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# Application of artificial intelligence in demand planning for supply chains: a systematic literature review

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## Abstract

**Purpose** – Demand planning (DP) is a key element of supply chain management (SCM) and is widely regarded as an important catalyst for improving supply chain performance. Regarding the availability of technology to process large amounts of data, artificial intelligence (AI) has received increasing attention in the DP literature in recent years, but there are no reviews of studies on the application of AI in supply chain DP. Given the importance and value of this research area, we aimed to review the current body of knowledge on the application of AI in DP to improve SCM performance.

**Design/methodology/approach** – Using a systematic literature review approach, we identified 141 peer-reviewed articles and conducted content analysis to examine the body of knowledge on AI in DP in the academic literature published from 2012 to 2023.

**Findings** – We found that AI in DP is still in its early stages of development. The literature is dominated by modelling studies. We identified three knowledge clusters for AI in DP: AI tools and techniques, AI applications for supply chain functions and the impact of AI on digital SCM. The three knowledge domains are conceptualised in a framework to demonstrate how AI can be deployed in DP to improve SCM performance. However, challenges remain. We identify gaps in the literature that make suggestions for further research in this area.

**Originality/value** – This study makes a theoretical contribution by identifying the key elements in applying AI in DP for SCM. The proposed conceptual framework can be used to help guide further empirical research and can help companies to implement AI in DP.

**Keywords** Demand planning, Demand forecasting, Artificial intelligence, Supply chain, Literature review

**Paper type** Literature review

## 1. Introduction

Demand planning (DP) has played a pivotal role in supply chain management (SCM) for academic scholars and practitioners over the past couple of decades (Seyedan and Mafakheri, 2020; Zhuang *et al.*, 2022). DP activities occur along the entire supply chain, from planning demand for procurement of components to predicting sales demand for finished products. DP is thus perceived as one of the main catalysts for creating value and increasing SCM performance (Aamer *et al.*, 2021; Nguyen *et al.*, 2022).

Concomitant with supply chains extending over the globe and becoming more complex in nature over the past decades, digitalisation has emerged as a key differentiator for creating competitive advantage (Ashok, 2023). Artificial intelligence (AI) is widely reported to be a popular facilitator to realise digitalisation strategies for SCM in Industry 4.0 (Mitra *et al.*, 2023).



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In DP, AI tools can be leveraged to facilitate complex and real-time decision-making that is not possible when using traditional regressive methods (Riahi *et al.*, 2021). Scholars reporting on the benefits of data-driven decision-making with AI in SCM have noted significant performance improvements (Feizabadi, 2020; Lauer and Wieland, 2021). Consequently, the growing recognition in recent years of the benefits of AI has led to extensive academic exploration of its applications in supply chain DP (Walter *et al.*, 2023).

Demand information is one of the key aspects of DP. Since the publication of Forrester's seminal article on information asymmetry in 1958 (Forrester, 1958), the flow and sharing of information has been a central topic for DP scholars because of the whiplash (bullwhip) effect it has on upstream supply chain inventories (Barlas and Gunduz, 2011; Pereira and Frazzon, 2021). The topic has been researched by many scholars in the SCM domain; their focus has been inventory and information that need to be shared with the upstream supply chain in a timely and efficient manner (Han and Dong, 2015; Hartzel and Wood, 2017).

In a second stream of DP research, scholars have investigated using demand information for time-series forecasting to predict future demand (Verma *et al.*, 2021). Traditional time-series models analyse past demand occurrences and extrapolate these to the future. They are thus prone to error under supply chain shocks or disruptions, or when historic demand data are intermittent. These forecasting models have evolved over the decades as computer processing power has increased and data storage cost and information transfer cost have decreased, to allow for increasingly complex mathematical models to process data in real time (Kilimci *et al.*, 2019).

The past decade has seen the emergence of AI for DP. Operational systems in SCM continue to capture ever-increasing volumes of data through Internet of Things devices or RFID scanners. At the same time, computer processing power to process this data has increased exponentially, resulting in an increasing number of publications on the use of AI in DP (Rolf *et al.*, 2023). The recent AI boom is epitomised by the explosion of generative AI applications, among which is ChatGPT [1]. ChatGPT is a generative deep learning model that uses natural language processing to identify patterns in data and learn from these patterns to predict what should happen next (Jin *et al.*, 2023). This functionality is also at the core of applying AI to DP for supply chains. By utilising the vast amounts of SCM data available, AI can detect patterns that were elusive in the past and thus assist in predicting future demand (Slimani *et al.*, 2017).

Literature reviews have focused on the application of AI to SCM (Riahi *et al.*, 2021) or ML in SCM (Akbari and Do, 2021; Younis *et al.*, 2021), though they have paid little attention to DP—one of the main functions of SCM that creates value and increases performance. Authors that mention AI for DP in supply chain applications in their review articles have focused narrowly on particular products (Kaizer *et al.*, 2022) or industries (Aamer *et al.*, 2021) and have not considered SCM DP as a whole. This article is motivated by a paucity of literature reviews on this particular topic. Prompted by this knowledge gap and responding to the call of Lee *et al.* (2023) to do more work to create an understanding of AI application in the context of different disciplines, the objective of this systematic literature review is to critically examine the current body of knowledge on AI adoption in supply chain DP for improving performance.

To address the knowledge gap in the DP literature, we formulated the following four research questions to guide this review:

*RQ1.* What are the trends in AI-based DP studies?

*RQ2.* What are the key AI knowledge areas applied in DP?

*RQ3.* What is a potential conceptual framework for applying AI in supply chain DP?

*RQ4.* What are the critical research gaps and opportunities for further investigation of AI in supply chain DP?

The rest of the paper is organised as follows. Section 2 provides a review of the background literature. Section 3 describes the research methodology. Section 4.1 analyses recent trends regarding AI in DP research publications (RQ1), while Section 4.2 presents a thematic analysis and critical reflection of key knowledge areas of AI in supply chain DP (RQ2). We discuss the trends (Section 5.1) and dominant knowledge areas for AI in DP (Section 5.2) before conceptualising the knowledge domains in a framework for AI in DP to provide insights into applying AI for DP processes that increase SCM performance (RQ3). Section 5.3 summarises critical research gaps (RQ4). Section 6 concludes the study by providing theoretical and practical implications and making recommendations for a future research agenda.

## 2. Definitions and review of the existing literature

### *2.1 Definition and taxonomy of artificial intelligence and demand planning*

To draw an outline for this study, we start by providing definitions for AI and DP. To sharpen the focus and understanding of the term AI, we discuss different AI types and learning methods.

*2.1.1 Artificial intelligence.* The literature offers an abundance of definitions for AI. Scholars agree that AI requires three basic components: computers (processors), algorithms (models) and data. Other key concepts of AI are learning and drawing on experience—traits that, on a cognitive level, are only available to humans, not to machines. In Table 1 we provide definitions for AI from the literature. In addition to computers, algorithms and data, most definitions of AI revolve around similar concepts, namely, its ability to mimic human intelligence.

The wide range of definitions of AI is grounded in the broad functional application of AI and the variety of technologies encapsulated in the term. To assist with the classification of the literature in this study, we adopted the definition of AI of Min (2010, p. 13): ‘AI is the combination of computers (processors), algorithms (models), and data for reasoning, recognising or sensing patterns, learning or understanding certain behaviours from experience,

**Table 1.** Selected AI definitions in the literature

| Reference | AI definition |
|---|---|
| Min (2010, p. 13) | “AI is referred to as the use of computers for reasoning, recognising patterns, learning or understanding certain behaviours from experience, acquiring and retaining knowledge developing various forms of inference to solve problems in decision-making situations where optimal or exact solutions are either too expensive or difficult to produce” |
| Burgess (2017, p. 5) | “theory and development of computer systems able to perform tasks normally requiring human intelligence” |
| Kazakova *et al*. (2020, p. 21) | “Artificial Intelligence: is technology that tries to automate one or more (human) cognitive functions or processes. It provides predictions, recommendations, or decisions to achieve specific objectives. It does so by continuously learning about its environment or results from its actions.” |
| Mikalef and Gupta (2021, p. 2) | “ability to interact, learn, adopt, and resort to information from experiences, as well as to deal with uncertainty” |
| Pournader *et al*. (2021, p. 2) | “AI is a field in computer science encompassing the development of systems capable of performing tasks that normally necessitate human intelligence” |
| Riahi *et al*. (2021, p. 1) | “A restrictive definition of AI can encompass every machine or equipment that uses computational abilities to mimic human intelligence” |
| Toorajipour *et al*. (2021, p. 502) | “. . . defined as the capability of machines to communicate with, and imitate the capabilities of, humans” |
| Younis *et al*. (2021, p. 1748) | “a computer science aiming to perform tasks that replicate human or animal intelligence and behaviour” |
| Madan and Ashok (2022, p. 188) | “a cluster of digital technologies that enable machines to learn and solve cognitive problems autonomously without human intervention” |

**Source(s):** Authors’ own work

acquiring and retaining knowledge; developing various forms of inference to solve problems in decision-making situations.

To understand or find patterns in data, four types of data analytics are used in AI applications: descriptive, predictive, prescriptive and cognitive (Puneeth *et al.*, 2018).

(1) ***Descriptive or diagnostic AI*** summarises all applications that capture and process information, for example, image recognition or anomaly detection (Burgess, 2017; Kazakova *et al.*, 2020).

(2) ***Predictive AI*** refers to data analytics tools that process data to understand future events by identifying patterns (through classification or clustering) in the data that assist in decision-making or to make recommendations. These tools include machine learning for pattern recognition or sensing in speech, text and visual applications (Pournader *et al.*, 2021).

