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Artificial intelligence and prescriptive analytics for supply chain resilience: a systematic literature review and research agenda

Conn Smyth[a], Denis Dennehy[b], Samuel Fosso Wamba[c], Murray Scott[a] and Antoine Harfouche[d]

[a]Business Information Systems Department, University of Galway, Galway, Ireland; [b]School of Management, Swansea University, Swansea, UK; [c]Department of Information, Operations and Management Sciences, TBS Business School, Toulouse, France; [d] CEROS, University Paris Nanterre, Paris, France

ABSTRACT

Artificial Intelligence (AI) and prescriptive analytics are increasingly being reported as having transformative powers to enable resilient supply chains (SC). Despite such a benefit, and the increase in popularity of AI and analytics in general, research is largely fragmented into streams based on different types of AI technologies across several SC contexts and through varying disciplinary perspectives. In response, we curate and synthesise this fragmented body of knowledge by conducting a systematic literature review of AI research in supply chains that have been published in 3* and 4* Chartered Association of Business Schools (CABS) ranked journals between 2000 and 2023. The search strategy retrieved 5, 293 studies, of which 76 were identified as primary papers relevant to this study. The study contributes to the accumulative building of knowledge by extending theoretical discourse about the specificities of AI for prescriptive analytics to enable SC resilience. This study proposes a strategic AI resilience framework to support SC decision-makers enhance the use and value of prescriptive analytics as an enabler to developing resilient SC. We make the call to action for an orchestrated effort within and between academic disciplines and organisations that are guided by a research agenda to guide future research initiatives.

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Artificial intelligence; analytics; supply chains; resilience; literature review

1. Introduction

AI and advanced analytics are increasingly being viewed by decision makers in supply chain-centric organisations as a data-driven approach that can improve supply chain (SC) resilience (Cannas et al. 2023; Merhi and Harfouche 2023; Papadopoulos et al. 2022). For example, the Covid-19 pandemic impacted over 85% of global supply (Remko 2020) and in some cases, the entire shut down of crucial SC activities (Ivanov and Dolgui 2020; Mishra, Singh, and Song 2022; Modgil, Singh, and Hannibal 2021). Although SCs are historically vulnerable to exogenous shocks (Badakhshan and Ball 2023b; Baryannis et al. 2019; Zeng and Yen 2017), they are becoming increasingly more complex in nature (Ben-Daya, Hassini, and Bahroun 2019; Ivanov and Dolgui 2019) due to increased product variety (Bozarth et al. 2009; Zheng et al. 2021), higher customer expectations (Simchi-Levi and Wu 2018), increased customer demand (Bodaghi, Jolai, and Rabbani 2018; Olan et al. 2022), greater emphasis on transparency and sustainability (Sodhi and Tang 2019; Barbosa-Póvoa, Da Silva, and Carvalho 2018), and multi-channel disruptions (Bode and Wagner 2015; Hosseini and Ivanov 2020).

In response to adverse advents, SC practitioners and researchers are shifting their focus from traditional risk management and efficiency techniques (i.e. lean, just-in-time) to developing resilient SC (e.g. Baryannis et al. 2019; Marucheck et al., 2011; Sá et al., 2019; Jüttner and Maklan 2011; Pettit, Croxton, and Fiksel 2013). SC resilience is defined as ‘the adaptive capability of a supply chain to prepare for and/or respond to disruptions, to make a timely and cost-effective recovery, and therefore progress to a post-disruption state of operations – ideally, a better state than prior to the disruption’ (Tukamuhabwa et al. 2015, 8). Developing resilient SC is critical to withstanding future global events that can impact supply chains (Kahiluoto, Mäkinen, and Kaseva 2020; Lerch et al, 2022;Sá de et al. 2019).

AI has been claimed to offer almost unlimited potential in the context of SC, ranging from configuration and optimisation (Dubey et al. 2020; Johnson, Albizri, and Simsek 2022; Preil and Krapp 2022), forecasting (Chien, Lin, and Lin 2020), increasing operational efficiency and supplier selection (Choy, Lee, and Lo 2003; Priore et al. 2019), predicting customer demand (Carbonneau, Laframboise, and Vahidov 2008; Kantasa-ard

CONTACT Denis Dennehy Denis.dennehy@swansea.ac.uk Fabian Way, Crymlyn Burrows, Skewen, Swansea SA1 8EN, UK

et al. 2020), improving visibility (Wichmann et al. 2020), identifying potential disruptions (Brintrup et al. 2020), decision support (Castañé et al., 2023; Gupta et al. 2022), and optimising internal structures and processes (Abbasi et al. 2020; Piramuthu 2005a). Due to the increased digitisation of supply chains, data creation and consumption have increased in terms of volume, variety, and velocity (Gupta, Modgil, and Gunasekaran 2020; Papadopoulos et al. 2017, 2022). Moreover, advances in data collection technology allow SC organisations to easily acquire effective market data (Yu and Cao 2020). This significant increase in data will need to be analysed in real-time using AI and advanced analytics (Merhi and Harfouche 2023; Sharma et al. 2020) due to its speed and accuracy (Toorajipour et al. 2021) and the ability to optimise and control autonomous-based systems (Kohtamäki et al. 2019).

Despite these technological advances and research contributions to understanding different aspects of AI and analytics to enable SC resilience, a comprehensive portrait of its utility is lacking. Specifically, analytics is frequently used as a synonym for different types of analytics. Yet, descriptive, and predictive analytics are foundational to any data-driven decision-making process (Davenport, Harris, and Morison 2010), while prescriptive analytics is the most advanced stage of analytics (Grossman 2018). In contrast to descriptive analytics, which helps decision makers to understand what has happened in the past, and predictive analytics which forecasts future possibilities (Dennehy 2020), prescriptive analytics shifts the focus from understanding and forecasting to recommending actions (Lepenioti et al. 2020). In the context of supply chain resilience, where rapid and informed decision-making is critical, prescriptive analytics offers direct pathways to action, making it a crucial area for in-depth investigation (Wang et al. 2016). Prescriptive analytics has a direct impact on decision-making, whereas, descriptive and predictive analytics provide necessary insights and forecasts (Hazen et al. 2016), they often stop short of suggesting specific actions. In contrast, prescriptive analytics leverages AI to not only predict future scenarios but also recommend specific decisions and actions to achieve optimal outcomes. This direct impact on decision-making is particularly valuable in managing complex, dynamic supply chain environments, especially in responding to disruptions (MacKenzie, Barker, and Santos 2014).

At this point, we see another major shortcoming in extant literature regarding prescriptive analytics. Despite its transformative transformations in SC operation, it remains underexplored compared to its descriptive and predictive counterparts. This study addresses this theoretical shortcoming, by contributing to a more balanced understanding of how AI can enhance all aspects of supply chain analytics (Bertsimas and Kallus 2019). Out of all the different stages of analytics that have potential to enable varying degrees of SC resilience, prescriptive analytics offers the most significant value in terms of predicting disruptions as it enables organisations to respond effectively and efficiently to mitigate the impact of a disruption to the SC (Belhadi et al. 2021). Further, prescriptive analytics, through AI-driven recommendations, aligns closely with the goal of enhancing supply chain resilience by providing actionable insights that enable proactive and reactive measures to be formulated and implemented (Belhadi et al. 2021).

Despite the hype surrounding AI and analytics in SC, this study identifies fundamental shortcomings in extant literature. First, research on AI in the SC context is largely fragmented into research streams based on different types of AI functions (i.e. machine learning (ML), expert systems). This resonates with the 'fragmented adhocracy' issue, which has previously overshadowed other disciplines. Second, little distinction is made between descriptive, predictive or prescriptive use of AI. Prescriptive analytics distinguishes itself through its advanced analytical depth, moving beyond the foundational insights and forecasts of descriptive and predictive analytics, to deliver strategic, actionable guidance for decision-making (Lepenioti et al. 2020; Wang et al. 2016). Third, there is a gap in AI and SC literature reviews, which fail to examine the relationships between AI and descriptive, predictive, and prescriptive analytics. Moreover, these studies have largely focused on a specific application of AI i.e. decision support system (Belhadi et al. 2022; Pereira et al. 2022), singular function of AI i.e. ML (Sharma et al. 2020), or a single aspect of SCs i.e. risk management (Baryannis et al. 2019) rather than providing a holistic view of AI in the SC. A comparison of AI and SC review papers is provided in Table 1.

To address this knowledge gap, this study's overarching aim is to advance understanding about AI research in the context of supply chain resilience, with a focus on delineating the pivotal function of prescriptive analytics and its critical links across the varying analytical elements within AI. This aim is achieved by:

1. Synthesising the AI functions and algorithms that have been applied to specific elements of the SC.
2. Identifying in which SC industries AI research has been conducted.
3. Comparing relationships between AI and descriptive, predictive, and prescriptive analytics for the SC.
4. Identifying specificities of AI for prescriptive analytics in the SC.

Table 1. Comparison of AI & SC literature review studies.

