130911-3-BR-3021.00077

Casabayó, M., Agell, N., & Sánchez-Hernández, G. (2015). Improved market segmentation by fuzzifying crisp clusters: A case study of the energy market in Spain. *Expert Systems with Applications, 42*, 1637–1643. https://doi.org/10.1016/j.eswa.2014.09.044

Chen, S. H., Jakeman, A. J., & Norton, J. P. (2008). Artificial Intelligence techniques: An introduction to their use for modelling environmental systems. *Mathematics and Computers in Simulation, 78*, 379–400. https://doi.org/10.1016/j.matcom.2008.01.028

Chong, A. Y.-L., & Bai, R. (2014). Predicting open IOS adoption in SMEs: An integrated SEM-neural network approach. *Expert Systems with Applications, 41*, 221–229. https://doi.org/10.1016/j.eswa.2013.07.023

Clifton, J. R., & Frohnsdorff, G. (2001). Applications of Computers and Information Technology. In V. S. Ramachandran, & J. J. Beaudoin (Eds.), *Handbook of Analytical Techniques in Concrete Science and Technology, 18* pp. 765–799). Norwich, NY: William Andrew Publishing. https://doi.org/10.1016/B978-081551437-4.50021-7.

Cohen, K. B. (2014). Chapter 6 - Biomedical Natural Language Processing and Text Mining. In I. N. Sarkar (Ed.), *Methods in Biomedical Informatics* (pp. 141–177). Oxford: Academic Press. https://doi.org/10.1016/B978-0-12-401678-1.00006-3.

Counsell, C. (1997). Formulating questions and locating primary studies for inclusion in systematic reviews. *Annals of Internal Medicine, 127*, 380–387.

Dechter, R. (2003). chapter 7 - Stochastic Greedy Local Search. In R. Dechter (Ed.), *Constraint Processing, The Morgan Kaufmann Series in Artificial Intelligence* (pp. 191–208). San Francisco: Morgan Kaufmann. https://doi.org/10.1016/B978-155860890-0/50008-6.

Denyer, D., Tranfield, D., 2009. Producing a systematic review. Sage Handb. Organ. Res. Methods, The Sage handbook of organizational research methods. - Los Angeles, Calif. [u.a.] : SAGE, ISBN 978-1-4462-0064-3. - 2009, p. 671-689.

Dias, J. C. Q., Calado, J. M. F., Osório, A. L., & Morgado, L. F. (2009). RFID together with multi-agent systems to control global value chains. *Annual Review in Control, 33*, 185–195. https://doi.org/10.1016/j.arcontrol.2009.03.005

Dimitrakopoulos, G., Uden, L., Varlamis, I., 2020. Chapter 16 - Transportation network applications, in: Dimitrakopoulos, G., Uden, L., Varlamis, I. (Eds.), The Future of Intelligent Transport Systems. Elsevier, pp. 175–188. https://doi.org/10.1016/B978-0-12-818281-9.00016-4.

Dirican, C. (2015). The impacts of robotics, artificial intelligence on business and economics. *Procedia Social and Behavioral Sciences, 195*, 564–573. https://doi.org/10.1016/j.sbspro.2015.06.134

Dubey, R., Gunasekaran, A., Childe, S. J., Bryde, D. J., Giannakis, M., Foropon, C., … Hazen, B. T. (2020). Big data analytics and artificial intelligence pathway to operational performance under the effects of entrepreneurial orientation and environmental dynamism: A study of manufacturing organisations. *International Journal of Production Economics, 226*, Article 107599. https://doi.org/10.1016/j.ijpe.2019.107599

Easwaran, G., & Üster, H. (2009). Tabu search and benders decomposition approaches for a capacitated closed-loop supply chain network design problem. *Transp. Sci., 43*, 301–320.

Edelkamp, S., Schrödl, S. (2012). Chapter 14 - Selective Search, in: Edelkamp, S., Schrödl, S. (Eds.), Heuristic Search. Morgan Kaufmann, San Francisco, pp. 633–669. https://doi.org/10.1016/B978-0-12-372512-7.00014-6.

Efendigil, T., Önüt, S., & Kahraman, C. (2009). A decision support system for demand forecasting with artificial neural networks and neuro-fuzzy models: A comparative analysis. *Expert Systems with Applications, 36*, 6697–6707. https://doi.org/10.1016/j.eswa.2008.08.058

Ellram, L. M., & Ueltschy Murfield, M. L. (2019). Supply chain management in industrial marketing–Relationships matter. *Industrial Marketing Management, 79*, 36–45. https://doi.org/10.1016/j.indmarman.2019.03.007

Ennen, P., Reuter, S., Vossen, R., & Jeschke, S. (2016). Automated Production Ramp-up Through Self-Learning Systems. *Procedia CIRP, 51*, 57–62. https://doi.org/10.1016/j.procir.2016.05.094

Eslikizi, S., Ziebuhr, M., Kopfer, H., & Buer, T. (2015). Shapley-based side payments and simulated annealing for distributed lot-sizingÕ. *IFAC-Paper, 48*, 1592–1597. https://doi.org/10.1016/j.ifacol.2015.06.313

Fang, F., & Wong, T. N. (2010). Applying hybrid case-based reasoning in agent-based negotiations for supply chain management. *Expert Systems with Applications, 37*, 8322–8332.