(3) ***Prescriptive AI*** embraces optimisation models that can make recommendations and automate processes (Kazakova *et al.*, 2020; Puneeth *et al.*, 2018).

(4) ***Cognitive AI*** sums up smart applications that act autonomously. These applications typically learn from large amounts of unstructured data to find answers and take action or make recommendations (Puneeth *et al.*, 2018).

In recent years, machine learning (ML), as a subset of AI, has evolved into the dominant predictive AI technique in data analytics (Ni *et al.*, 2020; Filali *et al.*, 2021). The term was coined by Samuel (1959), who designed algorithms that enabled computers to learn and perform specific tasks without the computers having to be explicitly programmed to do this. ML uses three learning methods in decision-making—supervised, reinforcement and unsupervised learning (Chen *et al.*, 2008)—each of which has advantages and disadvantages. Next, we discuss these learning methods.

Supervised learning is exploitative in nature because it relies on being provided with data that already have established input–output relationships (Ni *et al.*, 2020). This could be tagged data, which provides the required learning context for the model (e.g. this audio clip contains drums and guitars). Reinforcement learning is part of supervised learning and includes a feedback loop, enabling algorithms to learn how to take action or make decisions in an environment to optimise a reward (Chen *et al.*, 2008). Unsupervised learning can explore uncharted territory by using unstructured data to detect relationships and clusters (Jayant *et al.*, 2021). Unsupervised learning requires large amounts of data, especially in deep network topology. Data can be unstructured and does not need to be tagged. A specific form of ML is deep learning (DL), which has become popular in recent years (Januschowski *et al.*, 2018) because it automatically learns from data and works like a human when making decisions. DL works in unsupervised and supervised learning modes. DL obviates the need for complex feature engineering (or parameter selection) of neural networks, which can be time consuming.

Table 2 provides a summary of different ML methods derived from the literature: learning methods, knowledge acquisition type, algorithms and sample applications in industry. These methods can be used in descriptive, predictive, prescriptive or cognitive AI applications.

*2.1.2 Demand planning in supply chains.* According to the APICS dictionary [2], DP is “the process of combining forecasting techniques and judgement to construct demand estimates for products or service . . . across the supply chain from suppliers’ raw materials to customer needs”. In the APICS definition, DP includes forecasting but takes a more strategic, organisational view of SCM across all its functions, such as procurement, manufacturing, warehousing, sales and distribution. DP is omnipresent in SCM at all levels of value creation as components mature into finished products that might eventually become returns in closed-loop supply chains (Desport *et al.*, 2017). DP techniques are mixed and can use traditional time-series-based methods or AI methods. Many authors also used hybrid approaches to mix the two methods (Feizabadi, 2020). However, using AI-based DP can yield superior results if non-linear relationships of input factors (Seyedan and Mafakheri, 2020) and a large number of

Table 2. Different learning types and machine learning methods

| Learning type | ML method | Knowledge acquisition | Algorithm | Sample application | Reference |
|---|---|---|---|---|---|
| Supervised | Reinforcement | Classification/ Clustering | Artificial Neural Networks (ANN), Recurrent Neural Network (RNN), Genetic Adversarial Network (GAN) | Inventory management, transport and distribution, sourcing and procurement | Rolf *et al.* (2023) |
| | Instance based | Classification | K-Nearest Neighbour (KNN) | Forecasting of sporadic demand by applying class membership to each datapoint | Nikolopoulos *et al.* (2016), Soofi and Awan (2017) |
| | Logic based techniques | Classification | Hoeffding Tree, XG Boosting (XGB) | Mainly short term – forecast, i.e. number of daily picks in a fulfilment warehouse | Alsanad (2020), Mitra *et al.* (2023) |
| | Statistical learning | Classification/ Regression | Naïve Bays, Bayesian Networks | Forecast weekly sales by product and store for a supermarket | Islek and Oguducu (2015), Gaur *et al.* (2015) |
| | Perception based | Classification/ Clustering | Multi-layer perceptron (MLP), Feedforward Neural Network (FNN) | Forecast component demand for an automotive OEM | Gonçalves *et al.* (2021), Slimani *et al.* (2017) |
| Supervised/ Unsupervised | Deep Learning | Clustering/ Dimension reduction | FNN, Long-Short Term Memory (LSTM), RNN, MLP, SVM | Forecast demand for finished products for a large e-tailer | Terrada *et al.* (2022), Mediavilla *et al.* (2022) |
| Unsupervised | Neural Network | Clustering/ Dimension reduction | ANN, RNN, Genetic Programming (GP), Grid Search | Text mining to cluster products with similar demand patterns | Watanabe *et al.* (2019), Saraogi *et al.* (2021), Dellino *et al.* (2018) |

**Source(s):** Authors' own work

demand variables in large datasets that are beyond cognition levels of processing for human planners are considered (Khosrowabadi *et al.*, 2022). These features of AI become increasingly important in supply chains that are growing longer and more complex (Rolf *et al.*, 2023). Recent years have also seen an increasing number of external shocks that have increased supply chain uncertainty and risk (Akande *et al.*, 2022). In these conditions, AI-based DP often performs better than traditional regressive planning models (Riahi *et al.*, 2021).

*2.2 Relevant review articles on artificial intelligence in supply chain management*

We reviewed literature review articles on AI in the wider SCM domain. We identified 11 review articles in this area, of which nine were published after 2020. Thus, it appears that the interest of the literature in the application of AI in SCM is a recent phenomenon and the body of knowledge in this area is developing rapidly. The key review studies are summarised in Table 3.

**Table 3.** Summary of existing AI related literature review studies in supply chain

| | Review article | Scope/topic | Database used | Coverage | Key focus and outcomes |
|---|---|---|---|---|---|
| AI in SCM | Puneeth *et al.* (2018) | Review of several use cases and application of big data and AI algorithms in demand planning | Article selection process and database unspecified | 11 articles from peer reviewed and non-peer reviewed sources | Authors propose a framework for big data analytics, clustering applications into descriptive, diagnostic, predictive, prescriptive, and cognitive |
| | Pournader *et al.* (2021) | Authors review applications of AI in SCM and how these are applied in different SCM functions in the literature using bibliometric co-citation analysis | Scopus online databases | 150 from peer reviewed journal publications or conference proceedings published between 1998–2020 | Authors identify three knowledge clusters in the literature for AI in SCM: decision making, learning, and hybrid cluster. The three clusters validate the *a priori* AI taxonomy of the research which considers AI applications in sensing, learning, and decision making |
| | Toorajipour *et al.* (2021) | Authors review the most prevalent AI techniques in SCM in order to identify their potential to be deployed in SCM | Wiley Online Library, Science Direct, Emerald Insight, Taylor & Francis and JSTOR online databases | 64 peer reviewed articles, mainly from conference papers (75%) and also journals published between 2008–2018. Of which only five articles are related to demand planning | The literature is clustered around functional aspects of AI in SCM (marketing, Logistics, manufacturing applications), prevalent AI techniques deployed, and outcomes (experimental or conceptual) |
| | Riahi *et al.* (2021) | Establish current research trends for AI in SCM and outcomes that can be achieved through its application | Scopus online databases | 136 peer reviewed journals ranking at least 3 on the ABS Journal Portal and published between 1996–2020 | Authors cluster the literature along four dimensions: type of data analytics, algorithms used, industry application, and supply chain processes. For the latter they are using the SCOR model to sub-divide AI applications in various SCM functions |
| | Kamble *et al.* (2023) | Review big data applications (BDA) in SCM, thereby focusing on a classification along practical applications using the SCOR model | no reference to the sources used for article search | 220 peer reviewed journal and conference proceedings published between 2010 and 2018 | Authors reveal BDA applications in all four of the five SCOR domains: plan, source, make, deliver. The return domain is not covered in the current BDA literature in SCM |

(*continued*)

**Table 3.** Continued

| | Review article | Scope/topic | Database used | Coverage | Key focus and outcomes |
|---|---|---|---|---|---|
| ML in SCM | Ni *et al.* (2020) | Authors explore applications of ML in SCM by reviewing research trends in this area for researchers and practitioners | Emerald Insight, IEEE Xplore, Scopus, Science Direct, and Google Scholar | 123 articles from 75 journals. 63 from peer reviewed journals, 60 from undefined sources | Authors identify 10 frequently used ML algorithms in SCM. These algorithms are applied in SCM for sales forecasting, procurement, production, and distribution |
| | Younis *et al.* (2021) | Explore the applications of AI and ML in SCM. | Web of Science, Scopus and Google Scholar | 50 peer reviewed articles published in journal, conference proceedings and book chapters between 1996–2020 | Based on the SCOR model authors develop three propositions for the application of AI and ML in SCM, the methods can (1) create competitive advantage for firms, (2) add value to SCM, and (3) reduce the bullwhip effect |
| | Breitenbach *et al.* (2021) | Review of ML applications in SCM with focus on manufacturing using the SCOR framework | Scopus, Springer Link, IEEE Xplore, ACM DL, AIS Electronic Library | 73 from peer reviewed journal publications or conference proceedings | Authors identify six key areas in the literature where AI and ML techniques add value in manufacturing: factory scheduling, performance management, quality management, resource scheduling, operations intelligence, and asset tracking |
| | Akbari and Do (2021) | Authors attempt to discover ML techniques and algorithms used in SCM. | Scopus, Elsevier, Web of Science, Emerald Insights JSTOR, SAGE, Springer Link, Taylor and Francis | 110 articles from peer reviewed sources published between 1994-2019 | Authors identify barriers to ML adoption due to resource gaps in ML talent, management understanding of the technology, financial resources, and data resources. Whilst ML is applicable in many industries the literature is short on practical applications of ML that demonstrate the added value of the technology |
| AI in supply chain DP | Aamer *et al.* (2021) | Explore past and current findings on ML algorithms and techniques used in demand forecasting | Science Direct, Scopus, Taylor & Francis, IEEE Xplore, and Web of Science online databases | 77 articles from peer reviewed journals and conference proceedings published between 2010–2019 | The analysis of ML applications by industry sector shows that, electricity and manufacturing have the highest penetration of the technology. The twelve most prominent ML algorithms in these sectors are presented in the review |