Authors	Timeline	Objective	No. of primary studies	Supply Chain Industry Studied	Main contribution to AI & SC research
Baryannis et al. (2019)	1978–2018	Provide a comprehensive review of SC literature that addresses problems relevant to supply chain risk management (SCRM) that fall within the AI spectrum	276	Mixed	Examines the extent to which SCRM studies have effectively utilised AI-related capabilities in addition to highlighting the correlation between AI-related methodologies and SCRM tasks
Sharma et al. (2020)	2002–2019	Explores the application of ML in agricultural supply chains (ASC)	93	Agriculture	Highlights how ASCs can utilise ML applications for improved agricultural sustainability and productivity
Bodendorf, Merkl, and Franke (2021)	1995–2020	Review intelligent cost estimation methods in the manufacturing industry	47	Manufacturing	Outlines building blocks for a cost estimation system for part procurement
Pournader et al. (2020)	1998–2020	Examine the applications of AI in SCM	150	Mixed	Presents an AI taxonomy which collectively establishes the basis for present and future research
Toorajipour et al. (2021)	2008–2018	Identify the contributions of AI in SCM	64	Mixed	Identifies the most prevalent AI techniques as well as the SCM subfields these AI techniques can be employed to
Rolf et al. (2023)	2000–2021	Understand algorithms, applications, and practical adoption of reinforcement learning (RL) in SCM	103	Mixed	Provides a hierarchic classification framework that categories RL applications in SCM
Sharma et al. (2022)	1994–2021	Identify current trends, gaps, and research opportunities of AI applications in SCM	1076	Mixed	Uses science mapping techniques to identify specific research directions and to help better understand the relationships among past AI & SCM studies
Esteso et al. (2022)	1994–2021	Examine the use and applications of reinforcement learning in the production planning and control field	181	Mixed	Outlines RL applications, highlights, limits, and software characteristics in the PPC area.
Zamani et al. (2023)	2016–2021	Examine the applications of AI and big data analytics for improving supply chain resilience	23	Mixed	Identifies the phases of SCR that AI and BDA have been applied to in addition to synthesising the reported benefits of AI and BDA for SCR.
Pereira et al. (2022)	2011–2022	To explore literature on AI constructed customer models for decision support in the fashion retail industry	54	Retail	Offers information and methods to guide the development of AI-enabled customer recommendation systems for decision support
Vishwakarma et al., (2023)	2012–2022	To understand how AI contributes to building a resilient and sustainable healthcare system	89	Healthcare	Develops a framework that comprises AI applications' antecedents, practices, and outcomes for building a resilient and sustainable healthcare system
This review study	2000–2023	Examine the applications of AI and descriptive, predictive, and prescriptive analytics in the SC	76	Mixed	Compares the relationships and applications between AI and the three stages of analytics in the SC, in addition to categorising the reported benefits and challenges of AI

5. Categorising AI's reported benefits and challenges in the supply chain.

A systematic literature review is pertinent to this study as it provides (i) a means of accumulating knowledge about a topic area or phenomenon of interest, (ii) a process for evaluating and interpreting all available research, (iii) valuable new insights to identify where an issue can be rectified through additional primary studies, and (iv) a methodology that aims to be as unbiased as possible by being auditable and repeatable (Brereton et al., 200). The emphasis on prescriptive analytics within the realm of AI for SC resilience targets a strategic and significantly underexplored area, how AI can orchestrate direct responses to supply chain disruptions. Prescriptive analytics offer innovative opportunities due to its transformative power related to decision-making processes and its congruence with the objectives of enhancing supply chain resilience. By providing actionable insights, it becomes an indispensable tool for managing contemporary supply chains that are inherently complex data-driven, and inter-linked systems. This focus not only bridges a discernible gap in the existing literature but also contributes to a deeper comprehension of AI's instrumental role in strengthening the resilience of supply chains.

The paper is structured as follows. Background to AI functions and algorithms that are pertinent to this study and their related stages of analytics are presented. Next, the process that guided this systematic literature review is outlined. Then, the state-of-the-art of AI research is presented. This is followed by a discussion, which contains the implications of this research and a research agenda. The paper ends with a conclusion.

2. Related literature

2.1. AI functions and algorithms

The field of AI has experienced alternating periods of immense growth and significant decline since its introduction in the 1950s (Baryannis et al. 2019). The definition of AI has been widely debated among researchers for years, as a result of this no formal definition has been established. At its most basic, AI is a collection of technologies that combine large quantities of data, algorithms, and computing power to perform activities that require human intelligence (Borges et al. 2021a; Fragapane et al. 2021). AI systems have evolved from early applications in the form of decision support systems and expert systems to solve complex problems and perform specific tasks (Petrović et al. 2018; Abbasi et al. 2020). AI can be divided into two general forms: 'Strong AI', which can emulate human intelligence, and 'Weak AI', which can simulate human intelligence (Kaplan and Haenlein 2019). The 4 functions that fall under the umbrella of AI and are used as part of the analysis in this study are listed in Table 2.

Machine learning is one of the most popular AI functions used by SC researchers and practitioners, and its associated techniques and algorithms are listed in Table 3.

2.2. The three stages of analytics

There are three stages of analytics (Lepenioti et al. 2020):

Stage 1: Descriptive analytics that aims to help decision makers to understand *what* has happened in the past, and *why* it happened.

Stage 2: Predictive analytics that aims to predict what will happen in the future and why it will happen.

Stage 3: Prescriptive analytics that aims to prescribe what actions should be taken and why it should done.

Drawing on the work of Lepenioti et al. (2020) that classified the different algorithms between predictive and prescriptive methods, Table 4 classifies the most popular AI techniques and algorithms used by SC researchers between predictive and prescriptive methods.

2.3. Supply chain resilience

Supply chain resilience (SCR) has been widely defined as the ability of supply chains to plan for, respond to, and recover from disruptions efficiently and cost-effectively;

Table 2. AI functions.

AI Function	Description	Citations
Machine Learning	Is the study of algorithms and computational models that enable computers to learn from experience.	(Tirkel 2013; Portugal, Alencar, and Cowan 2018; Sharma et al. 2020)
Expert System	A rule-based computer programme that reasons with knowledge of some subject with a view of providing advice or solving problems.	(Liao, 2005; Yigin et al., 2007; Golini and Kalchschmidt 2015)
Artificial Intelligence Autonomous Robotics	Is the science of extending human motor capabilities with machines that utilise AI for navigation.	(Hidalgo-Paniagua, Vega-Rodríguez, and Ferruz 2016; Cebollada et al., 2021; Fragapane et al. 2021)
Machine Vision	Uses digital input and pattern recognition to inspect, analyse and extract information from objects automatically.	(Wen and Tao 1999; Abbasgholipour et al.2011; Ravikumar, Ramachandran, and Sugumaran 2011)

Table 3. Machine learning techniques and algorithms.

ML Techniques & Algorithms	Description	Citations
Decision Tree	Learns in the form of a tree structure, which consists of decision nodes and leaf nodes. Each decision node contains a branching rule which decides if the example should take a left or right path. The leaf node contains the value to predict when the example reaches it.	(Tirkel 2013; Ma, Wang, and Wang 2018; Morin et al. 2020)
Random Forest	Is an ensemble method consisting of many individual trees. It draws upon bootstrap sampling to create the training set and then grows regression trees on each bootstrap. These resulting trees are then averaged in order to yield a prediction.	(Abbasi et al. 2020; Brintrup et al. 2020; Sharma et al. 2020)
Artificial Neural Network (ANN)	A set of interconnected input and output nodes act as processing units. Each connection is associated with a weight which learn to reduce error between the actual and predicted values. ANNs classify perceptron networks, backpropagation networks, recurrent neural networks and Hopfield networks.	(Carbonneau, Laframboise, and Vahidov 2008; Cheng, Chen, and Lin 2010; Tirkel 2013)
Support Vector Machine	Classifies data by nonlinearly mapping the original data to high dimensional feature spaces first, then finds the decision boundary to separate the data set of one class from another.	(Ma, Wang, and Wang 2018; Brintrup et al.2020)
Classification	Supervised ML technique where the model attempts to predict the correct label of new observations based on given input data.	(Abbasi et al. 2020; Brintrup et al. 2020; Morin et al. 2020)
Clustering	The unsupervised classification of patterns into groups using algorithms to recursively find nested clusters either in a top-down or bottom-up fashion.	(Srinivasan and Narendran 1991; Celebi et al.2013; Sharma et al. 2020)
Regression Analysis	A classical predictive model that expresses the relationship between inputs and an output parameter as an equation (i.e. linear regression, logistic regression, polynomial regression).	(Tanaka, Hayashi, and Watada 1989; Ma, Wang, and Wang 2018; Sharma et al. 2020)
Reinforcement Learning Algorithms	Reinforcement learning (RL) is one of three main branches of ML. RL algorithms learn through trial and error. Where agents interact with an environment by performing actions and perceiving environmental states and must learn a 'correct behaviour' through a feedback reward system. RL algorithms primarily fall under two classifications: value-based algorithms such as, classic-Q learning and SARSA, and policy optimisation algorithms such as, SMART and policy gradient.	(Esteso et al.2023; Rolf et al.2023)
Hybrid Algorithms	This is when two or more simple algorithms work together to solve problems that they are not designed to solve alone. Includes various types of techniques that interact with the data in different ways.	(Bagloee et al., 2018; Mojrian et al., 2020)
Natural Language Processing Algorithms	Combines computational linguistics, rule-based modelling of human language and statistics to enable machines to understand, interpret, and derive meaning from human languages.	(Arazy and Woo 2007; Sangers et al.2013; Sidorov et al., 2014)

Table 4. Classification of AI algorithms between predictive and prescriptive.