Ferreira, L., & Borenstein, D. (2012). A fuzzy-Bayesian model for supplier selection. *Expert Systems with Applications, 39*, 7834–7844. https://doi.org/10.1016/j.eswa.2012.01.068

Ferreira, L., & Borenstein, D. (2011). Normative agent-based simulation for supply chain planning. *J. Oper. Res. Soc., 62*, 501–514. https://doi.org/10.1057/jors.2010.144

Franklin, R., & Paez, A. (2018). *Population loss: The role of transportation and other issues*. Policy Plan: Adv. Transp.

Frayret, J.-M., D'Amours, S., Rousseau, A., Harvey, S., & Gaudreault, J. (2007). Agent-based supply-chain planning in the forest products industry. *International Journal of Flexible Manufacturing Systems, 19*, 358–391.

García, F. T., Villalba, L. J. G., & Portela, J. (2012). Intelligent system for time series classification using support vector machines applied to supply-chain. *Expert Systems with Applications, 39*, 10590–10599.

Geem, Z. W., & Roper, W. E. (2009). Energy demand estimation of South Korea using artificial neural network. *Energy Policy, Carbon in Motion: Fuel Economy, Vehicle Use, and Other Factors affecting CO2 Emissions From Transport, 37*, 4049–4054. https://doi.org/10.1016/j.enpol.2009.04.049

Geman, S., & Johnson, M. (2001). Probabilistic Grammars and their Applications. In N. J. Smelser, & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 12075–12082). Oxford: Pergamon. https://doi.org/10.1016/B0-08-043076-7/00489-7.

Ghallab, M., Nau, D., & Traverso, P. (2004). *Automated Planning: Theory and practice*. Elsevier.

Gholami, R., & Fakhari, N. (2017). Chapter 27 - Support Vector Machine: Principles, Parameters, and Applications. In P. Samui, S. Sekhar, & V. E. Balas (Eds.), *Handbook of Neural Computation* (pp. 515–535). Academic Press. https://doi.org/10.1016/B978-0-12-811318-9.00027-2.

Giannakis, M., & Louis, M. (2011). A multi-agent based framework for supply chain risk management. *Journal of Purchasing and Supply Management, 17*, 23–31.

Gligor, A., Dumitru, C.-D., & Grif, H.-S. (2018). Artificial intelligence solution for managing a photovoltaic energy production unit. *Procedia Manufacturing, 22*, 626–633. https://doi.org/10.1016/j.promfg.2018.03.091

Glover, F., Laguna, M., & Marti, R. (2008). *Tabu Search.*. https://doi.org/10.1007/978-1-4615-6089-0

Glover, F., & Marti, R. (2006). Tabu Search. In E. Alba, & R. Martí (Eds.), *Metaheuristic Procedures for Training Neutral Networks, Operations Research/Computer Science Interfaces Series* (pp. 53–69). US, Boston, MA: Springer. https://doi.org/10.1007/0-387-33416-5_3.

Grimm, V., & Railsback, S. F. (2005). *Individual-based Modeling and Ecology*. Princeton University Press.

Guosheng, H., & Guohong, Z. (2008). Comparison on neural networks and support vector machines in suppliers' selection. *Journal of Systems Engineering and Electronics, 19*, 316–320.

Hand, D.J., 2013. Data Mining Based in part on the article "Data mining" by David Hand, which appeared in the Encyclopedia of Environmetrics., in: Encyclopedia of Environmetrics. American Cancer Society. https://doi.org/10.1002/9780470057339.vad002.pub2.

Heger, J., Branke, J., Hildebrandt, T., & Scholz-Reiter, B. (2016). Dynamic adjustment of dispatching rule parameters in flow shops with sequence-dependent set-up times. *International Journal of Production Research, 54*, 6812–6824. https://doi.org/10.1080/00207543.2016.1178406

Hongmao, S., 2016. Chapter 5 - Quantitative Structure–Activity Relationships: Promise, Validations, and Pitfalls, in: Hongmao, S. (Ed.), A Practical Guide to Rational Drug Design. Woodhead Publishing, pp. 163–192. https://doi.org/10.1016/B978-0-08-100098-4.00005-3.

Hossein Javaheri, S., Mehdi Sepehri, M., & Teimourpour, B. (2014). Response modeling in direct marketing: A data mining based approach for target selection. *Data Min. Appl. R*, 153–178.