(*continued*)

**Table 3.** Continued

| Review article | Scope/topic | Database used | Coverage | Key focus and outcomes |
|---|---|---|---|---|
| Kaizer *et al.* (2022) | Review how quantitative demand planning for perishable products is conducted in the literature with focus on data and models involved | IEEE Xplore, ACM DL, Web of Science and Science Direct online databases | 17 peer reviewed articles from journal publications and conference proceedings published between 2017–2021 | Most studies use quantitative models focusing on perishable food items. The use of external data to complement models is widespread in DP for perishable products. ARIMA is the most popular model deployed for DP of perishable products |

**Source(s):** Authors' own work

(1) ***AI in SCM:*** The majority of reviews on AI focused on SCM broadly. All authors of reviews of AI in SCM treated SCM as a concept, without having a specific focus on an explicit SCM domain, such as DP. For example, Riahi *et al.* (2021) and Kamble *et al.* (2023) summarised possible applications for AI and big data analytics in SCM. Puneeth *et al.* (2018) developed an AI taxonomy around descriptive, predictive, prescriptive and cognitive analytics, which is reiterated by Riahi *et al.* (2021) in their literature review. Literature reviews by Pournader *et al.* (2021), Toorajipour *et al.* (2021), Riahi *et al.* (2021) and Kamble *et al.* (2023) focused on more general applications of AI in SCM, and DP is mentioned only very briefly.

(2) ***ML in SCM:*** This group of reviews focused on ML applications in SCM or for solving SCM problems. For example, Ni *et al.* (2020) and Akbari and Do (2021) provided a broad overview of ML applications in SCM and the sales demand forecasting function of the supply chain and did not consider applications of this technology for DP in a wider supply chain context.

(3) ***AI in supply chain DP:*** Table 3 shows that only two reviews on AI in supply chain DP or demand forecasting were conducted. The article by Kaizer *et al.* (2022) focused narrowly on DP models for supply chains of perishable products. This article reviewed only 17 studies that used quantitative models for perishable food items, specifically. Another review, by Aamer *et al.* (2021), was conducted on ML applications for demand forecasting, particularly for the electricity and manufacturing industries. The study identified the 12 most prominent ML algorithms in these sectors.

In summary, it appears that the review articles on AI in supply chain DP focused broadly on AI or ML in SCM (Aamer *et al.*, 2021; Ni *et al.*, 2020); or across several industries, such as agriculture (Sharma *et al.*, 2022) and electricity (Aamer *et al.*, 2021); and some focused on functional SCM domains, such as manufacturing (Breitenbach *et al.*, 2021), procurement (Pournader *et al.*, 2021), or supply chain risk management (Younis *et al.*, 2021). In other words, literature review studies were wide in scope and had a general focus on applications of AI in SCM. To our knowledge, no literature review has focused specifically on AI in supply chain DP. However, DP is an important element of SCM, particularly in push supply chains, for which prediction of demand is crucial. Also, since there is an increasing number of publications in this area it is worthwhile conducting a systematic review of the literature on the use of AI in supply chain DP; this review is expected to contribute to the literature on SCM and AI.

## 3. Research methodology

A systematic literature review is a structured and reproducible approach to collecting data and synthesising the existing body of knowledge in a specific field or discipline (Kraus *et al.*, 2022). In conducting this systematic literature review study, we adopted the following three-stage structured analysis for literature review protocols recommended by Tranfield *et al.* (2003), combined with the systematic literature review and meta-analysis (PRISMA) guidelines (Moher *et al.*, 2015):

(1) Planning and preparing a reproducible review (design, development, inclusion and elimination criteria, literature research approach)

(2) Doing data screening, synthesis, and analysis (execution)

(3) Dissemination (reporting).

### *3.1 Planning and preparing a reproducible review*

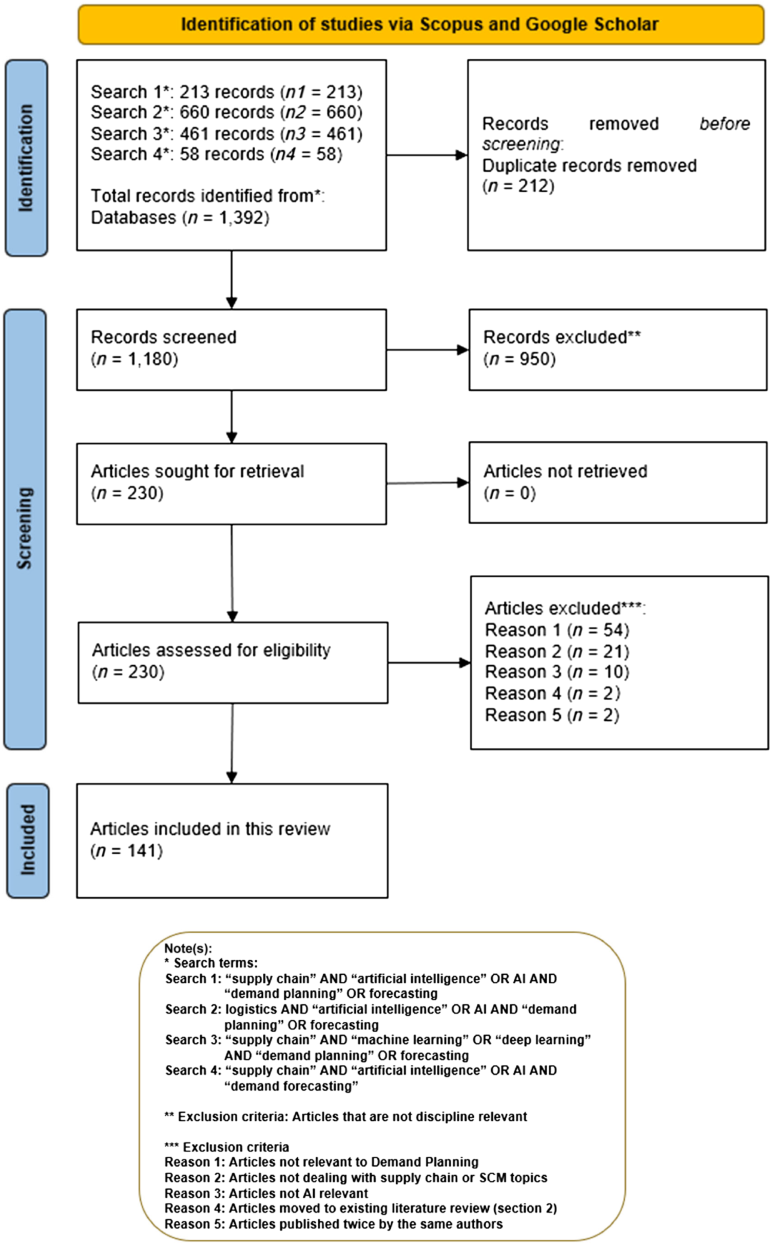
Planning a systematic literature review involves identifying the field of literature that is to be reviewed, the unit of analysis, the database(s) that will be used to source materials, the keywords that will be used to conduct the literature search, the inclusion and exclusion criteria for data clean-up, and the means for storing data for analysis and reporting (Ahsan and Rahman, 2021). In selecting relevant articles to be included in this review, we followed the steps of the PRISMA method (Figure 1): identification, screening and inclusion (Moher *et al.*, 2015).

Because our overarching objective was to investigate research trends of AI in supply chain DP, our unit of analysis was a single article that focused explicitly on AI-based DP. To search for targeted articles, we relied on the Scopus database, which is a widely used and reliable source of data for literature reviews (Ahsan *et al.*, 2021). Given that the topic has evolved rapidly in recent years (Section 4.1.1), we used Google Scholar as a secondary source, to ensure no relevant publications were missed and to capture more recent articles, because online publishing tends to occur in a timelier manner. We included all the publications categorised as article, conference paper, and book chapter available in the database that had a status of “final” or “article in press”. To hone our focus on the most relevant articles, the search terms considered only publication titles, abstracts and keywords. To identify relevant articles, we used four sets of search terms (Figure 1). These keywords formed the search protocol to identify literature pertaining to AI in supply chain DP. Searches were limited to articles published in English between 2012 and 2023.

Once all duplicate publications had been removed, the search resulted in a total of 1,180 articles. We investigated these articles carefully to eliminate “loosely related” articles, that is, those with content not consistent with the objectives of the study. In the first review stage, the titles and subject areas of all extracted articles were reviewed and all articles lacking domain or subject relevance were excluded. These loosely related articles were mainly from disciplines unrelated to supply chain or operations management, such as medicine or chemistry. In a second round of review, the research team scrutinised the full texts of all remaining articles to decide whether publications were relevant for this systematic literature review. This exclusion exercise led to a total of 89 articles being excluded. Finally, a total of 141 relevant publications were selected for full review. Information on the entire search process is auditable for reviewing and tracking purposes. For each of the 141 identified articles, bibliometric data (bibliometric information, abstract, keywords and references) were extracted for analysis.