Algorithms	Descriptive & Predictive Methods	Prescriptive Methods
Decision Tree	Mainly used for description and prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Random Forest	Mainly used for prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Artificial Neural Network (ANN)	Mainly used for prediction	Can be used for prescription
Support Vector Machine	Mainly used for prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Classification	Mainly used for description and prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Clustering	Mainly used for description and prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Reinforcement Learning	Can be used for prediction in specific contexts	Mainly used for prescription
Regression Analysis	Mainly used for diagnostic (descriptive) and prediction	Must be combined with optimisation algorithms or expert systems in a probabilistic context
Hybrid Algorithm	Can be used for prediction in specific contexts	Mainly used for prescription

it's the ability to take actions that should return the SC to its original state or better than before the disruption (Kahiluoto, Mäkinen, and Kaseva 2020; Sá de et al. 2019; Wieland and Wallenburg 2013). SCR entails a number of phases: preparedness, response, recovery, and growth or adaption (Li and Zobel 2020; Sá de et al. 2019; Stone and Rahimifard 2018). These disruptions can be internal, such as Volkswagen having to halt production at three plants due to man-made disruption (Bier, Lange, and Glock 2020), or external, such as the flood of Tabasco in 2007, which severely impacted Mexico's agricultural SC (Rodríguez-Espíndola et al. 2020). To mitigate disruptions, companies must actively understand the risk landscape, determine where the risks are best owned and managed, and strengthen the elements that help confront those risks (Kahiluoto, Mäkinen, and Kaseva 2020). These disruptions affect the supply of goods and services and have been shown to decrease stock prices (Hendricks and Singhal 2005).

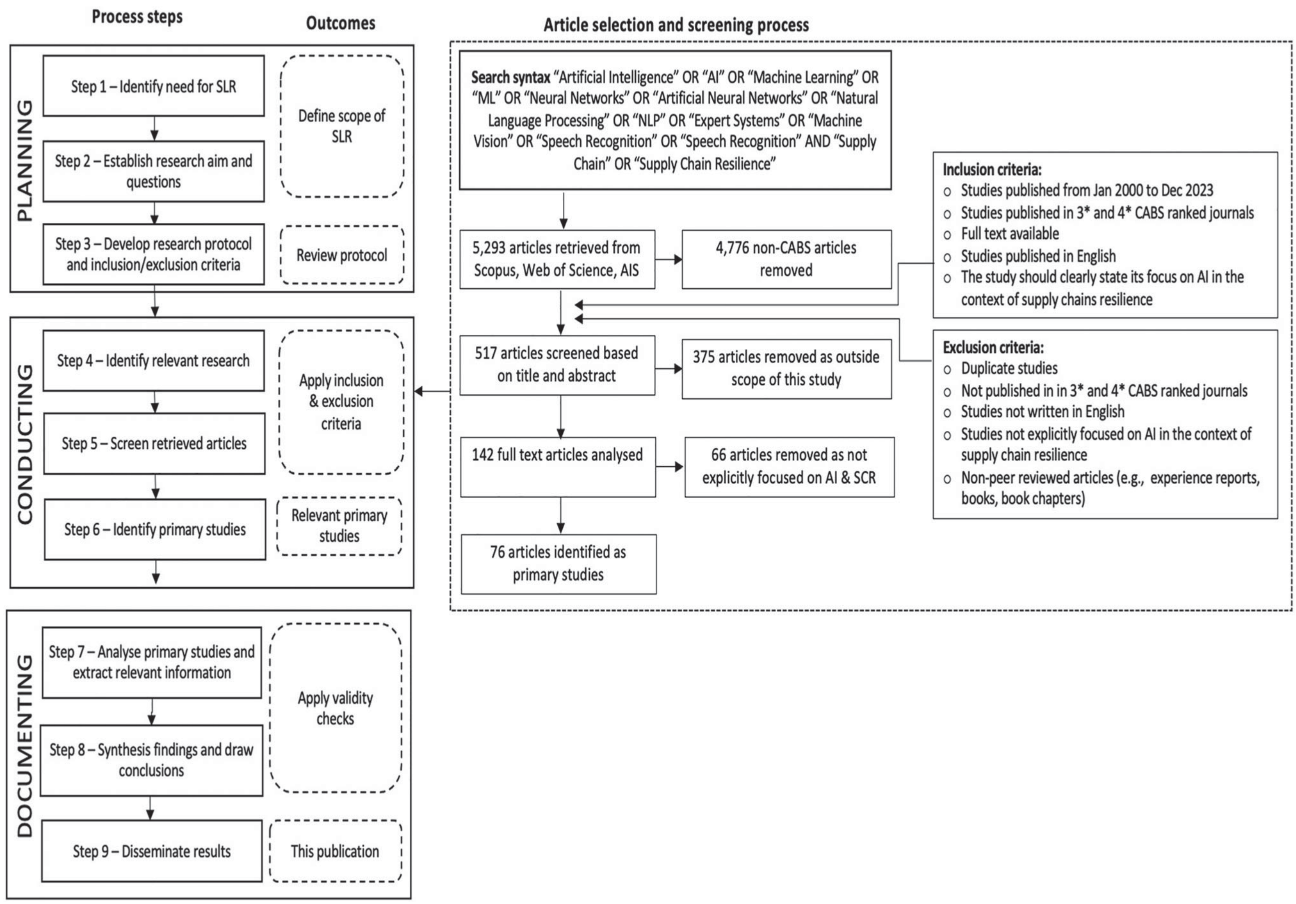


Figure 1. SLR process followed in this study.

3. Research methodology

The section outlines the process adopted in this study, which follows the established guidelines and procedures that Kitchenham et al. proposed (2004). This process consists of 9 steps across three phases (see Figure 1), namely, planning (3 steps), conducting (3 steps), and documenting (3 steps). The rational for choosing the Kitchenham et al. (2004) guidelines for conducting this study over the many other widely used guidelines (e.g. Fisch and Block 2018; Page 2021; Okoli and Schabram 2010; Webster and Watson 2002) was primarily influenced by the specific needs of our review process. For example, while PRISMA and its subsequent extensions provide a checklist for improving the reporting of various knowledge synthesis studies, emphasising transparency, replicability, and the usability of research findings (Mishra and Mishra 2023; Sarkis-Onofre et al. 2021), it does not however, include recommendations for methodological guidelines i.e. designing and conducting literature searches (Page et al. 2021). On the other hand, the Kitchenham (2004) guidelines offer a rigorous approach to the entire systematic review process, from initial planning to protocol development to the execution and reporting of the review. This comprehensive methodology, which includes detailed procedures for quality assessment and data synthesis, proved invaluable in enhancing the methodological rigour, analytical depth and clarity of the tabular data reported in this study. The three phases of the Kitchenham (2004) approach and their respective steps are discussed in the remainder of the section.

3.1. *Planning the review*

This section presents steps one, two, and three of the planning stage of this SLR. The motivation for this SLR is to curate and synthesise the fragmented body of knowledge related to the different types of AI technologies used to enable supply chain resilience across varying contexts (Step 1). To achieve this objective, the following research questions (Step 2) will be answered.

RQ.1 What is the current state of AI and supply chain literature?

RQ1.1 What 3* and 4* ranked journals are publishing AI research in the context of supply chains?

RQ1.2 What supply chain industries has AI research been applied to?

RQ1.3 What elements of supply chain has AI functions been applied to?

RQ1.4 What AI functions have been studied in SC research?

RQ.2 What are the different relationships between AI and descriptive, predictive, and prescriptive analytics in SC research?

RQ2.1 What methods are mostly used for descriptive, predictive, and/or prescriptive analytics in SC?

RQ2.2 What are the specificities of AI for prescriptive analytics in SC?

RQ.3 What are the reported challenges of AI in the context of supply chains?

RQ.4 What are the claimed benefits of AI in the context of supply chains?

Next, the search string, and inclusion and exclusion criteria was developed based on the scope of this study (Step 3).

3.2. Conducting the review

This section presents steps four, five, and six that were applied when conducting the review. To ensure the retrieval of the most relevant publications (Step 4), the search was conducted within three databases (i.e. Scopus, Web of Science, AIS) as these are the largest databases for abstracts and citations (Ballew 2009; Manikandan and Amsaveni 2016). The search retrieved 5, 293 AI and SC publications from January 2000 to December 2023. The 3* and 4* CABS ranking criteria were applied, which resulted in 517 remaining papers. The 517 papers were screened based on title and abstract (Step 5), which resulted in 142 remaining papers. Next, an in-depth review and quality assessment of the 142 papers was conducted independently by two authors to identify the relevant primary studies (Step 6). This process resulted in the identification of 76 primary studies (see Appendix).