Huin, S. F., Luong, L. H. S., & Abhary, K. (2003). Knowledge-based tool for planning of enterprise resources in ASEAN SMEs. *Robotics and Computer-Integrated Manufacturing, 19*, 409–414. https://doi.org/10.1016/S0736-5845(02)00033-9

Humphreys, P., McIvor, R., & Chan, F. (2003). Using case-based reasoning to evaluate supplier environmental management performance. *Expert Systems with Applications, 25*, 141–153.

Jarrahi, M. H. (2018). Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business Horizons, 61*, 577–586. https://doi.org/10.1016/j.bushor.2018.03.007

Jiang, J., Kou, Y., Bie, Z., & Li, G. (2019). Optimal real-time pricing of electricity based on demand response. *Energy Procedia, Renewable Energy Integration with Mini/Microgrid, 159*, 304–308. https://doi.org/10.1016/j.egypro.2019.01.011

Jiao, J. R., You, X., & Kumar, A. (2006). An agent-based framework for collaborative negotiation in the global manufacturing supply chain network. *Robotics and Computer-Integrated Manufacturing, 22*, 239–255.

Kadadevaramath, R. S., Chen, J. C., Shankar, B. L., & Rameshkumar, K. (2012). Application of particle swarm intelligence algorithms in supply chain network architecture optimization. *Expert Systems with Applications, 39*, 10160–10176.

Kannan, G., Sasikumar, P., & Devika, K. (2010). A genetic algorithm approach for solving a closed loop supply chain model: A case of battery recycling. *Applied Mathematical Modelling, 34*, 655–670.

Kaplan, A., & Haenlein, M. (2020). Rulers of the world, unite! The challenges and opportunities of artificial intelligence. *Business Horizons, 63*, 37–50. https://doi.org/10.1016/j.bushor.2019.09.003

Kasabov, N. (2019). Chapter 6 - Evolving and Spiking Connectionist Systems for Brain-Inspired Artificial Intelligence. In R. Kozma, C. Alippi, Y. Choe, & F. C. Morabito (Eds.), *Artificial Intelligence in the Age of Neural Networks and Brain Computing* (pp. 111–138). Academic Press. https://doi.org/10.1016/B978-0-12-815480-9.00006-2.

Kasie, F. M., Bright, G., & Walker, A. (2017). Decision support systems in manufacturing: A survey and future trends. *Journal of Modelling in Management*. https://doi.org/10.1108/JM2-02-2016-0015

Kay, M., Gawron, J. M., & Norvig, P. (1994). *Verbmobil: A translation system for face-to-face dialog.* Stanford, CA: Center for the Study of Language and Information.

Kearney, V., Chan, J. W., Valdes, G., Solberg, T. D., & Yom, S. S. (2018). The application of artificial intelligence in the IMRT planning process for head and neck cancer. *Oral Oncology, 87*, 111–116. https://doi.org/10.1016/j.oraloncology.2018.10.026

Keramitsoglou, I., Cartalis, C., & Kiranoudis, C. T. (2006). Automatic identification of oil spills on satellite images. *Environmental Modelling & Software, 21*, 640–652. https://doi.org/10.1016/j.envsoft.2004.11.010

Ketter, W., Collins, J., Gini, M., Gupta, A., & Schrater, P. (2012). Real-time tactical and strategic sales management for intelligent agents guided by economic regimes. *Information Systems Research, 23*, 1263–1283. https://doi.org/10.1287/isre.1110.0415

Kitchenham, B., Brereton, O. P., Budgen, D., Turner, M., Bailey, J., & Linkman, S. (2009). Systematic literature reviews in software engineering–a systematic literature review. *Information and Software Technology, 51*, 7–15.

Klumpp, M. (2018). Automation and artificial intelligence in business logistics systems: Human reactions and collaboration requirements. *International Journal of Logistics Research and Applications, 21*, 224–242. https://doi.org/10.1080/13675567.2017.1384451

Knoll, D., Prüglmeier, M., & Reinhart, G. (2016). Predicting future inbound logistics processes using machine learning. *Procedia CIRP, 52*, 145–150. https://doi.org/10.1016/j.procir.2016.07.078

Kohtamäki, M., Parida, V., Oghazi, P., Gebauer, H., & Baines, T. (2019). Digital servitization business models in ecosystems: A theory of the firm. *Journal of Business Research., 104*, 380–392. https://doi.org/10.1016/j.jbusres.2019.06.027

Kotler, P., 1982. Marketing for nonprofit organizations.

Kotler, P., Manrai, L. A., Lascu, D.-N., & Manrai, A. K. (2019). Influence of country and company characteristics on international business decisions: A review, conceptual model, and propositions. *International Business Review, 28*, 482–498. https://doi.org/10.1016/j.ibusrev.2018.11.006

Kraft, D. H., Petry, F. E., Buckles, B. P., & Sadasivan, T. (1997). Genetic algorithms for query optimization in information retrieval: Relevance feedback. In *Genetic Algorithms and Fuzzy Logic Systems: Soft Computing Perspectives* (pp. 155–173). World Scientific.