### *3.2 Execution*

We used VOSviewer as reputable, reliable and validated software to conduct the co-word analysis (van Eck and Waltman, 2014) and to develop networks of keyword co-occurrences that identify groups of well-connected author and index keywords (themes) related to the scope of the study (Callon *et al.*, 1983).




**Source(s):** Authors’ own work

**Figure 1.** Article selection process

Co-word analysis is a prominent technique for mapping a subject area using a publication’s keywords and establishing links between them across all publications under review, to measure similarity (Ahsan and Rahman, 2021). This analysis assumes that each field of study can be characterised by a list of keywords, and the keywords of each publication can be assessed for similarity to determine whether there is a relationship between two publications (de la Hoz-Correa *et al.*, 2018). In co-word analysis of keywords, the unit of analysis is a concept, not a document, reference, author or journal, and it is not related to time function (Zupic and Čater, 2015; Ahsan and Rahman, 2021).

To prepare the input for co-word analysis, we removed formatted abstract titles, copyright information, punctuation marks and symbols. We amalgamated words conveying similar meaning and concepts (e.g. supply chain and supply chains) to make the analysis more pragmatic (Cobo *et al.*, 2011). As the theme or scope of the research was to group AI in DP knowledge areas, keywords such as "journal", "paper", "finding", "research", "study" and "analysis" were excluded from the cluster analysis.

With VOSviewer software, we used a minimum occurrence threshold of four for each keyword and obtained 22 keywords. We then clustered the themes using the keyword occurrence clustering method. We used four as the minimum number of items under each cluster, with random start 10 feature of VOSviewer, iteration 10 and with the default resolution of 1. The cluster analysis generated three clusters of 22 keywords or themes, each of which is shown in a separate colour (blue, red and green) in Figure 2 and Table 4. The three clusters are 1) AI tools and techniques for DP (blue), 2) AI applications in different SCM functions (red) and 3) impact of AI-based DP in digital SCM (green). The clusters are not mutually exclusive, because many articles straddle across clusters. In Figure 2, nodes represent the keywords and links represent the connections between two keywords. We then conducted a detailed narrative content analysis of each article according to the clusters identified in the bibliometric analysis.

### *3.3 Reporting*

The reporting stage considers the reviewed literature along with the research questions. We adopted the twofold reporting approach of Tranfield *et al.* (2003): descriptive analysis and thematic analysis. Using the bibliometric data of 141 articles, we conducted an in-depth descriptive analysis of the articles (Section 4.1). For this analysis we used NVivo, which is a popular qualitative data analysis tool (Ahsan *et al.*, 2021). In NVivo we uploaded pdf versions of all 141 articles and reviewed each article based on the identified keyword clusters, examining how each article addressed the theme of that cluster. Using these clusters, we analysed the underlying themes and knowledge areas related to AI in supply chain DP research (Section 4.2).

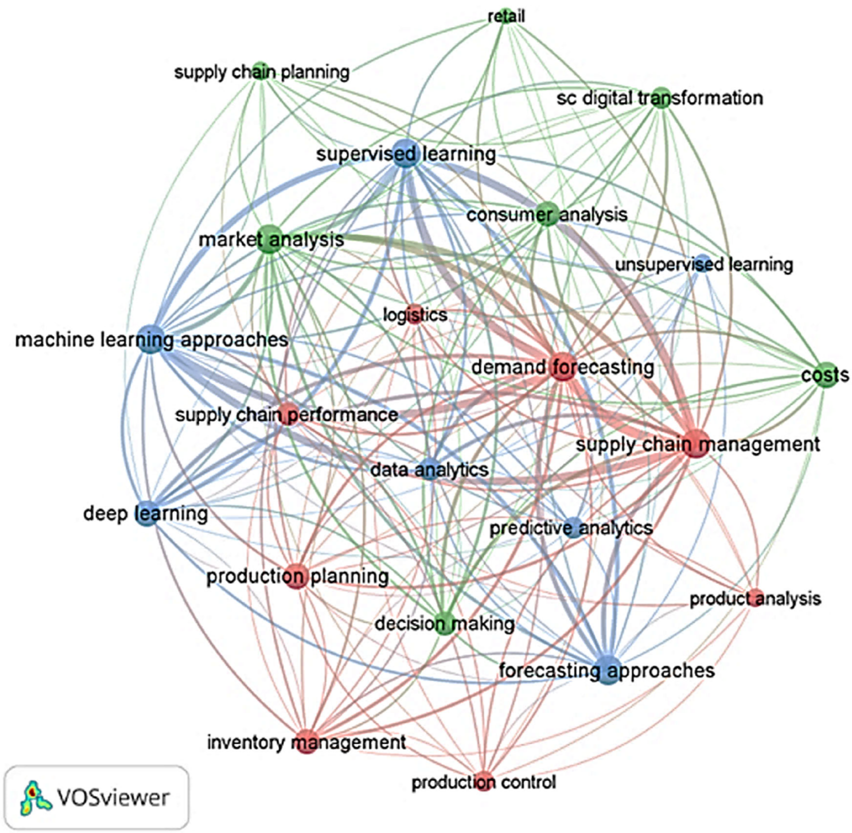
## 4. Literature analysis

### *4.1 Trend analysis of the literature*

*4.1.1 Evolution of research on artificial intelligence in demand planning.* Research interest in AI-based DP was low until 2018; there were an average of five publications per year between 2012 and 2018 (Figure 3). From 2019, we observe an increase in interest in AI in DP, with around 81% of the reviewed articles published since 2019. The number of publications on this topic peaked in 2023, with 37 articles in that year alone.

A total of 325 authors contributed to the 141 articles selected for this review (Appendix 1). Articles were published in 112 different publication sources: 56 journals, 50 conference proceedings and six book series. Using the AI taxonomy introduced in Section 2.1, we analysed the most prominent AI domains in DP over time (Figure 3). It appears that research on predictive AI is most prevalent, with 79% of the publications (111 articles) in this category. This is followed by prescriptive AI studies (25 articles); cognitive (4 articles) and descriptive AI (1 article) are less common.

We also analysed AI applications in a two-dimensional matrix along supply chain function and product dimensions (Figure 4). In the product dimension, DP for finished products is dominant and covered by 80% of the publications (114 articles). Most of these




**Cluster 1:** AI tools and techniques for DP

**Cluster 2:** AI applications for different supply chain functions

**Cluster 3**: Impact of AI based DP in SCM and contingent elements

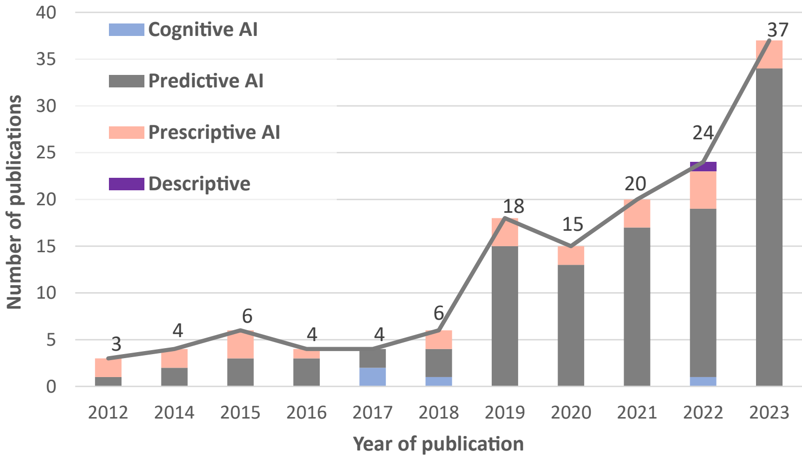
**Source(s):** Authors' own work

**Figure 2.** Bibliographic map of keywords and clusters for AI in demand planning

**Table 4.** Bibliometric keyword clusters of AI in DP literature

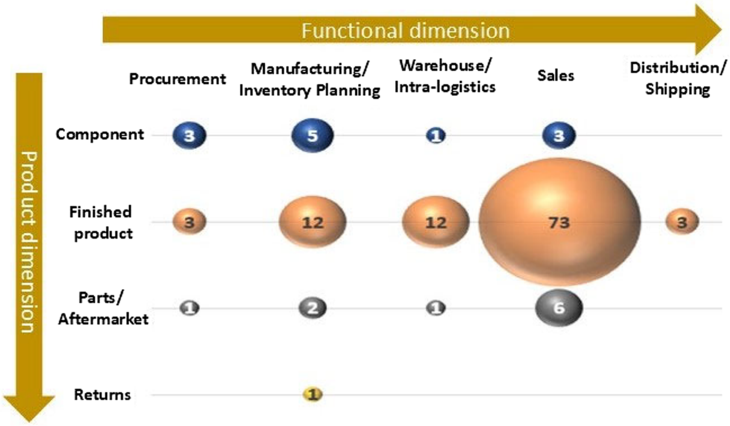
| | Cluster 1<br>AI tools and techniques for DP (blue) | Cluster 2<br>AI applications for different supply chain functions (red) | Cluster 3<br>Impact of AI based DP in SCM and contingent elements (green) |
|---|---|---|---|
| Themes | Machine learning<br>Supervised learning<br>Unsupervised learning<br>Deep learning<br>Forecasting approaches<br>Data analytics<br>Predictive Analytics | Supply Chain Management<br>Inventory management<br>Production planning<br>Production control<br>Logistics<br>Product analysis<br>Demand forecasting<br>Supply chain performance | Market analysis<br>Consumer analysis<br>Decision making<br>Supply chain planning<br>Costs<br>Retail (Sales)<br>SC Digital transformation |