3.3. Documenting the review

This section presents steps seven, eight, and nine which were applied to document the analysis and reporting of this review. The 76 primary papers were subject to an in-depth analysis (Step 7) using bibliometric analysis as this approach studies bibliographic material using quantitative methods (Martínez-López et al. 2018) and it has been previously used to study SC management (Fahimnia, Sarkis, and Davarzani 2015; Mishra et al. 2018), economics (Bonilla, Merigó, and Torres-Abad 2015), and big data analytics (Batistič and van der Laken 2019; Zhang et al. 2019). This study follows the guidelines proposed by Gaviria-Marin, Merigó, and Baier-Fuentes (2019) and uses the 'h-index' and its derivative 'm-index' as the main statistics used to evaluate productivity and influence. The h-index is the number of papers with citation number $\geq$ h, where h represents the number of papers published. The major advantage of using the h-index as one of the main statistics is that it measures both productivity and influence in a single number criterion (Bornmann and Daniel 2005). The m-index is calculated by dividing the h-index by the 'academic age' of the individual. Academic age is the number of years since the first publication of the individual. The additional statistics utilised in this study are derived from citation counts and yearly research output.

A synthesis of the findings (Step 8) was completed to provide the current state of AI and analytics in supply chain resilience literature, which includes the classification of the 76 primary studies across the descriptive, predictive, and prescriptive stages and identification of their relationships with AI for SC. A synthesis and categorisation of the reported challenges and claimed benefits of these technologies is also provided. Step 9 is the publication of this review.

4. Key findings and analysis

This section presents the state-of-the-art of AI research in the context of SC, based on the following (i) publication by year, (ii) type of journals, (iii) citation count, (iv) industry type, (v) elements of the SC, (vi) AI functions, (vii) reported challenges, and (ix) claimed benefits. The acronyms used in Figures 2–5 are presented below;

- TP: Total publications included in the study
- ≥ 200, ≥ 100, ≥ 50: Articles with more than 200, 100, and 50 citations
- < 50: Articles with less than 50 citations
- TC: Total citations
- C/Y: Citations per year
- Avg Cit: Average citations
- IF: Impact factor
- YFP: Year of first publication
- YP: Year published

4.1. RQ 1.1 What 3* and 4* ranked journals are publishing AI research in the context of supply chains between 2000 and 2023?

No studies were reported in 2000 and 2001, followed by two publications in 2002. The number of articles that met the inclusion criteria grew from 2 in 2002 to 76 at the end of 2023, this represents over a 38-fold increase in a 21-year span. During the seven-year period between

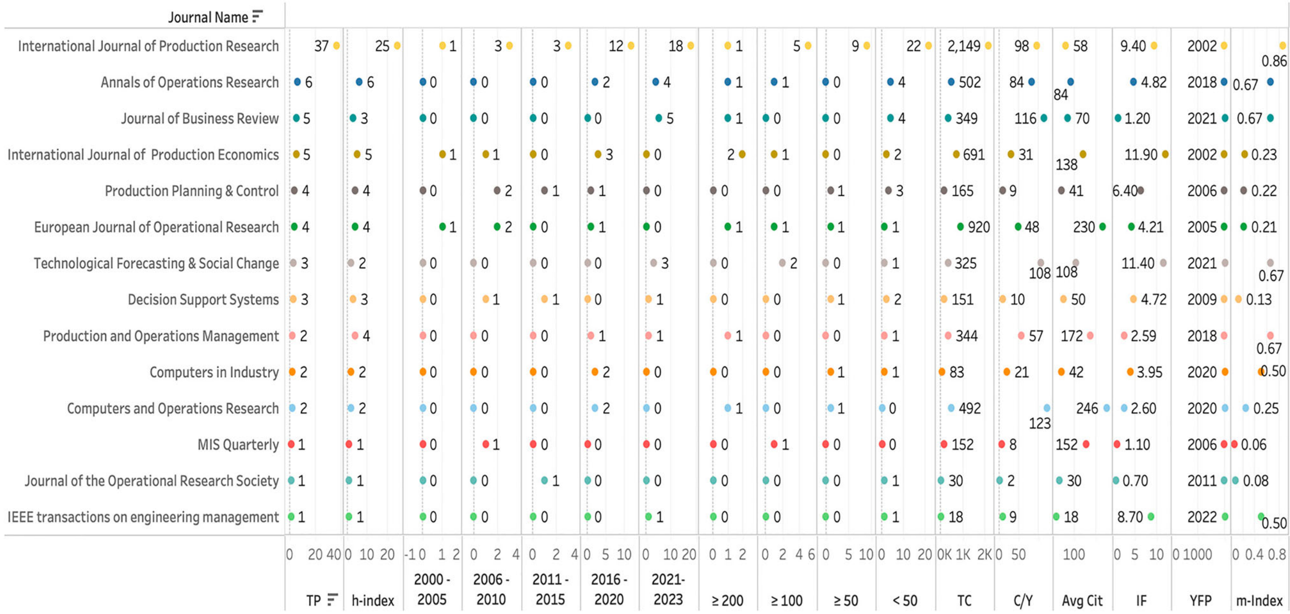


Figure 2. Journal sources of AI and supply chain research.

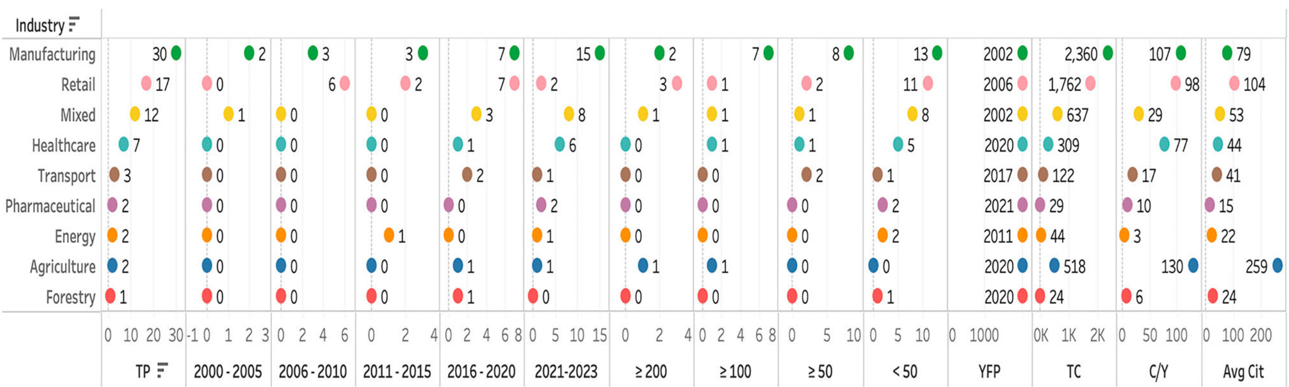


Figure 3. Supply chain industries where AI research been applied.

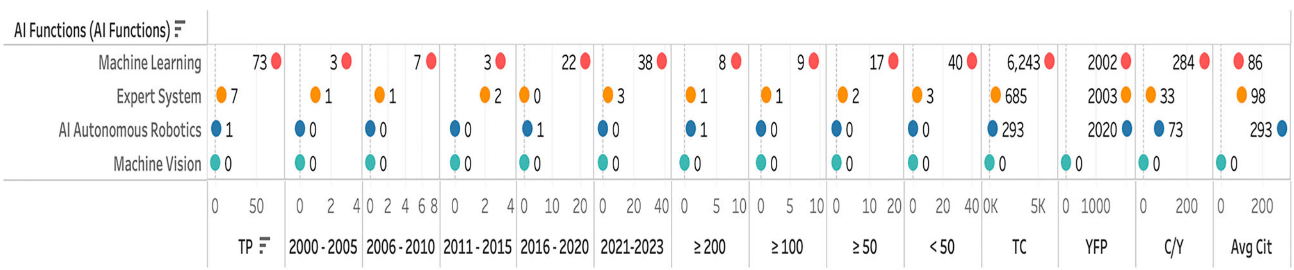


Figure 4. AI functions studied in supply chain research.

2016 and 2023, 57 out of the 76 primary papers were published, nearly three times the number of publications received in the 16 years prior. A possible explanation for this recent surge in interest is partly due to the increasing capabilities of various technologies (Baryannis et al. 2019; Fragapane et al. 2021) and that AI research has spread into a variety of contexts (Borges et al. 2021b; Grover, Kar, and Dwivedi 2020).

The articles included in this study were sourced from a total of 14 journals (see Figure 2), with the *International Journal of Production Research (IJPR)* accounting for approximately 49% of the analysed articles. The journals are ordered according to the total publications included (TP) and the h-index of the journal, which is calculated based on the citations and number of publications.

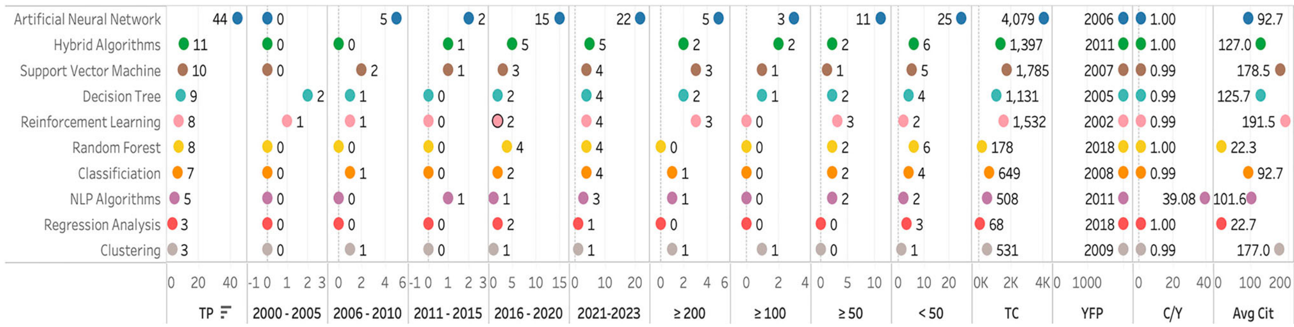


Figure 5. Machine learning paper statistics.