Kucukkoc, I., & Zhang, D. Z. (2015). A mathematical model and genetic algorithm-based approach for parallel two-sided assembly line balancing problem. *Production Planning, 26*, 874–894. https://doi.org/10.1080/09537287.2014.994685

Küfner, T., Uhlemann, T.H.-J., Ziegler, B., 2018. Lean Data in Manufacturing Systems: Using Artificial Intelligence for Decentralized Data Reduction and Information Extraction. Procedia CIRP, 51st CIRP Conference on Manufacturing Systems 72, 219–224. https://doi.org/10.1016/j.procir.2018.03.125.

Kumar, S. K., Tiwari, M. K., & Babiceanu, R. F. (2010). Minimisation of supply chain cost with embedded risk using computational intelligence approaches. *International Journal of Production Research, 48*, 3717–3739.

Kumar, V., Ramachandran, D., & Kumar, B. (2020). Influence of new-age technologies on marketing: A research agenda. *Journal of Business Research*. https://doi.org/10.1016/j.jbusres.2020.01.007

Kwon, O., Im, G. P., & Lee, K. C. (2007). MACE-SCM: A multi-agent and case-based reasoning collaboration mechanism for supply chain management under supply and demand uncertainties. *Expert Systems with Applications, 33*, 690–705.

Kwong, C. K., Jiang, H., & Luo, X. G. (2016). AI-based methodology of integrating affective design, engineering, and marketing for defining design specifications of new products. *Engineering Applications of Artificial Intelligence, 47*, 49–60. https://doi.org/10.1016/j.engappai.2015.04.001

Ładyżyński, P., Żbikowski, K., & Gawrysiak, P. (2019). Direct marketing campaigns in retail banking with the use of deep learning and random forests. *Expert Systems with Applications, 134*, 28–35. https://doi.org/10.1016/j.eswa.2019.05.020

Lapira, E., Bagheri, B., Zhao, W., Lee, J., Henriques, R., Pereira, C., … Guimarães, C. S. S. (2013). *A Systematic Approach to Intelligent Maintenance of Production Systems with a Framework for Embedded Implementation Intelligent Manufacturing Systems.*. https://doi.org/10.3182/20130522-3-BR-4036.00092

Ławrynowicz, A. (2008). Integration of Production Planning and Scheduling Using an Expert System and a Genetic Algorithm. *Journal of the Operational Research Society, 59*, 455–463.

Leake, D. B. (2001). Problem Solving and Reasoning: Case-based. In N. J. Smelser, & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 12117–12120). Oxford: Pergamon. https://doi.org/10.1016/B0-08-043076-7/00545-3.

Lee, C. K. M., Ho, W., Ho, G. T. S., & Lau, H. C. W. (2011). Design and development of logistics workflow systems for demand management with RFID. *Expert Systems with Applications, 38*, 5428–5437. https://doi.org/10.1016/j.eswa.2010.10.012

Lee, W.-I., Shih, B.-Y., & Chen, C.-Y. (2012). Retracted: A hybrid artificial intelligence sales-forecasting system in the convenience store industry. *Human Factors and Ergonomics in Manufacturing & Service Industries, 22*, 188–196. https://doi.org/10.1002/hfm.20272

Lesser, V. R. (1995). Multiagent systems: An emerging subdiscipline of AI. *ACM Computing Surveys CSUR, 27*, 340–342.

Letheren, K., & Glavas, C. (2017). *Embracing the bots: How direct to consumer advertising is about to change forever*. The conversation.

Li, E. Y. (1994). Artificial neural networks and their business applications. *Information and Management., 27*, 303–313. https://doi.org/10.1016/0378-7206(94)90024-8

Li, X., Chan, C. W., & Nguyen, H. H. (2013). Application of the Neural Decision Tree approach for prediction of petroleum production. *Journal of Petroleum Science and Engineering, 104*, 11–16. https://doi.org/10.1016/j.petrol.2013.03.018

Littman, M. L. (2001). Markov Decision Processes. In N. J. Smelser, & P. B. Baltes (Eds.), *International Encyclopedia of the Social & Behavioral Sciences* (pp. 9240–9242). Oxford: Pergamon. https://doi.org/10.1016/B0-08-043076-7/00614-8.

Lou, P., Chen, Y.-P., & Ai, W. (2004). Study on multi-agent-based agile supply chain management. *International Journal of Advanced Manufacturing Technology, 23*, 197–203.