**Source(s):** Authors' own work




**Source(s):** Authors' own work

**Figure 3.** Publications of AI in demand planning per year

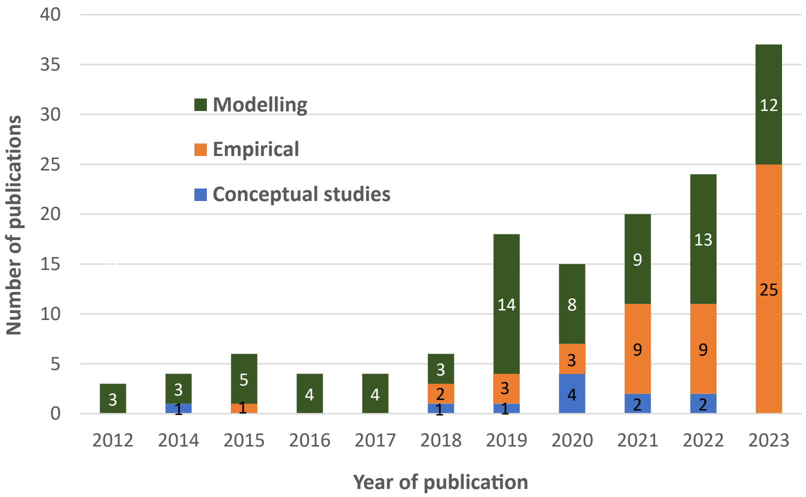



**Source(s):** Authors' own work

**Figure 4.** AI publications in the demand planning taxonomy along SC functions and product context

articles (73) deal with DP in the sales function of the supply chain. In 38 out of these 73 articles that report on retail/e-tail sectors, the authors deal with modelling of retail forecasting problems (Wanchoo, 2019; Pereira and Frazzon, 2021). Publications focusing on components are typically centred on the manufacturing and inventory planning functions of SCM (Lin *et al.*, 2019; Jung and Park, 2020; Jayant *et al.*, 2021). It appears that AI research in supply chain DP pays little attention to spare parts and returns along all functional dimensions of SCM.

*4.1.2 Methodology trends of research on artificial intelligence in demand planning.* We categorised the literature on AI in supply chain DP according to research methodologies employed, which were conceptual (8%), empirical (37%) and modelling (55%) (Figure 5) (Wowak and Boone, 2015; Ahsan and Rahman, 2021).




**Source(s):** Authors' own work

**Figure 5.** Research methodologies for AI in demand planning

Conceptual studies were less common in the literature. Conceptual studies analyse SCM holistically; they do not consider specific datasets or a single SCM scenario. Instead, the authors consider the impact of AI-based supply chain DP in the context of a specific industry, such as the fashion industry (Jin and Shin, 2020). Other conceptual studies focus on behavioural elements in AI-based DP, such as trust (Khosrowabadi *et al.*, 2022) or the role of domain experts in the model calibration process (Dowie and Grothmann, 2021).

Empirical studies can be divided into secondary data studies, survey methods and case studies (Ahsan and Rahman, 2021). Empirical studies have become more popular since 2020. Empirical studies test the performance of a particular model or compare the performance of several different AI techniques using a specific dataset. These datasets can be company-specific data (case study) or publicly available secondary data. Secondary datasets originate from a range of industries, such as semiconductors (Lingitz *et al.*, 2018), automotive (Rožanec *et al.*, 2021) and retail or e-tail (Van Belle *et al.*, 2021). The growing popularity of empirical research is related to the availability of large, publicly available datasets on online platforms such as Kaggle [3]; Vallés-Pérez *et al.*, 2022). In our review, 30 articles (21%) made use of these secondary datasets for their studies. Another 16 articles used company-specific data applied in a case study approach.

Modelling research employs techniques such as analytic, simulation or econometrics modelling and ML (Ahsan and Rahman, 2021). Modelling research uses a variety of tools, such as forecasting (52 articles), ML in optimisation (16 articles) and simulation modelling (10 articles). While conceptual and empirical studies are typically predictive in nature, modelling studies are prescriptive. The prescriptive nature of modelling studies materialises in optimisation modelling, which often aims to find a global optimum in an entire system and provide recommendations to decision-makers.

*4.1.3 Theoretical lens of research on artificial intelligence in demand planning.* There is a lack of theory addressed in AI research for supply chain DP even though there is a rich body of research in general technology adoption theory. These general technology adoption theories include technology affordance and constraints theory (Markus and Silver, 2008), the technology acceptance model (Davis *et al.*, 1989), socio-technical systems theory (Clegg, 2000) and the technology–organisation–environment (TOE) framework (Tornatzky and

Fleischer, 1990). The absence of theory in most articles can be explained by the methodology of the studies, which mainly used modelling approaches. These studies, especially in mathematical and optimisation modelling, are deductive in nature and tend to test a model rather than theory. In articles that do refer to theory or conceptual aspects, the Forrester or bullwhip effect is the most prevalent and cited by five articles. Slimani *et al.* (2017) and Van Belle *et al.* (2021) studied information uncertainty and considered the effect of information sharing on the bullwhip effect in multi-echelon supply chains. These authors argue that using AI techniques in agile forecasting can have a positive effect on mitigating the bullwhip effect.

### *4.2 Thematic analysis of research on artificial intelligence in demand planning*

By using VOSviewer for bibliometric clustering of co-occurrence of publication keywords, we identified three knowledge clusters with 22 themes. In response to RQ2, we found that research on AI in supply chain DP broadly clusters under three themes: (1) AI tools and techniques for DP; (2) AI applications for supply chain functions; and (3) impact of AI-based DP in digital SCM (Table 4). We analyse these clusters in the following subsections.

*4.2.1 Cluster 1: AI tools and techniques for demand planning.* Most studies in DP are focused on AI tools and techniques and various types of ML algorithms in the DP domain, among which are forecasting approaches; ML approaches, particularly supervised and unsupervised learning and DL; and predictive and other data analytics techniques.

*Forecasting approaches:* In AI, forecasting is a process that uses algorithms to learn from historical data and make predictions about future events. In AI-based DP, selecting the appropriate forecast model is of fundamental importance (Watanabe *et al.*, 2019; Moroff *et al.*, 2021) because it directly affects forecast accuracy. We identified 30 articles in this cluster that distinguish forecasting approaches, such as traditional time-series methods (moving average or exponential smoothing), regression-based techniques (such as ARIMA) and ML models such as decision trees or neural networks (Zietsman and van Vuuren, 2023; Ji *et al.*, 2019; Nasseri *et al.*, 2023). Because different models tend to vary in performance for different datasets, authors propose using hybrid approaches or combining traditional time-series or regression and ML approaches (Grygor *et al.*, 2022; Terrada *et al.*, 2022). Forecasting for ML and AI studies highlights the importance of data preparation (Moroff *et al.*, 2021), model selection, parameter selection or feature engineering (Panda and Mohanty, 2023), model training (Mbonyinshuti *et al.*, 2022) and measuring model accuracy (Kilimci *et al.*, 2019). Most articles applied standard statistical measures, such as mean average percentage error, mean average error, root mean squared error, harmonic analysis or support vector analysis to measure model accuracy.

*Machine learning approaches to forecasting:* ML is one of the popular themes in this cluster, which highlights the dominance of ML in solving contemporary DP problems and increasing SCM resilience (Mitra *et al.*, 2023). ML can be descriptive, predictive, prescriptive or cognitive. Sources that considered ML focused mostly on ML technologies and platforms (Dellino *et al.*, 2018), algorithms (Chapados, 2014; Filali *et al.*, 2022a), or ML techniques such as supervised (61 articles), unsupervised (5 articles) and deep (26 articles) learning. One of the advantages of using ML in DP is that the model can consider external data in addition to internal data sources (Zhuang *et al.*, 2022); this makes ML-based forecasting a highly dynamic and flexible planning tool that enables agile planning and increases accuracy (Wen and Yan, 2019). The most used ML algorithm is long short-term memory (LSTM), which is a specific type of recurrent neural network. LSTM performs particularly well on datasets with irregular demand patterns (Joseph *et al.*, 2022; Mediavilla *et al.*, 2022) and intermittent demand, which is common for spare parts. Other ML algorithms identified include decision trees (Hoeffding Tree, XG Boost), artificial neural network, feedforward neural network, support vector machine and k-nearest neighbour.

Regardless of the model used, preparing forecast data, selecting models and training them can be time consuming (Sohrabpour *et al.*, 2021). Using an external AI platform can alleviate this challenge by providing the ability to select forecast models based on small data samples and providing access to experienced data engineers (Walter *et al.*, 2023).

*Unsupervised learning:* Unsupervised learning received relatively little attention in the articles included in this review; only four articles cover this technique (Islek and Oguducu, 2015; Nita, 2015; Venkateswaran *et al.*, 2020; Mediavilla *et al.*, 2022). Unsupervised learning is typically used as a conduit that enables forecasting, rather than in the forecasting process itself. Mediavilla *et al.* (2022) introduced unsupervised learning as a prescriptive aggregation technique–a dimension reduction method in data mining that can improve forecast outcomes–to cluster products with similar demand patterns into homogeneous clusters. Other authors used unsupervised learning techniques without referring to the term in their work. Ahmed *et al.* (2020), for example, utilised principal component analysis, another unsupervised learning technique, for dimension reduction. Nita (2015) introduced heterogeneous mixture learning for dimension reduction.