IJPR was the most productive and influential journal in this field with 37 publications and a h-index of 25, gathering a total of 2149 citations. While technological forecasting and social change and journal of business review only made their first AI and SC publications in 2021, their included papers have averaged 108 and 116 citations per paper respectively, indicating their high level of influence. Interestingly, 7 out of the 14 journals made their first publications in this field in the last 5 years, highlighting the growing interest among researchers and journals.

4.2. RQ1.2 What supply chain industries has AI research been applied to?

The articles in this study applied their research in a number of different industries. The industries are presented in Figure 3, ordered by TP.

Manufacturing and retail are the most widely studied industries in AI and SC research, with 30 and 17 publications respectively, accounting for 62% of the primary papers. Additionally, manufacturing and retail account for 71% of all citations. Prior to 2016 a total of three SC industries had been the focus of AI research, however since 2020, AI research has branched into four new industries; healthcare, agriculture, forestry, and pharmaceutical.

4.3. RQ1.3 What elements of supply chains have AI functions been applied to?

The studies where AI functions have been applied across supply chain elements are listed in Table 5. Most notable is that only 3 out of the 4 AI functions have been reported in the 76 primary studies.

The findings of this review indicate that AI has a vast potential for applications across the SC industry. The data that is generated in each of these stages can be used to support various AI functions to perform specific tasks. ML as expected, has the largest application area among all AI functions. However, ML should not overshadow the benefits that can be achieved through the remaining functions of AI. The findings suggest that AI can improve overall efficiency, provide effective decision support, and address the industry's most alarming challenges, such as forecasting, SC configuration,

Table 5. Elements of supply chain where AI has been applied.

AI Functions	Supply chain elements	Primary paper source
Machine Learning	Demand forecasting	P1, P7, P16, P17, P21, P34, P38, P42, P44, P50, P52, P58, P66, P67, P69, P70, P71, P74
	Supplier selection and evaluation	P35, P69
	Automation and decision support for inventory management and replenishment	P3, P6, P18, P20, P23, P36, P43, P48, P58, P63, P66, P67, P68, P69, P70, P71, P73, P74, P76
	Optimisation of processes and procedures	P2, P5, P16, P39, P41, P46, P48, P49, P54, P65
	Risk management	P8, P11, P42, P46, P47, P70, P72, P75, P76
	Predict disruptions	P30, P47
	Selecting appropriate forecasting models	P33
	SC visibility	P9, P25, P28, P32, P37, P42, P57
	Automation and decision support for SCCDP	P5, P8, P11, P12, P13, P14, P15, P19, P26, P27, P29, P39, P48, P51, P59, P60, P61, P62, P64, P65, P68, P71, P73, P74, P75, P76
	Provide insight into customers	P3
	Extract supply chain maps	P9
	Obtain previously inaccessible data	P3, P57, P70, P71
	Improve production and quality control	P17, P22, P53, P55, P56, P58, P74
Expert Systems	Supplier selection	P10
	Decision support for SCCDP	P40, P45, P70, P71, P75
	Solve SC optimisation and logistic problems	P24
AI Autonomous Robotics	Advanced automation	P4

Table 6. ML algorithms used in supply chain research.

Machine learning algorithms	Primary paper source
Decision Tree	P14, P27, P36, P40, P48, P51, P69, P74, P76
Random Forest	P2, P16, P18, P36, P37, P49, P54, P69
Artificial Neural Network (ANN)	P1, P6, P7, P9, P10, P11, P12, P14, P16, P17, P18, P19, P21, P22, P24, P25, P28, P30, P31, P32, P33, P35, P38, P39, P42, P44, P45, P46, P47, P50, P52, P53, P55, P57, P58, P59, P60, P61, P62, P68, P69, P70, P73, P74
Support Vector Machine	P1, P37, P40, P42, P51, P52, P57, P58, P70, P74
Classification	P2, P16, P36, P37, P68, P69, P70
Clustering	P6, P17, P74
Reinforcement Learning	P15, P20, P33, P63, P66, P67, P68, P70
Regression Analysis	P5, P40, P47
Hybrid Algorithm	P3, P8, P23, P26, P46, P54, P56, P58, P65, P68, P69
Natural Language Processing Algorithms	P3, P9, P57, P70, P71

Table 7. Relationships between AI and the different stages of analytics.

	Stages of analytics	Methods used	Primary study
1	Predictive	Machine learning, neural network, fuzzy control, statistical analysis methods	P1, P14, P17, P19, P22, P27, P28, P29, P30, P32, P34, P38, P44, P47, P50, P52, P57, P59, P60, P61, P62, P64
2	Prescriptive	Simulation, mathematical programming, and stochastic optimisation models, reinforcement learning (RL), Markov decision processes (MDP)	P2, P3, P4, P5, P6, P10, P11, P15, P16, P18, P20, P23, P24, P36, P37, P40, P41, P43, P45, P49, P51, P53, P54, P55, P56, P63, P65, P66, P67, P68, P70, P71, P73
3	Predictive and Prescriptive	Machine learning, data mining algorithms, Expert systems, Hybrid classification model combining probabilistic neural network, rough sets and decision tree, Markov chain, Neural Networks combined with optimisation models	P4, P7, P8, P9, P12, P13, P21, P25, P26, P31, P33, P35, P39, P46, P48, P58, P69, P72, P74, P75, P76

design, and planning (SCCDP), optimisation, and managing SC disruptions. The potential benefits of AI can enable SC organisations to survive in turbulent market conditions.

4.4. RQ 1.4 What AI functions have been studied in SC research?

Figure 4 presents the 4 AI functions that have been applied in SC research, and ordered according to the TP included in the study.

The popularity of ML algorithms being used in SC research is listed in Table 6. This is primarily due to a wide array of ML applications (Carbonneau, Laframboise, and Vahidov 2008; Ma, Wang, and Wang 2018; Sharma et al. 2020). Mahmud et al. (2017) claim that AI research has evolved into two main directions, namely, ML and Expert Systems (ES). The findings of this study support this claim as ML is examined in 73 of the 76 primary papers, ES accounts for 7, and AI autonomous robotics for 1. Although the AI functions outside of ML have received little attention from the SC research community to date, this study indicates this is changing. For example, AI autonomous robotics was first published in a SC journal in 2020, yet, it has the second-highest average citations, indicating the evident relevancy and interest among researchers.

Further evidence of the growing popularity of ML in SC research is evidenced in Figure 5, with 52 ML publications being received between 2021 and 2023, 22 of these publications focusing on Artificial Neural Networks (ANN). ANN is the most widely applied ML algorithm in the SC industry. A possible explanation for this increase in this likely due to the predictive power of ANN and the flexibility of its architecture (Hou et al. 2017; Lau, Ho, and Zhao 2013; Tsai and Huang 2017). Despite 6 out of the 10 ML algorithms receiving their first publications before 2010, 89 out of the 108 ML algorithms examined in the 76 primary papers were published after 2016. Again, this reiterating the growing trend of ML research in SCs. In contrast, clustering algorithms have received little attention since its introduction in 2009, with only two additional studies being published over a 14-year span. Despite this, clustering has the highest average citations out of all algorithms, indicating the prominent influence of the clustering studies and outlining the potential interest for future clustering research.

4.5. RQ 2 What are the relationships between AI and predictive and prescriptive analytics?

How the various AI methods used can be related to the stages of analytics are listed in Table 7. None of the papers was descriptive. We have added a section for predictive and prescriptive analytics as a number of authors have intentionally underlined clearly the double objective of their methodology.

Machine learning and data mining algorithms (e.g. ANN) were used in SC primarily for prediction (P1, P30, P38), while other papers were combined with optimisation and probabilistic models to add prescriptive aims (P7, P9, P12, P25, P26, P31, P35, P46). While simulation, mathematical programming, and stochastic optimisation models were used for prescription. Hybrid Algorithms (P3, P20, P23, P26), Reinforcement Learning algorithms such as Semi-Markov Average Reward Technique (P11) were also used only for prescriptive analytics. Regression can be combined with optimisation methods for prescriptive designs (P5, P40). Reinforcement Learning algorithms (P20) can be used for prescriptive aims but also can improve forecasting methods. Support Vector Machine, a predictive method (P1, P52) was also combined with other algorithms (such k-Nearest Neighbour for example) to offer prescriptive outputs (P37, P40, P51). Worth noting is that predictive methods such as Support Vector Machines inherently focus on forecasting outcomes based on historical data. To transition from merely predicting to prescribing actions, these methods must be integrated with optimisation techniques. This integration enables the formulation of actionable recommendations by not just forecasting outcomes but also evaluating and suggesting optimal decisions based on those forecasts. Random Forest was only used in prescriptive designs (P2, P16, P18, P36, P37, P49, P54).