Ma, Z., Leung, J. Y., & Zanon, S. (2018). Integration of artificial intelligence and production data analysis for shale heterogeneity characterization in steam-assisted gravity-drainage reservoirs. *Journal of Petroleum Science and Engineering, 163*, 139–155. https://doi.org/10.1016/j.petrol.2017.12.046

Madhavaram, S., & McDonald, R. E. (2010). Knowledge-based sales management strategy and the grafting metaphor: Implications for theory and practice. *Industrial Marketing Management Selling and Sales Management, 39*, 1078–1087. https://doi.org/10.1016/j.indmarman.2009.12.009

Mahroof, K. (2019). A human-centric perspective exploring the readiness towards smart warehousing: The case of a large retail distribution warehouse. *International Journal of Information Management, 45*, 176–190. https://doi.org/10.1016/j.ijinfomgt.2018.11.008

Martinez-Barbera, H., & Herrero-Perez, D. (2010). Development of a flexible AGV for flexible manufacturing systems. *Ind. Robot Int. J., 37*, 459–468. https://doi.org/10.1108/01439911011063281

Martínez-López, F. J., & Casillas, J. (2013). Artificial intelligence-based systems applied in industrial marketing: An historical overview, current and future insights. *Industrial Marketing Management Special Issue on Applied Intelligent Systems in Business-to-Business Marketing, 42*, 489–495. https://doi.org/10.1016/j.indmarman.2013.03.001

Martínez-López, F. J., & Casillas, J. (2009). Marketing Intelligent Systems for consumer behaviour modelling by a descriptive induction approach based on Genetic Fuzzy Systems. *Industrial Marketing Management., 38*, 714–731. https://doi.org/10.1016/j.indmarman.2008.02.003

Mayr, A., Weigelt, M., Masuch, M., Meiners, M., Hüttel, F., & Franke, J. (2018). Application Scenarios of Artificial Intelligence in Electric Drives Production. *Procedia Manufacturing, 24*, 40–47. https://doi.org/10.1016/j.promfg.2018.06.006

Melo, M. T., Nickel, S., & Saldanha-da-Gama, F. (2012). A tabu search heuristic for redesigning a multi-echelon supply chain network over a planning horizon. *International Journal of Production Economics, 136*, 218–230.

Merlino, M., & Sproģe, I. (2017). *The Augmented Supply Chain. Procedia Eng., 178*, 308–318. https://doi.org/10.1016/j.proeng.2017.01.053

Miles, M.B., Huberman, A.M., 1994. Qualitative data analysis: an expanded sourcebook.

Min, H. (2015). Genetic algorithm for supply chain modelling: Basic concepts and applications. *Int. J. Serv. Oper. Manag., 22*, 143–163. https://doi.org/10.1504/IJSOM.2015.071527

Min, H. (2010). Artificial intelligence in supply chain management: Theory and applications. *Int. J. Logist. Res. Appl., 13*, 13–39. https://doi.org/10.1080/13675560902736537

Mobarakeh, N. A., Shahzad, M. K., Baboli, A., & Tonadre, R. (2017). Improved Forecasts for uncertain and unpredictable Spare Parts Demand in Business Aircraft's with Bootstrap Method. *IFAC-Pap., 50*, 15241–15246. https://doi.org/10.1016/j.ifacol.2017.08.2379

Munguia, J., Bernard, A., & Erdal, M. (2011). Proposal and evaluation of a KBE-RM selection system. *Rapid Prototyp. J., 17*, 236–246. https://doi.org/10.1108/13552541111138351

Nishant, R., Kennedy, M., & Corbett, J. (2020). Artificial intelligence for sustainability: Challenges, opportunities, and a research agenda. *International Journal of Information Management, 53*, Article 102104. https://doi.org/10.1016/j.ijinfomgt.2020.102104

O'Donnell, T., Humphreys, P., McIvor, R., & Maguire, L. (2009). Reducing the negative effects of sales promotions in supply chains using genetic algorithms. *Expert Systems with Applications, 36*, 7827–7837. https://doi.org/10.1016/j.eswa.2008.11.034

Oghazi, P., Rad, F. F., Karlsson, S., & Haftor, D. (2018). RFID and ERP systems in supply chain management. European Journal of Management and Business Economics.

Olsson, E., & Funk, P. (2009). Agent-based monitoring using case-based reasoning for experience reuse and improved quality. *J. Qual. Maint. Eng., 15*, 179–192. https://doi.org/10.1108/13552510910961129

Orwin, R. G., Cooper, H., & Hedges, L. V. (1994). The handbook of research synthesis. *N. Y. NY Russell Sage Found.*, 139–162.

Parida, V., Oghazi, P., & Cedergren, S. (2016). A study of how ICT capabilities can influence dynamic capabilities. Journal of Enterprise Information Management.

Parrott, L., Lacroix, R., & Wade, K. M. (2003). Design considerations for the implementation of multi-agent systems in the dairy industry. *Computers and Electronics in Agriculture, 38*, 79–98.

Peter, S. C., Dhanjal, J. K., Malik, V., Radhakrishnan, N., Jayakanthan, M., & Sundar, D. (2019). Quantitative Structure-Activity Relationship (QSAR): Modeling Approaches to Biological Applications. In S. Ranganathan, M. Gribskov, K. Nakai, & C. Schönbach (Eds.), *Encyclopedia of Bioinformatics and Computational Biology* (pp. 661–676). Oxford: Academic Press. https://doi.org/10.1016/B978-0-12-809633-8.20197-0.