*Supervised learning:* About half the articles that relate to ML focused on supervised learning, which is well suited for forecasting in DP because of its reliance on historical demand data (Slimani *et al.*, 2015a). Supervised learning utilises labelled training data to learn and apply insights to unlabelled datasets, to uncover hidden patterns in the data (Jayant *et al.*, 2021). Human intervention is crucial for the design and training of supervised learning models, to optimise results by selecting parameters (feature engineering) and adjusting their weight (Praveen *et al.*, 2019). Dowie and Grothmann (2021) suggest that involving experts from the functional supply chain domain can speed up the model design and training process. Business domain knowledge can help build causality models and assist data engineers with feature engineering by leveraging planning experience and intuition in the process. However, collaboration between data engineers and supply chain domain experts to develop causality models for DP receives little attention in the literature (Lee *et al.*, 2023).

*Deep learning:* The use of DL models in supervised and unsupervised learning across various algorithms is extensively studied in the literature, with 26 articles referring to it. Advances in technology and computing power in recent years have allowed for increasingly complex neural network architectures to be developed. Other than conventional neural networks, which consist of three layers (input, hidden, output layers), DL networks add additional intermediate (hidden) layers to handle complex data more efficiently (Jung and Park, 2020). DL demonstrates superior performance in handling large multivariate or unstructured datasets, such as social media data for sentiment analysis (Mediavilla *et al.*, 2022; Ma *et al.*, 2023). Combining internal and external datasets in DP can enhance planning accuracy. However, the complexities of DL models, which require large datasets and computational resources for training, have cost implications for the DP process (Karthikeswaren *et al.*, 2021).

*Data analytics and predictive analytics:* Data-driven decision-making in SCM that is enabled by AI technology platforms or digital platforms is referred to as data analytics. These AI platforms can provide cloud resources, pre-trained learning algorithms and models, or inter-supply chain connectivity (Monteleone *et al.*, 2015). Data analytics enables decision-makers to understand the underlying relationships in their SCM data that drive demand and find patterns in the data (Agatic *et al.*, 2021). Data analytics is the practical application of descriptive, predictive and prescriptive AI tools and techniques that connect them to real-world supply chain problems. In total eight articles in this review refer to predictive analytics directly through keywords. However, if we consider ML, big data, regression, optimisation, forecasting or other related keywords for predictive analytics, the number of articles is much higher. The emergence of ML in supply chain DP is closely connected to the ascent of big data analytics in the literature. Big data analytics is predictive analytics AI applications in ML (Falatouri *et al.*, 2022). In DP applications, big data analytics provides the input for ML models to make predictions based on large amounts of internal or external SCM data (Agatic *et al.*, 2021; Seyedan and Mafakheri, 2020).

*4.2.2 Cluster 2: AI applications for different supply chain functions.* The second knowledge cluster pivots around the utility of AI tools and techniques used in DP and forecasting for SCM: demand forecasting, inventory management, SCM, SCM performance, production planning and control, and product analysis.

*Demand forecasting:* Demand forecasting emerged as the most prevalent theme, with 101 articles having this or similar amalgamated keywords, such as demand prediction and sales forecasting. The frequency of the term corresponds directly to the search terms used for article selection (Figure 1); it also reflects that most articles consider demand forecasting to predict future sales of a specific product or product group (Buttner and Rabe, 2021). Forecasts can be categorised as micro forecasts that target individual products and stores, or aggregated forecasts for entire product groups, which each require a different forecast approach (Dellino *et al*., 2018). Methodologies vary depending on demand types which include erratic, smooth, seasonal, lumpy and intermittent demand (Silva and Rupasinghe, 2017). Regression-based techniques are effective for erratic and smooth demands, while ML-based methods are better suited for lumpy or intermittent demand (Rožanec *et al*., 2022). ML models offer advantages over traditional regression models by considering more variables and uncovering hidden data patterns, particularly in short time-series data (Seyedan and Mafakheri, 2020; Kamble *et al*., 2023).

*Inventory management:* DP has a direct impact on inventory management for raw materials and finished goods (Gonçalves *et al*., 2021; Zhu *et al*., 2021) and is therefore an essential element of the SCM literature. DP errors and supply chain uncertainties typically materialise in inventory management through overstock or stock-out events. 16 articles in this cluster consider the inventory management theme. Most authors applied prescriptive ML-based optimisation methods to inventory management and inventory routing problems. They considered the time, place and quantity function of inventory management to create competitive advantage and avoid stock-out or overstock events in all product dimensions (Figure 4) for DP, such as components (Gonçalves *et al*., 2021), finished products (Boru *et al*., 2019; Joseph *et al*., 2022) and spare parts (Jonás *et al*., 2016).

*Supply chain and logistics management:* The academic DP literature covers various SCM functions, such as procurement, manufacturing and inventory planning, warehousing, sales and distribution (Zhuang *et al*., 2022). For example, Karthikeswaren *et al*. (2021) compared the performance of different forecasting models in procurement. DP was also researched for inventory management in manufacturing (Dowie and Grothmann, 2021) or intra logistics (Alsanad, 2020) to predict demand for labour in large fulfilment centres. In the sales function of SCM, authors researched DP to make forecasts in the automotive industry (Andersson and Siminos, 2023), retail and e-tail (Mitra *et al*., 2023), pharmaceuticals (Koç and Türkoğlu, 2021) and perishable products (Dellino *et al*., 2018). In addition to the functional SCM context, DP was researched in a product-dimension context for value creation. For example, Jayant *et al*. (2021) investigated demand for components, Laaziz (2020) researched finished-product demand, and Fan and Cai (2019) proposed a planning model for future/expected product returns. In reviewing the DP literature across most SCM functions, we observed little use of AI applications for return products. Furthermore, AI has found little application in the distribution function of SCM across all product dimensions.

*Supply chain performance:* Managing inventory is closely linked to supply chain performance (Boru *et al*., 2019; Tang *et al*., 2023), although only four articles in our review dealt with this theme. Authors argue for the efficiency of their proposed forecast model using standard performance measures, such as root mean squared error, mean average percentage error, mean average error or $R^2$ coefficient variance (Fu *et al*., 2018). In these studies, the literature correlates a low forecast error with high model accuracy, which has a positive impact on supply chain performance and can materialise in improved inventory management. A common deficit in the literature is authors evaluating planning efficiency based on model effectiveness (Weng *et al*., 2020; El Filali *et al*., 2022). While a higher $R^2$ or lower mean average percentage error might indicate a particular model having an impact on a task in terms of forecast accuracy, this should not be confused with model efficiency, which drives value creation and must involve cost–benefit considerations. In this theme, model or planning cost was typically not considered by authors. Additional to the cost implications of ML-based DP, supply chain performance can deteriorate in the absence of supply chain collaboration. Integrated supply chains rely on timely data sharing; failure to do so leads to upstream actors training AI models with outdated data, which leads to model inaccuracy and thus deterioration of supply chain performance (Zhuang *et al.*, 2022).

*Production planning and production control:* Accurate DP enables supply chain resilience for manufacturing organisations, especially in pull supply chains, where the manufacturer often lacks visibility of downstream demand fluctuations (Mediavilla *et al.*, 2022). Production planning and control—a central theme in manufacturing—is covered by 11 articles. The theme is increasingly being viewed from a digital perspective in smart manufacturing applications of Industry 4.0 (Falatouri *et al.*, 2022). Brintrup *et al.* (2020) proposed a model to increase resilience by predicting supply chain disruptions. They used ML methods to analyse low impact high frequency supply chain events that cause productivity losses. DP directly affects production planning by assisting with plant organisation and allocation of resources in manufacturing, such as the scheduling of raw materials, tooling and labour (Rožanec *et al.*, 2021). A further application of ML-based DP in production planning and control is presented by Fu and Chien (2019), who report that, for the manufacturing of products with intermittent demand, companies hold excessive safety stock that can make up to 60% of their total inventory investment.

*Product (life cycle) analysis:* Four articles in our review covered product analysis. Authors focused on short-life-cycle products because inventory management issues and risk of obsolete stock or lost sales are amplified by the shorter sales window of these products (Watanabe *et al.*, 2019). To mitigate risk, Fu and Chien (2019) introduced a model that uses temporal aggregation to improve DP for short-life-cycle products with intermittent demand. During the introduction phase of the product life cycle, historic demand information is scarce because of the novelty of the product. Watanabe *et al.* (2019) proposed an ML-based attribute decomposition model to predict highly accurate demand patterns for new products, based on an analysis of historical documentation and technical manuals of similar products.

*4.2.3 Cluster 3: impact of AI-based demand planning in supply chain management and contingent elements.* Research articles in the third cluster explored how certain contingent elements can change or vary according to specific conditions or situations, which might include market and consumer conditions and technological advances such as digital transformation of supply chains that affect decision-making or strategy. This cluster also analysed how AI-based DP affected decision-making in increasingly digital supply chains that are moving to Industry 4.0 (Falatouri *et al.*, 2022; Singh *et al.*, 2023) and now, Industry 5.0 (Rolf *et al.*, 2023).

*Digital transformation of supply chains:* Studies in this knowledge area discuss how AI applications in DP drive digitalisation and digital transformation of SCM. There are nine articles in this cluster. Digital transformation is often linked to Industry 4.0 applications in SCM and refers to concepts such as the internet of Things (Seyedan and Mafakheri, 2020), smart manufacturing (Falatouri *et al.*, 2022) and cyber physical systems (Pfutzenreuter *et al.*, 2023). Whereas all these topics are critical elements of digital transformation in SCM, this study focused on AI applications in DP. Research on AI applications in digital transformation emphasises organisational and digital capability for use of technology, such as AI approaches (Mitra *et al.*, 2023) and benefits of digital transformation for value creation through DP (Vairagade *et al.*, 2019). Organisations need to orchestrate all capabilities to enable digital transformation and implementation of AI in DP (Agatic *et al.*, 2021). We conceptualise the interaction of capabilities to enable AI that creates value in DP in the next section (5.2.2) of this article.