4.6. RQ2.2. What are the specificities of AI for prescriptive analytics in SC?

Building on Table 7, there is a growing trend towards combining methods to implement more and more prescriptive designs to solve SC problems. Prescriptive designs offer the possibility to benefit from timely informed decisions based on real-time data analyses. The combination of Machine Learning and data mining algorithms with optimisation and probabilistic models is considered as a way to modelise real-world complexity and uncertainty (P33). Prescriptive models have also the advantage to rely on expert knowledge represented in the Expert systems (P10, P24, P40, P45). Experts' input can reduce the sensitivity of prescriptive designs to hidden and unchecked data biases (Merhi and Harfouche 2023) compared with predictive algorithms that uses only the available data to develop their models. Since the business environment is becoming more volatile and unpredictable (Akter and Wamba 2019), a timely response to changes plays a key role in organisations' capacity to survive. Prescriptive designs can implement adaptation technics (the reinforcement mechanisms for example) that offer the unique possibility to include new constraints when there are changes in the business environment (P15, P20, P33).

4.7. RQ3 What are the reported challenges of AI in the context of supply chains?

The primary studies in this review outlined challenges faced by the SC industry, which the study later addressed through the implementation of an AI. This review has synthesised these challenges and categorised them into seven categories (see Table 8). Each challenge is explained based on the analysis of primary papers.

Challenge 1 – Problems resulting from using traditional forecasting techniques: Twenty-one studies reported forecasting-related issues, making it the most prominent challenge from AI and SC literature. Forecasting refers to customer demand forecasting or making predictions about internal processes and operations. Traditional forecasting techniques (TFT) are severely limited when applied to complex systems (Chien, Lin, and Lin 2020; Jaipuria and Mahapatra 2014; Wong and Guo 2010). Considering the growing intricacies of SCs (Bozarth et al. 2009), TFTs will struggle to yield effective and efficient predictions.

Challenge 2 – Difficulties of selecting appropriate suppliers and managing supplier relationships: Four studies highlighted supplier selection (SS) and supplier management problems. Due to rising global competitiveness (Zhao and Yu 2011) and customers growing need for efficient delivery (Aksoy and Öztürk 2011), SS and supplier management have become increasingly a challenging decision for SC organisations (Sharma et al. 2020). Therefore, to make an informed decision, companies must incorporate a large number of tangible and intangible factors

Table 8. Reported challenges of AI in the context of supply chains.

	Challenges	Primary study source
1	Problems resulting from using traditional forecasting techniques	P1, P7, P13, P14, P18, P19, P21, P28, P31, P33, P34, P37, P38, P39, P52, P58, P66, P67, P69, P71, P74
2	Difficulties of selecting appropriate suppliers and managing supplier relationships	P5, P10, P44, P69
3	Managing supply chain disruptions and risk mitigation	P8, P11, P17, P18, P22, P26, P30, P42, P46, P47, P48, P50, P57, P59, P68, P69, P70, P72, P75, P76
4	Managing inventory and selecting appropriate replenishment strategies	P6, P16, P18, P20, P23, P58, P63, P66, P67, P68, P69, P71, P73, P74, P76
5	Issues related to supply chain configuration, design, and planning (SCCDP)	P5, P12, P15, P24, P27, P29, P32, P36, P40, P42, P45, P48, P51, P57, P59, P60, P61, P62, P64, P68, P70, P71, P73, P74, P75, P76
6	Problems faced during the production process	P4, P17, P53, P55, P56, P58, P74
7	Difficulties in optimising supply chain processes and procedures	P2, P5, P8, P36, P39, P41, P48, P49, P54, P65

into the decision-making process (Choy, Lee, and Lo 2003).

Challenge 3 – Managing supply chain disruptions and risk mitigation: Twenty studies reported challenges related to disruptions and risk management. SC disruptions and risk management are grouped as they have the same objective: to minimise SC interruptions and delays. The aversion of risks has long been a troubling task for SC organisations (Baryannis et al. 2019; Modgil, Singh, and Hannibal 2021), SC risk management aims to ensure that these risk do not turn into disruptions. SC disruptions pose a significant threat to business operations and can result in increased costs, damaged company reputation and lose of profit (Bier, Lange, and Glock 2020; Hendricks, Singhal, and Zhang 2009; Wagner and Bode 2008).

Challenge 4 – Managing inventory and selecting appropriate replenishment strategies: Fifteen papers highlighted inventory and vendor-related challenges. Customer demand continuously evolves and grows (Bodaghi, Jolai, and Rabbani 2018), forcing SC companies to become more responsive to change (Golpîra 2020). As inventory is the cornerstone of every SC (Badakhshan and Ball 2023a; Jauhar et al. 2023), SC must evolve to meet customer demand, and therefore, the inventory and vendor management strategy must adapt to the changing environment. This in conjunction with the complexity of today's SCs makes ensuring a smooth flow of material a difficult task for all SC companies (Chi et al. 2007; Vanvuchelen, Gijsbrechts, and Boute 2020).

Challenge 5 – Issues related to supply chain configuration, design, and planning: 26 studies reported SC configuration, design, and planning (SCCDP) problems. SCCDP plays a critical role in establishing a competitive advantage and ensuring the responsiveness of the SC (Parmigiani, Klassen, and Russo 2011). It must harmoniously draw upon all the available resources and capabilities to meet demand. Considering the disruptions (Brintrup et al. 2020; Nezamoddini, Gholami, and Aqlan 2020), and fluctuations in demand (Chien, Lin, and Lin 2020; Fragapane et al. 2021) that contemporary SCs endure, ensuring that the SCCDP is optimal is critical.

Challenge 6 – Problems faced during the production process: 7 studies reported production-related problems. As a result of the increasing pressure to provide higher quality products (Rong, Akkerman, and Grunow 2011) and increased transparency into SC processes (Sodhi and Tang 2019), SC production is under increased scrutiny.

Challenge 7 – Difficulties in optimising supply chain processes and procedures: Ten studies highlighted SC optimisation issues, which has been a frequent challenge for the SC industry (cf. Philpott and Everett 2001; Fahimnia, Sarkis, and Davarzani 2015). This issue is exacerbated due to the increasing scale and complexity of SCs (Abbasi et al. 2020). Traditional methods for solving optimisation problems typically lack the ability to capture the nonlinearity and complexity of SCs, resulting in an underper-
forming SC.

The most prominent reported challenge in AI and SC research is issues relating to SCCDP. However, studies like Ferreira and Borenstein (2011) have demonstrated the potential of using non-traditional methods for solving SCCDP issues such as simulations, which allow for SC logistics to be realistically modelled and observed for improvements. Research question three will highlight how can AI can address the aforementioned challenges.

4.8. RQ3 What are the claimed benefits of AI in the context of supply chains?

This research question aims to identify and synthesise the claimed benefits of using AI in the SC industry. These benefits were categorised into eight categories (see Table 9), this review acknowledges that some of these categories could be mapped to more than one category, however, to avoid complexity they are mapped to the most relevant category. Each reported benefit is explained based on the analysis of 76 primary papers.

Benefit 1 – Improved demand forecasting (DF) accuracy: A total of 17 predictive and prescriptive papers reported the benefits of using ML for DF, making DF the third most reported benefit of AI. DF plays a critical role in the design and operation of SCs (Jaipuria and Mahapatra 2014; Turrado García, García Villalba, and Portela

Table 9. Reported benefits of AI in supply chains.

	Benefits	Primary study source
1	Improved demand forecasting accuracy	P1, P7, P8, P19, P21, P28, P33, P34, P38, P39, P52, P58, P66, P67, P69, P71, P74
2	Increased supply chain visibility and responsiveness	P8, P9, P11, P17, P22, P25, P30, P37, P42, P47, P48, P50, P57, P68, P70, P72, P75, P76
3	Enhanced data extraction	P3, P44, P70
4	Strengthened supply chain configuration, design, and planning	P5, P12, P13, P15, P26, P27, P29, P32, P36, P40, P42, P45, P48, P51, P57, P59, P60, P61, P62, P64, P68, P69, P70, P71, P73, P74, P75, P76
5	Optimised supply chain processes and procedures	P2, P5, P8, P24, P41, P36, P39, P46, P48, P49, P54, P63, P65
6	More efficient and higher quality production	P4, P14, P17, P28, P31, P53, P55, P56, P58, P74
7	Improved supplier selection and management	P10, P35, P69
8	Enhanced inventory and vendor management	P6, P16, P18, P20, P23, P43, P58, P66, P67, P68, P69, P71, P73, P74, P76

2012). Forecasting was the most challenging problem facing the SC industry. Traditional DF methods can result in a demand to fluctuate and become distorted (Carbonneau, Laframboise, and Vahidov 2008), however, as the 17 primary papers suggest, ML can accurately make predictions into customer demand. These DF predictions enable SC organisations to align production output (Kantasa-ard et al. 2020) and enable effective SC planning (Lau, Ho, and Zhao 2013).