Peterson, S., & Flanagan, A. B. (2009). Neural Network Hedonic Pricing Models in Mass Real Estate Appraisal. *J. Real Estate Res., 31*, 147–164.

Pino, R., Fernández, I., de la Fuente, D., Parreño, J., & Priore, P. (2010). Supply chain modelling using a multi-agent system. *J. Adv. Manag. Res., 7*, 149–162.

Pióro, M., Medhi, D., 2004. CHAPTER 5 - General Optimization Methods for Network Design, in: Pióro, M., Medhi, D. (Eds.), Routing, Flow, and Capacity Design in Communication and Computer Networks, The Morgan Kaufmann Series in Networking. Morgan Kaufmann, San Francisco, pp. 151–210. https://doi.org/10.1016/B978-012557189-0/50008-1.

Ponis, S. T., & Ntalla, A. (2016). Crisis Management Practices and Approaches: Insights from Major Supply Chain Crises. Procedia Econ. Finance, 3rd GLOBAL CONFERENCE on BUSINESS. *ECONOMICS, MANAGEMENT and TOURISM, 39*, 668–673. https://doi.org/10.1016/S2212-5671(16)30287-8

Quiñónez-Gámez, O. P., & Camacho-Velázquez, R. G. (2011). Validation of production data by using an AI-based classification methodology; a case in the Gulf of Mexico.

Journal of Natural Gas Science and Engineering, 3, 729–734. https://doi.org/10.1016/j.jngse.2011.07.015

Ransbotham, S., Kiron, D., Gerbert, P., & Reeves, M. (2017). *Reshaping business with artificial intelligence: Closing the gap between ambition and action* (p. 59). Rev: MIT Sloan Manag.

Redding, S. J., & Turner, M. A. (2015). Chapter 20 - Transportation Costs and the Spatial Organization of Economic Activity. In G. Duranton, J. V. Henderson, & W. C. Strange (Eds.), *Handbook of Regional and Urban Economics, Handbook of Regional and Urban Economics* (pp. 1339–1398). Elsevier. https://doi.org/10.1016/B978-0-444-59531-7.00020-X.

Regal, T., & Pereira, C. E. (2018). Ontology for Conceptual Modelling of Intelligent Maintenance Systems and Spare Parts Supply Chain Integration. *IFAC-Pap., 51*, 1511–1516. https://doi.org/10.1016/j.ifacol.2018.08.285

Rekha, A. G., Abdulla, M. S., & Asharaf, S. (2016). Artificial Intelligence Marketing: An application of a novel Lightly Trained Support Vector Data Description. *J. Inf. Optim. Sci., 37*, 681–691. https://doi.org/10.1080/02522667.2016.1191186

Rowley, J., & Slack, F. (2004). Conducting a literature review. *Manag. Res. News, 27*, 31–39.

Saka, M. P., Doğan, E., & Aydogdu, I. (2013). Analysis of Swarm Intelligence-Based Algorithms for Constrained Optimization. In X.-. S. Yang, Z. Cui, R. Xiao, A. H. Gandomi, & M. Karamanoglu (Eds.), *Swarm Intelligence and Bio-Inspired Computation, 2* pp. 25–48). Oxford: Elsevier. https://doi.org/10.1016/B978-0-12-405163-8.00002-8.

Salido, M. A., Rodriguez-Molins, M., & Barber, F. (2012). A decision support system for managing combinatorial problems in container terminals. *Knowledge-Based Systems, 29*, 63–74. https://doi.org/10.1016/j.knosys.2011.06.021

Sanders, D., & Gegov, A. (2013). AI tools for use in assembly automation and some examples of recent applications. *Assem. Autom., 33*, 184–194. https://doi.org/10.1108/01445151311306717

Sarvari, P. A., Ustundag, A., & Takci, H. (2016). Performance evaluation of different customer segmentation approaches based on RFM and demographics analysis. *Kybernetes, 45*, 1129–1157. https://doi.org/10.1108/K-07-2015-0180

Schutzer, D. (1990). Business expert systems: The competitive edge. *Expert Systems with Applications, 1*, 17–21. https://doi.org/10.1016/0957-4174(90)90065-3

Shakya, S., Chin, C. M., & Owusu, G. (2010). An AI-based system for pricing diverse products and services. *Knowledge-Based Systems, 23*, 357–362. https://doi.org/10.1016/j.knosys.2009.11.013

Shaw, M. J., Subramaniam, C., Tan, G. W., & Welge, M. E. (2001). Knowledge management and data mining for marketing. *Decision Support Systems, 31*, 127–137.