*Decision-making and supply chain planning:* AI has numerous applications in decision-making for planning areas related to supply chain demand fulfilment, such as supplier selection, purchasing decisions (procurement), pricing decisions (Bottani *et al*., 2019) and store inventory allocation (Pereira and Frazzon, 2021). These themes are covered by 11 articles in our review. These articles emphasise the importance of AI application for handling large volumes of data to facilitate decision-making in SCM, which is otherwise a daunting task for managers (Rolf *et al*., 2023). Using predictive and prescriptive AI methods assists planners to cluster and categorise these large volumes of data to enable decision-making. Rather than advocating for AI to replace humans, studies stress the importance of considering factors such as available human knowledge (Lauer *et al*., 2020; Wibowo, 2023) and expertise in data processing and model selection (Kamble *et al*., 2023). This knowledge deficit in AI adoption can only be overcome by human–machine interaction (Lauer *et al*., 2020; Wibowo, 2023). Trust in machine-generated decisions is another important concept in human–machine interaction; machine-generated forecast results have little value unless they are trusted and actioned by human agents because few planning systems operate fully autonomously (Lauer *et al*., 2020). The challenge of a lack of trust often stems from inadequate understanding and management support, which impedes organisational readiness and fosters resistance to AI tools (Brau *et al*., 2023).

*Market analysis:* Market analysis is a contingent factor that provides important input to DP, which may explain the extensive coverage of this theme in the literature, by 32 articles. Market analysis facilitates accurate decision-making for pricing, sourcing and manufacturing (Singha and Panse, 2022). The application of AI in market analysis for SCM mitigates uncertainties and reduces volatility in DP, as demonstrated by various authors (Terrada *et al*., 2022; Pfutzenreuter *et al*., 2023). In a practical application, Jin and Shin (2020) show how AI-based data mining of consumer feedback is used in the fashion industry to create new styles that match current trends, thereby reducing SCM uncertainty and reducing inventory and the number of returns. Competitive analysis is another key area highlighted in the literature in relation to market analysis; it involves using external variables to map competitors' actions, such as price promotions that affect demand when forecasting store-based product allocation (Bi *et al*., 2022).

*Consumer analysis:* The market analysis example of Jin and Shin (2020) intersects with the consumer analysis theme, which is covered by 10 articles in this review. Consumer analysis, using AI-based DP, improves customer service levels and increases customer satisfaction, mainly by improving product availability. This applies in a retail context (Falatouri *et al*., 2022) and to fashion products in particular, where sentiment analysis is used to predict short-term demand. Analysing social media data enables the prediction of popularity of certain styles and compensates for the lack of historic data that would be used in traditional time-series DP (Jin and Shin, 2020).

*Cost:* Cost tracking and reduction is one of the key drivers of SCM performance and is closely related to DP (Boru *et al*., 2019). While eight articles in our review explicitly address this theme, other articles discuss related topics, such as storage, logistics and transportation cost across various functional areas of the supply chain for different product dimensions. For component demand, AI-based planning methods help reduce procurement costs and optimise inventory management cost (Zietsman and van Vuuren, 2023). For finished products, AI tools related to neural networks were used in predictive or prescriptive methods to reduce the cost of all supply chain functions, such as purchasing (Bottani *et al*., 2019), inventory management (Pereira and Frazzon, 2021), warehouse intra-logistics (Boru *et al*., 2019) and sales forecasting (Mascle and Gosse, 2014).

## 5. Discussion and research gaps

### *5.1 Trends in the artificial-intelligence-based demand planning literature*

Considering RQ1, we found a significant increase in interest in AI applications for supply chain DP in the past five years, as reflected by an increasing number of published on the topic (Figure 3). We also observed a trend towards publications in conference proceedings, which might reflect the rapid evolution of the topic, because this medium is typically quicker to publish and not quite as rigorous in its peer review process.

Considering research methods deployed, we noticed a trend from modelling studies towards empirical research. Earlier publications in our review period focused on modelling AI to solve DP problems. These studies often developed and then tested new AI models, many of which are predictive in nature, to extend knowledge and advance new AI approaches. Recent years have seen a shift towards empirical studies that test existing AI models on particular datasets. These studies typically focused on a particular DP problem and were narrower in their approach, which limits generalisability of their findings. Examples are studies on particular datasets from retail or e-tail that are available in public libraries on the Internet.

While modelling research can be considered more foundational, because it researches new models and techniques, empirical research extends knowledge by evaluating existing models against specific datasets or supply chain contexts. Both approaches have their place in research, although empirical research often has limitations regarding transferability and creates less generalisable insights into DP. Empirical studies also often fail to consider the operational and technical challenges that prevail in industry, for example, selecting and harmonising data from various sources or applications in the business (Ma *et al.*, 2023).

A recent trend towards conceptual studies could overcome these shortcomings, with this type of research supporting theory building and foundation-type research by, for example, considering organisational elements or cognitive AI models in digital transformation. The conceptual studies we reviewed show potential to produce more general research in AI that can solve DP problems across industries or in specific supply chain contexts. Future research can be conducted on leading-edge companies, as case studies, to understand how they incorporate AI into DP and SCM as part of their digital transformation. Amazon, for example, uses advanced data analytics and ML to forecast demand and optimise its inventory management, and to ensure that products are available to customers when and where they need them (Jin and Shin, 2020).

### *5.2 Key knowledge areas and conceptual framework for application of AI in supply chain demand planning*

This section discusses the dominant AI knowledge areas and themes (RQ2), and the conceptual framework for applying AI in supply chain DP to enhance supply chain performance (RQ3).

*5.2.1 Dominant artificial intelligence knowledge areas applied to demand planning research.* We identified 22 prominent research themes for AI in supply chain DP, which we grouped into three knowledge clusters (see Section 4.2).

Cluster 1 focuses on seven themes centred on ML and data analytics for solving DP problems. This cluster underscores the fundamental AI tools and techniques that drive digital transformation in supply chains. Key aspects, such as model selection, training and calibration are critical for determining the impact of AI in DP. Organisations can turn to external providers for digital platforms (Dellino *et al.*, 2018), including ML tool selection, model training and for accessing skilled data engineers (Kilimci *et al.*, 2019). To address diverse demand patterns, several authors have suggested hybrid models that employ mixed model forecast approaches. Supervised learning remains a common method, while DL technologies have gained traction because of their ability to manage increasing data and planning complexities. Notably, LSTM models, with their neural network topology and forget gates, have become widely used, which reflects the significant role of ML in contemporary DP practices.

Cluster 2 is focused on applications of AI in DP for supply chain functions, such as inventory management, production planning, and control and logistics planning. This cluster highlights how AI-based DP research can contribute to supply chain functional areas, such as demand forecasting, inventory management (Jayant *et al*. (2021), production planning (Benhamida *et al*. (2021) and product life-cycle analysis (Gonçalves *et al*. (2021). The literature we reviewed indicates that AI applications extend across all supply chain functions; which encompass procurement, inventory planning, warehousing, sales and distribution; and cover all product dimensions, including components, finished goods and returns. These findings from the literature provide an interesting contrast to the traditional view of DP, which involves creating sales forecasts for finished products (Mascle and Gosse, 2014).

Knowledge Cluster 3 examines the impact and contingent elements associated with AI application in DP. A prominent theme in this cluster is cost reductions achieved through AI-based supply chain planning. As highlighted in Cluster 2, inventory planning emerges as a crucial area where these cost efficiencies are realised. Improved inventory planning not only reduces costs but also contributes to sustainability by minimising waste, thereby supporting more sustainable supply chains (Hamdan *et al.*, 2023). Additionally, this cluster addresses contingent elements, such as market and consumer conditions, which influence decision-making and outcomes based on specific situational factors. The literature in this cluster also explores digital transformation themes, including the organisational elements necessary for successful AI-based DP, and their interplay with market, consumer and product dynamics within Industry 4.0.

Clusters 1, 2 and 3 briefly mention organisational elements related to technology adoption, yet in none of these clusters are these factors' central themes. Effective AI-based DP depends significantly on resource and capability issues, such as AI knowledge, talent for AI model development and adoption (Ransbotham *et al.*, 2017; Lee *et al.*, 2023). In Cluster 3, only a few studies highlight the importance of human knowledge. Rather than advocating for AI to replace humans, studies stress the importance of considering factors such as available human knowledge (Lauer *et al.*, 2020; Wibowo, 2023) of and expertise in data processing and model selection (Kamble *et al.*, 2023). A knowledge deficit in AI adoption can only be overcome by human–machine interaction (Lauer *et al.*, 2020; Wibowo, 2023). Trust in machine-generated decisions is another important concept in human–machine interaction; machine-generated forecast results hold little value unless they are trusted and actioned by human agents because few planning systems operate fully autonomously (Lauer *et al.*, 2020). This lack of trust often stems from inadequate understanding and management support, which impede organisational readiness and foster resistance to AI tools (Brau *et al.*, 2023). Another review study on AI in SCM identified inter-organisational collaboration, in particular, as imperative for AI application (Pournader *et al.*, 2021). Despite these insights, many studies overlook the critical organisational conditions needed for effective adoption of AI tools in the supply chain context to achieve effective AI-driven planning outcomes.