Benefit 2 – Increased supply chain visibility and responsiveness: 18 primary prescriptive studies demonstrated the benefits of AI for improving SC visibility and responsiveness. This study has highlighted the evident need for SCR in today's turbulent environment. SC visibility and responsiveness are some of the key contributors in building a resilient SC. Implementing AI can dramatically improve SC visibility as it has the ability to process and feedback information in real time (Hong, Kim, and Kim 2010), and can automate SC mapping (Wichmann et al. 2020), providing SC organisations with a more comprehensive and detailed view of the entire SC, which in turn benefits SC disruption risk management (Ivanov, Dolgui, and Sokolov 2019). Moreover, ML has the ability to predict SC disruptions (Brintrup et al. 2020; Liu et al. 2016), which enables organisations to plan and become more responsive to interruptions and delays adequately.

Benefit 3 – Enhanced data extraction: This was the least reported benefit of AI along with supplier selection and management, with 3 primary studies conveying AI's ability to extract and distil unstructured data from previously unobtainable sources. ML algorithms can sieve through vast information, extract what's applicable, and then transform into structured useable data (Arazy and Woo 2007). This data is valuable to organisations as it provides an improved insight into customers (Maiyar et al. 2019), and the additional data can improve MLs' predictive capabilities (Cui et al. 2018).

Benefit 4 – Strengthened supply chain configuration, design, and planning (SCCDP): SCCDP was the most reported challenge facing SC organisations (Table 7), however, it is evident that the various applications of AI can be advantageous for SCCDP as it was the most claimed benefit of AI. As previously highlighted, effective SCCDP is a primary element of a successful SC organisation (Parmigiani, Klassen, and Russo 2011). SCCDP is more relevant now than ever before as SC organisations endure more turbulence and complexity than ever before. Prescriptive AI designs can provide efficient and effective decision support for SCCDP problems. For example, Morin et al. (2020) utilised ML models to solve wood allocation issues in sawmills, a design and configuration decision that involves a multitude of variables. AI can simulate SC operations to provide decision-makers a more in-depth insight into their processes (Ferreira and Borenstein 2011; Thomas, Thomas, and Suhner 2011). Moreover, AI can take a more prominent role and automate SC configuration and formation (Piramuthu 2005a; 2005b).

Benefit 5 – Optimised SC processes and procedures: 13 prescriptive studies reported benefits of AI for SC optimisation. As previously mentioned SC optimisation is a continuous challenge for SC organisations. These optimisation problems often include a large amount of variables, meaning that traditional methods can be time-consuming and often lack the capabilities to adequately address the complexity of the issues (Yan et al. 2017). However, AI excels at optimisation problems and saving time and resources of the organisation (Abbasi et al. 2020; Nezamoddini, Gholami, and Aqlan 2020).

Benefit 6 – More efficient and higher quality production: 10 primary studies indicated that AI can improve SC production, which is highly susceptible to external pressures. As a result, SC production must seek alternative methods to help address these pressing concerns. The primary studies illustrate that AI based autonomous agents can provide physical assistance to production (Fragapane et al. 2021), additionally, ML can be used for quality inspection and control of products (Karimi-Mamaghan et al. 2020; Ma, Wang, and Wang 2018; Zhang et al. 2011).

Benefit 7 – Improved supplier selection and management: 3 studies reported benefits of AI for supplier selection and management. Under the SC environment's current complexity, selecting and evaluating suppliers has become critical for an enterprise's healthy growth (Zhao and Yu 2011). ML and ES can incorporate a large number of variables into the decision-making process (Aksoy and Öztürk 2011; Belhadi et al. 2022; Choy, Lee, and Lo 2003), meaning that the results will be comprehensive and provide an accurate depiction.

Benefit 8 – Enhanced inventory and vendor management (IVM): 15 studies indicated that AI can improve IVM. Similarly to SC optimisation, IVM requires organisations to consider a large of factors to determine the correct strategy. Moreover, the fast-changing environment of modern SCs requires organisations to continuously adapt their IVM strategies (Priore et al. 2019). However through the adoption of AI, SC organisations can automate the identification of the optimal replenishment strategy (Chi et al. 2007; Vanvuchelen, Gijsbrechts, and Boute 2020) and improve their inventory management (Doganis, Aggelogiannaki, and Sarimveis 2008; Giannoccaro and Pontrandolfo 2002).

5. Discussion, implications, and future research

This review addresses a prominent gap in AI and SC literature. Previous SLRs have been largely fragmented into different research streams failing to provide a complete overview of AI in SCs. These reviews have either focused on a specific function of AI such as machine learning (Hosseini and Ivanov 2020; Sharma et al. 2020), or a single aspect of supply chains such as risk management (Baryannis et al. 2019), or a particular application of AI such as decision support systems (Ngai et al. 2014). However, this review broadens the focus of previous SLRs to include all functions, aspects, and applications of AI in the SC industry, forming a complete picture for both researchers and practitioners to build upon.

The results and analysis of the study reveal novel insights. Firstly, AI research in the context of SCs has only covered 3 of the 4 functions of AI. While this could be largely due to the capabilities of current technology, it still illustrates a prominent gap in the literature that is impeding both SC researchers and practitioners from leveraging the full potential of AI, and analytics in general. Despite that 73 of the 76 primary papers examined ML, the benefits of the remaining functions of AI should not be overshadowed, AI autonomous robotics in particular. Despite only one primary paper that analysed AI autonomous robotics in SCs, the potential increase in efficiency and control was evident. While this reinforces the need for more research, it is vital that researchers diversify away from a heavy ML focus and not only investigate the applications of the different functions of AI, but also how these functions collectively interact with each other to achieve previously inaccessible gains. Lastly, the synthesisation of the applications, challenges, and benefits highlighted in AI and SC literature has enabled this review to provide a comprehensive view of AI in SCs that has not been provided to date, to the best of the author's knowledge. Therefore, based on this aggregation of this knowledge, this review shows that AI has the potential to enable supply chain-centric organisations to thrive in increasingly complex, and turbulent environments. Nevertheless, we make the call to action for an orchestrated effort within and between academic disciplines and organisations reliant on global SC (e.g. agri-food, humanitarian response) to ensure AI can be leveraged for economic and social value. Against this background, we provide a roadmap for future SC researchers to address these issues (see Table 10).

Table 10. AI in SC – a research agenda.

AI Function	Research Questions
Machine Learning	(1) What ML algorithms perform best for predicting SC Disruptions? (2) How can ML be used for SC risk identification and mitigation? (3) Can ML be integrated with machine vision to improve SC visibility?
Expert System	(1) How effective are expert systems at selecting suppliers in comparison to ML? (2) How can expert systems be used to optimise and solve SC logistic problems? (3) Can expert systems be integrated with robotics to improve their reasoning capabilities?
AI Autonomous Robotics	(1) How can robotics be used for advanced automation in SCs? (2) What benefits would robotic automation have for SCR? (3) Can integrating machine vision with robotics enable for more complex tasks to be automated?
Machine Vision	(1) Can machine vison be used to improve SC visibility? (2) What benefits can be generated from integrating machine vision across the SC? (3) Can machine vision be used to monitor production quality?

To enhance the resilience and efficiency of supply chains through AI, future research should focus on the integration of various AI functions, the exploration of emerging technologies, and the development of collaborative models between AI and human expertise. Investigating sector-specific applications, ethical and sustainability considerations, and the role of AI in global supply chains are also crucial. Additionally, longitudinal studies and advanced AI-driven analytics for scenario planning will provide deeper insights into the evolving impact of AI on supply chain resilience. This comprehensive approach will pave the way for innovative solutions and responsible management practices in the face of increasingly complex supply chain challenges.

5.1. Implications for decision makers

This review of AI in SCs can help key decision makers towards a better understanding of AI and it's applications, moreover as it highlights how AI can aid in the development of SCR, which is becoming an increasingly challenging task in today's turbulent environment (Remko 2020; Zheng et al. 2021). This review indicates the inherent challenges of traditional methods that are widely adopted across SCs. These traditional methods are used for demand forecasting, supplier selection, and the optimisation of SC configuration, inventory management, and internal processes. SCs are growing in complexity (Bode and Wagner 2015; Bozarth et al. 2009; Hosseini and Ivanov 2020a), therefore, SC organisations should consider alternative methods to address this escalating intricacy, as traditional techniques are severely limited when applied to complex systems (Chien, Lin, and Lin 2020; Jaipuria and Mahapatra 2014; Wong and Guo 2010). Additionally, this review illustrates the difficulties SC organisations can experience with managing the risk of SC disruptions. However, the potential benefits