Sheremetov, L. B., González-Sánchez, A., López-Yáñez, I., & Ponomarev, A. V. (2013). Time Series Forecasting: Applications to the Upstream Oil and Gas Supply Chain. *IFAC Proc., 46*, 957–962. https://doi.org/10.3182/20130619-3-RU-3018.00526

Sinha, A. K., Zhang (Chris), W. J., & Tiwari, M. K. (2012). Co-evolutionary immuno-particle swarm optimization with penetrated hyper-mutation for distributed inventory replenishment. *Engineering Applications of Artificial Intelligence, 25*, 1628–1643. https://doi.org/10.1016/j.engappai.2012.01.015

Soni, N., Sharma, E. K., Singh, N., & Kapoor, A. (2020). Artificial Intelligence in Business: From Research and Innovation to Market Deployment. Procedia Comput. Sci. *International Conference on Computational Intelligence and Data Science, 167*, 2200–2210. https://doi.org/10.1016/j.procs.2020.03.272

Sousa, A. R., & Tavares, J. J. P. Z. S. (2013). Toward Automated Planning Algorithms Applied to Production and Logistics. *IFAC Proc., 46*, 165–170. https://doi.org/10.3182/20130911-3-BR-3021.00081

Stalidis, G., Karapistolis, D., & Vafeiadis, A. (2015). Marketing Decision Support Using Artificial Intelligence and Knowledge Modeling: Application to Tourist Destination Management. *Procedia - Soc. Behav. Sci., 175*, 106–113. https://doi.org/10.1016/j.sbspro.2015.01.1180

Sun, M., Ji, J., & Ampimah, B. C. (2018). How to implement real-time pricing in China? A solution based on power credit mechanism. *Applied Energy, 231*, 1007–1018. https://doi.org/10.1016/j.apenergy.2018.09.086

Surana, A., Kumara, S., Greaves, M., & Raghavan, U. N. (2005). Supply-chain networks: A complex adaptive systems perspective. *International Journal of Production Research, 43*, 4235–4265.

Syam, N., & Sharma, A. (2018). Waiting for a sales renaissance in the fourth industrial revolution: Machine learning and artificial intelligence in sales research and practice. *Industrial Marketing Management, 69*, 135–146. https://doi.org/10.1016/j.indmarman.2017.12.019

Tan, K. H., Zhan, Y., Ji, G., Ye, F., & Chang, C. (2015). Harvesting big data to enhance supply chain innovation capabilities: An analytic infrastructure based on deduction graph. *International Journal of Production Economics, 165*, 223–233.

Taratukhin, V., & Yadgarova, Y. (2018). Towards a socio-inspired multiagent approach for new generation of product life cycle management. *Procedia Computer Science, 123*, 479–487. https://doi.org/10.1016/j.procs.2018.01.073

Taylan, O., & Darrab, I. A. (2012). Fuzzy control charts for process quality improvement and product assessment in tip shear carpet industry. *J. Manuf. Technol. Manag., 23*, 402–420. https://doi.org/10.1108/17410381211217434

Thow-Yick, L., & Huu-Phuong, T. (1990). Management expert systems for competitive advantage in business. *Inf. Manage., 18*, 195–201.

Ting, S. L., Tse, Y. K., Ho, G. T. S., Chung, S. H., & Pang, G. (2014). Mining logistics data to assure the quality in a sustainable food supply chain: A case in the red wine industry. *International Journal of Production Economics, 152*, 200–209.

Townsend, D. M., & Hunt, R. A. (2019). Entrepreneurial action, creativity, & judgment in the age of artificial intelligence. *J. Bus. Ventur. Insights, 11*, Article e00126. https://doi.org/10.1016/j.jbvi.2019.e00126

Tranfield, D., Denyer, D., & Smart, P. (2003). Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *British Journal of Management, 14*, 207–222.

Trentesaux, D., & Thomas, A. (2012). Product-Driven Control: A State of the Art and Future Trends. *IFAC Proc., 45*, 716–721. https://doi.org/10.3182/20120523-3-RO-2023.00081

Tsafarakis, S., Saridakis, C., Baltas, G., & Matsatsinis, N. (2013). Hybrid particle swarm optimization with mutation for optimizing industrial product lines: An application to a mixed solution space considering both discrete and continuous design variables. *Industrial Marketing Management, 42*, 496–506. https://doi.org/10.1016/j.indmarman.2013.03.002

Tsang, Y. P., Choy, K. L., Wu, C. H., Ho, G. T. S., Lam, C. H. Y., & Koo, P. S. (2018). An internet of things (IoT)-based risk monitoring system for managing cold supply chain risks. *Industrial Management & Data Systems., 118*, 1432–1462. https://doi.org/10.1108/IMDS-09-2017-0384

Vahdani, B., Iranmanesh, S. H., Mousavi, S. M., & Abdollahzade, M. (2012). A locally linear neuro-fuzzy model for supplier selection in cosmetics industry. *Applied Mathematical Modelling, 36*, 4714–4727. https://doi.org/10.1016/j.apm.2011.12.006

Van den Broeck, E., Zarouali, B., & Poels, K. (2019). Chatbot advertising effectiveness: When does the message get through? *Computers in Human Behavior, 98*, 150–157. https://doi.org/10.1016/j.chb.2019.04.009