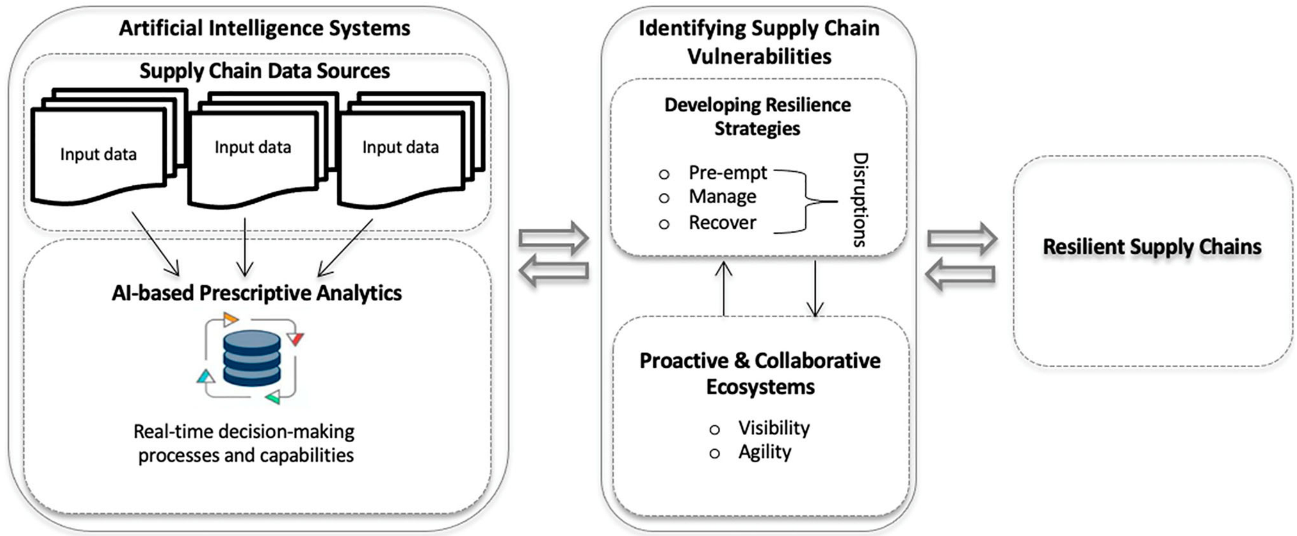


Figure 6. Strategic AI Resilience Framework.

of AI can significantly outweigh the risk of not embedding AI into SC to enhance its resilience. Further, this review offers a concise overview of the applications of the different functions of AI, in addition to the benefits of AI that can enable organisations to manage their SC effectively and efficiently. As a result, this review can conclusively say that AI has the potential to positively impact all major aspects of the SC. This includes but not limited to, providing an improved insight into customers, selecting appropriate suppliers, optimising internal processes, strengthening SC configuration and planning, improving SC visibility, and process automation. Worth noting is the potential of AI as a cybersecurity tool, an application of AI that was not studied in the primary papers. Radanliev et al. (2022) illustrate how the advancements of AI will cause the current methods of cybersecurity to fail. However, by developing cybersecurity solutions based on AI algorithms, organisations can achieve improved cyber risk management (Radanliev et al. 2022a; 2022b), indicating that AI will become an essential cyber risk management tool for all organisations.

The reported benefits of AI and analytics can greatly improve the resiliency of SC across the four phases, namely preparedness, responsiveness, recovery, and growth or adaption (Li and Zobel 2020; Sá de et al. 2019; Wieland and Wallenburg 2013). From the applications highlighted in this review, it is evident that AI has the potential to greatly improve an organisation's preparedness and responsiveness. *Preparedness* refers to anticipation of a disruption and requires the continuous monitoring of the environment (Stone and Rahimifard 2018), AI's ability to enhance insight into customer demand and preferences, predict disruptions, and increase visibility along the supply chain to significantly improve an organisation's preparedness for a disruption. Moreover, *responsiveness* refers to the pre-planned elements that mitigate the impact of disruptions (Fahimnia and Jabbarzadeh 2016; Leat and Revoredo-Giha 2013), it has been reported that AI can improve an organisation's risk management, select appropriate suppliers that are less likely to fulfil orders and strengthen SC configuration making the SC as a whole less susceptible to disruptions. The aggregation of the collective knowledge on AI in SCs provides practitioners a clear benchmark of the potential of AI. Therefore, this review not only illustrates the rationale for organisations to adapt, but it also serves as a reference point for organisations seeking to implement AI, providing an overview of the many applications and benefits AI has to offer the SC industry.

Through the analysis of the primary papers and theorisation of AI for SC resilience, we propose the Strategic AI Resilience Framework (see Figure 6) that enables decision-makers to strategically leverage AI for enhancing supply chain resilience, by focusing on identifying vulnerabilities, integrating AI technologies, and developing resilience strategies. This framework articulates how AI applications can be systematically applied to preempt, manage, and recover from disruptions to the SC. This framework includes the assertion that AI-driven prescriptive analytics significantly improves decision-making processes, enabling proactive responses to potential supply chain disruptions. Additionally, the framework proposes the exploration of the role of AI in fostering collaborative SC ecosystems, enhancing visibility, agility, and ultimately resilience.

5.2. Implications for research

Building on previous research, this study contributes to the analysis of the application of AI in the SC industry guided by an SLR that covers studies conducted over 20 years. Firstly, this research describes the current state of AI and SC resilience literature, illustrating publication trends, journals, and influential articles, which collectively provide researchers with the most updated knowledge of relevant studies. Secondly, this paper provides an evidenced-based research agenda that outlines important research questions about each AI function in the context of SCs. This study synthesis the applications of the different AI functions (i.e. machine learning) in the context of SCs. Moreover, studies that have included all the functions of AI have focused on a specific application of AI in SCs (e.g. risk management) rather than SCs as a whole. Therefore, this research contributes to the accumulation of knowledge and provides researchers a complete picture of AI in SCs. Collectively, this review provides researchers with a strong foundation of knowledge that will enable them to further examine the extent of the applications of AI in the context of SCs.

5.3. Limitations

This work is not without limitations. Firstly, three international databases were used to source articles. Future studies which means that any articles not indexed in these will not have been covered. Secondly, this review only covers literature published in the last 23 years. Lastly, the articles selected for review are drawn from 3* and 4* CABS journals. Other CABS ranked journals and non CABS ranking journals, as well as conference papers and non-peer reviewed materials were not in the scope of this study. Future studies could include these sources which might offer a broader understanding of this research topic.

6. Conclusion

The vulnerability of SCs highlighted by recent global events motivated this study to provide a state-of-the-art of AI and predictive analytics research in supply chains, with the overarching goal of outlining the applications that can enable the development of supply chain resilience. The findings suggest that AI has a vast array of applications and benefits to SC organisations and that AI has the potential to address many of the challenges identified in SC literature. Notably, AI is increasingly being utilised for the development of prescriptive analytics to enable supply chain resilience. Moreover, the claimed benefits of AI can play a role in creating a SC that is aligned with their customer needs, is more streamlined and efficient, has greater visibility, and can ultimately adapt to the rapidly changing and turbulent global environment that supply chain organisations operate in. Further research, however, is warranted to advance understanding of the potential of AI as a key enabler of supply chain resilience.

Disclosure statement

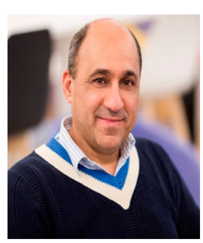
No potential conflict of interest was reported by the author(s).

Notes on contributor

Conn Smyth is a doctoral researcher at University of Galway, Ireland. His research focuses on the application of artificial intelligence as an enabler of supply chain resilience. He holds a master's degree in Business Analytics and bachelor's degree in Project Management from University of Galway, Ireland.

Denis Dennehy is Associate Professor of Business Analytics and School Research Lead at the School of Management, Swansea University. His research primarily focuses on the mediating role of technologies and data, and its implications for teams, organisations, and society. He is co-editor-in-chief for *Communications of the Association for Information Systems,* senior editor for *Information Technology and People*, and he has edited many special issues related to his field. He received the *AIS Sandra Slaughter Service Award* in 2023.

Samuel Fosso-Wamba is a Full Professor in Information Systems and Data Science and the Associate Dean for Research at TBS Education, France. He is also a Distinguished Visiting Professor at The University of Johannesburg, South Africa. He earned his Ph.D. in industrial engineering at the Polytechnic School of Montreal, Canada. His current research focuses on information technology's business value, adoption of inter-organisational systems, use and impacts, supply chain management, electronic commerce, blockchain, artificial intelligence for business, social media, business analytics, big data, and open data. He has published papers in a variety of information systems and operations management journals.



Dr. Antoine Harfouche is an Associate Professor in Information Systems (IS) and Artificial Intelligence (AI) at University Paris Nanterre. He teaches various courses including IS, AI, Big Data, and Quantitative Methods. Recognised for his exceptional teaching, research, and services for the community, Dr. Harfouche was honoured with the *AIS Sandra Slaughter Service Award* in 2020. He earned his M.Sc. and Ph.D. in Management Information Systems from Paris Dauphine University, with collaboration with Georgia State University. His research focuses on the impact of Ethical and Responsible AI and Augmented Intelligence on organisations. Dr. Harfouche has published widely in peer-reviewed journals (e.g. International Journal of Production

Research, Information Systems Frontiers, International Journal of Information Management, Industrial Management & Data Systems, the Annals of Operation Research, etc.) and conference proceedings and serves on the editorial boards of several academic journals. He has secured significant funding for his research, including the ANR SCHOPPER project on a new AI framework incorporating human input and the ERASMUS + project VRAILEXIA, which integrates AI with Virtual Reality to aid higher education students with dyslexia, scoring first place in 2020 by the ERASMUS + agency.

Dr. Murray Scott is a College Lecturer in Business Information Systems at the J.E. Cairnes School of Business & Economics, National University of Ireland Galway, Ireland. His main research interests lie in IS success, e-government and Social Information Systems. He received his Ph.D from NUI Galway and has published in leading journals such as the European Journal of Information Systems, Communication of the Association for Information Systems and Business Process Management Journal.

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