Vargas Florez, J., Lauras, M., Okongwu, U., & Dupont, L. (2015). A decision support system for robust humanitarian facility location. *Engineering Applications of Artificial Intelligence, 46*, 326–335. https://doi.org/10.1016/j.engappai.2015.06.020

Verma, S., & Gustafsson, A. (2020). Investigating the emerging COVID-19 research trends in the field of business and management: A bibliometric analysis approach. *Journal of Business Research, 118*, 253–261. https://doi.org/10.1016/j.jbusres.2020.06.057

Wang, H., Fang, H., Yu, X., & Liang, S. (2018). How real time pricing modifies Chinese households' electricity consumption. *Journal of Cleaner Production, 178*, 776–790. https://doi.org/10.1016/j.jclepro.2017.12.251

Wang, J., & Yue, H. (2017). Food safety pre-warning system based on data mining for a sustainable food supply chain. *Food Control, 73*, 223–229. https://doi.org/10.1016/j.foodcont.2016.09.048

Wang, T., Ramik, D. M., Sabourin, C., & Madani, K. (2012). Intelligent systems for industrial robotics: Application in logistic field. *Ind. Robot Int. J., 39*, 251–259. https://doi.org/10.1108/01439911211217071

Wei, M. M., & Zhang, F. (2018). Recent research developments of strategic consumer behavior in operations management. *Computers & Operations Research, 93*, 166–176. https://doi.org/10.1016/j.cor.2017.12.005

Whitley, D. (1994). A genetic algorithm tutorial. *Statistics and Computing, 4*, 65–85. https://doi.org/10.1007/BF00175354

Yang, H., & Chen, H. (2015). Biomass gasification for synthetic liquid fuel production. In R. Luque, & J. G. Speight (Eds.), *Gasification for Synthetic Fuel Production, Woodhead Publishing Series in Energy, 11* pp. 241–275). Woodhead Publishing. https://doi.org/10.1016/B978-0-85709-802-3.00011-4.

Yang, X.-S., & Karamanoglu, M. (2013). Swarm Intelligence and Bio-Inspired Computation: An Overview. In X.-. S. Yang, Z. Cui, R. Xiao, A. H. Gandomi, & M. Karamanoglu (Eds.), *Swarm Intelligence and Bio-Inspired Computation, 1* pp. 3–23). Oxford: Elsevier. https://doi.org/10.1016/B978-0-12-405163-8.00001-6.

Yeh, W.-C., & Chuang, M.-C. (2011). Using multi-objective genetic algorithm for partner selection in green supply chain problems. *Expert Systems with Applications, 38*, 4244–4253.

Zadeh, L. A. (1965). Fuzzy sets. *Information and Control, 8*, 338–353.

Zgaya, H., Zoghlami, N., Hammadi, S., & Bretaudeau, F. (2009). Negotiation model in a multi-agent supply chain system for the crisis management. *IFAC Proceedings, 42*, 1026–1031. https://doi.org/10.3182/20090603-3-RU-2001.0069

Zhang, X., Chan, F. T. S., Adamatzky, A., Mahadevan, S., Yang, H., Zhang, Z., & Deng, Y. (2017). An intelligent physarum solver for supply chain network design under profit maximization and oligopolistic competition. *International Journal of Production Research, 55*, 244–263. https://doi.org/10.1080/00207543.2016.1203075

Reza Toorajipour holds MSc in international business administration at Shahid Beheshti University. He works at Shiraz Oil Refining Company where he serves as business expert. His research interests include business model innovation, supply chain management and industry 4.0 technologies.

Dr. Vahid Sohrabpour has a multidisciplinary approach in research. He is passionate about the research on Industry 4.0 and the use of technologies such as Internet of Things (IoT), Cloud Computing, Block Chain, Big Data and Artificial Intelligence in Supply Chain Management. These technologies lead to establish Smart Supply Chain, Smart Manufacturing and Smart Product which are related to his background in Packaging Logistics, Supply Chain Management, Operations Management, Quality Management and Computer Engineering

Dr. Ali Nazarpour is Assistant Professor in Management at Maynooth University School of Business. Ali has been awarded PhD in Operations and Supply Chain Management from University College Dublin, Smurfit School of Business. He earned his BSc degree in Industrial Engineering and Master's degree in Business Administration from Iran University of Science and Technology. Prior to his PhD studies, he worked in the construction sector and in the automotive industry where he served as Sales Supervisor, Marketing and Sales Planning Chief, and Inventory Management Project Manager.

Dr. Pejvak Oghazi is Professor in Business Studies and head of Department at School of Social Sciences, Sodertorn University. He holds an MSc in Industrial and Management Engineering in addition to a PhD in Industrial Marketing. Prior to his current position, Professor Oghazi worked as an industrial manager at national and international level. Professor Oghazi's current research interests revolve around topics in Business studies.

Maria Fischl Research Associate and Project Manager at University Of St Gallen Hsg