*5.2.2 A conceptual framework for application of artificial intelligence in demand planning.* After considering the findings of cluster analysis (Section 4.2), making comparisons with theories of technology adoption in supply chains (Yang *et al.*, 2021) and AI adoption in supply chain organisations (Lee *et al.*, 2023), we developed a conceptual framework (Figure 6) for applying AI in DP to enhance supply chain performance (RQ3). We conceptually combined the AI technology domain (AI toolbox) with the SCM functional aspects (AI applications in supply chain DP) to illustrate how these connections can create supply chain performance in DP (impact on supply chain performance). Additionally, we incorporated contingent elements, including market conditions, consumer and product factors and organisational issues from Cluster 3. The proposed conceptual framework (see Figure 6) encompasses the following interrelated domains:

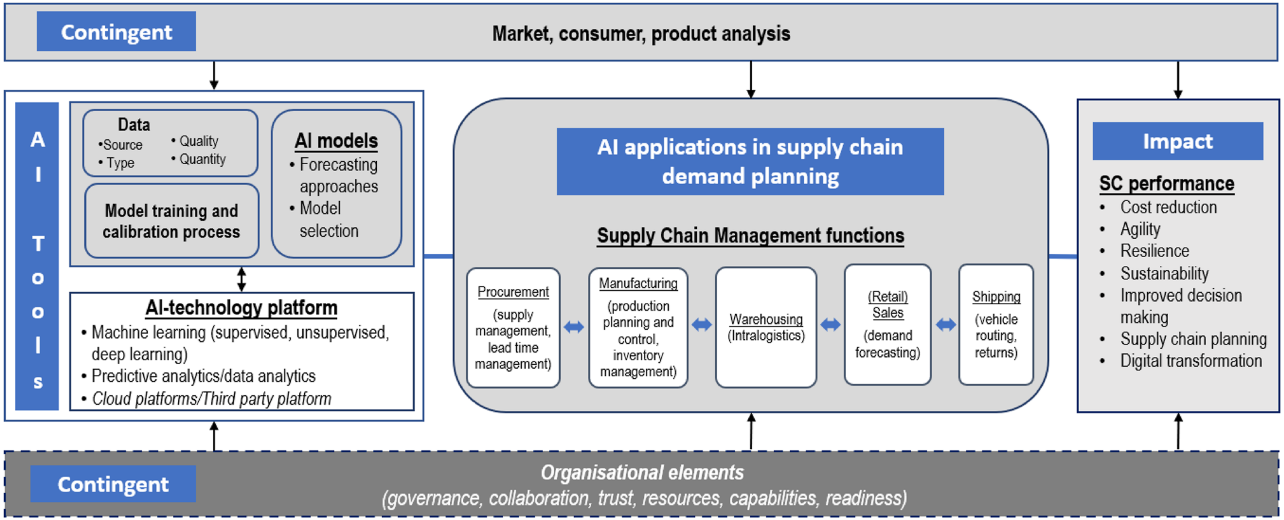
(1) AI toolbox—enablers for AI in supply chain DP (Cluster 1)

(2) AI applications in supply chain DP functions (Cluster 2)

(3) Impact on supply chain performance (Cluster 3)

(4) External contingent elements—market, consumer and product analysis (Cluster 3)

(5) Internal contingent elements—organisational (Cluster 3).




**Source(s):** Authors' own work

**Figure 6.** A conceptual framework of AI application for demand planning

Next, we discuss these major components of the framework and compare our findings with the existing theories of AI or technology adoption.

(1) Enablers of artificial intelligence application—artificial intelligence toolbox

The AI toolbox represents the technology dimension of AI application and consists of data, model selection and calibration, and the AI technology platform. These technology elements form the toolkit that enables AI adoption in supply chain DP (Slimani *et al*., 2015b).

Data-related factors of the AI toolbox are reflected as source, type, quality and quantity (Sohrabpour *et al*., 2021; Benhamida *et al*., 2021). Organisations need to evaluate where the data for planning will come from (contingent elements: market, product and consumer). Data sources can be internal like historical consumer or product demand data, data from production machines, or other data sources in the company supply chain (Zhuang *et al*., 2022; Rolf *et al*., 2023). External data sources can be social media data or other external data, such as weather data or general market data. Data types can be unstructured or structured, which affects their value in different AI models for DP. Data quality needs to be considered in terms of dimensionality, noisiness and whether the data needs to be cleaned to be useful for processing in an AI model. Data quantity is relevant for large ML models that require large datasets for training. When ML or DL techniques are deployed, the size of the training datasets increases exponentially with the depth (number of layers) and width (number of parameters) of the neural network. For some products, historical data for training may be difficult to obtain, especially for innovative products or products with short life cycles.

Model selection and training in the AI toolbox are thus closely related to available data sources (Slimani *et al*., 2015b) and are therefore represented in the same element of our conceptual framework. While supervised learning methods require structured and labelled datasets, unsupervised learning can work with unstructured data (Mediavilla *et al*., 2022). Different models have different data requirements in terms of size and quality. The calibration of the model and the number of parameters chosen determine the size of the training dataset required for the model. The literature shows that no single AI model is a panacea for solving all AI-based DP problems. Different AI models have different strengths depending on the planning task and data structure; the forecast approach needs to be selected carefully to match (Gonçalves *et al*., 2021).

An important aspect of the AI toolbox is the AI technology platform or digital platform. Digital platforms provide the foundations that underpin AI-based DP in the supply chain organisation (Benhamida *et al*., 2021). They can be internal to the organisation or outsourced to a third-party (cloud) platform provider that offers pre-trained learning models, cloud-based computing resources and supply chain interconnectivity for predictive analytics. The AI technology platform enables and controls the operational elements of the AI toolbox, data, model selection and training, and required AI tools to facilitate DP using predictive analytics. It provides support to perform model selection automatically and, in some cases, these platforms can also calibrate the model and perform parameter selection (semi) autonomously (Walter *et al*., 2023). Once the data sources and model selection have been aligned and the model has been calibrated and trained; ML-based learning algorithms execute the DP process to perform data analytics and pattern recognition within the dataset to predict future demand for various SCM functions. Hence, technology platforms integrate devices and data sources across the supply chain, connect all stakeholders in the supply chain, automate processes and analyse data within the supply chain in real time. However, supply chain organisational elements such as trust and collaboration must be embedded within the technology platform to ensure smooth operations of AI tools (de Reuver *et al*., 2018).

The AI toolbox presented here is a useful conceptualisation of the technology elements in AI-based supply chain DP that receive extensive coverage in the literature of knowledge Cluster 1. In summarising and linking the relevant technology elements of AI adoption, the toolbox might assist SCM practitioners and managers who are often more familiar with the functional domain of SCM to understand the technology and appreciate the challenges in their organisational context.

(2) Artificial intelligence application for supply chain demand planning

The application of the AI toolbox in SCM planning functions constitutes the actual planning process that is applying the AI toolbox in various SCM areas. As mentioned, AI application is linked to domains: AI toolbox, supply chain performance and contingent elements (Figure 6). To apply AI in supply chain DP, inputs are the AI toolbox, which helps to select a suitable AI model (explained in the previous section) for a particular context of DP from procurement, inventory planning, warehousing, sales and distribution across all product dimensions of components, finished products and returns. The two domains are linked because data sources and quality, model selection and forecast approaches all depend on the actual application in SCM, depending on different demand patterns, forecast horizons or planning goals. When the AI toolbox has been aligned correctly with the planning context of the SCM function, supply chain planning abilities and decision-making are improved, which can lead to better supply chain performance.

Functional applications of the AI toolbox can be found in procurement, manufacturing, warehousing, sales and shipping, with different permutations of data, forecast approaches and model calibration. DP in procurement, for example, might require considering various lead time parameters to establish exact availability of components and finished products when they are required (Brintrup *et al.*, 2020; Dong, 2022). To plan manufacturing and ensure that all components are available in time and in their place in the production process, the procurement function, especially for components, often feeds into production planning and control parameters (Jung and Park, 2020; Jayant *et al.*, 2021). Inventory planning and control are directly affected, because one of the main functions of DP is to synchronise supply and demand in order to avoid stock-out or overstock events, both of which can reduce supply chain performance (Pereira and Frazzon, 2021; Pfutzenreuter *et al.*, 2023). Planning demand for finished-product sales typically considers completely different datasets, which might include weather, store location or seasonality (Joseph *et al.*, 2022).

Accordingly, the contingent factors around product, consumer and market analysis are linked to the domain because availability and requirements of data depend on the DP context, as explained above. Contingent organisational factors, such as organisational readiness for AI adoption, affect all domains in the framework.

(3) Impact of application of artificial intelligence in demand planning

AI-based DP can provide direct benefits in the form of cost reductions through improved inventory management that lowers stock levels (Gonçalves *et al.*, 2021). For supply chains with intermittent demand, this is achieved by grouping products by demand type and applying an appropriate forecasting model to each group (Fu and Chien, 2019). Inventory management can also be optimised by adjusting inventory location. Placing products where they are required is a challenge for omni-channel retailers that must coordinate multiple distribution channels by constantly adjusting inventory locations to meet demand. In this case, AI-based DP can offer benefits by optimising inventory locations across the entire omni-channel distribution network in real time (Pereira and Frazzon, 2021).

By considering a range of external parameters, AI-based DP models can adjust forecasts in real time, thereby supporting supply chain agility. Doing so increases SCM performance because planning models can adapt quickly by sensing and adjusting demand based on the weather, markets, competitor actions, changes in consumer taste, or external supply chain disruptions (Singh *et al.*, 2023). In pull supply chains, this provides additional benefits to manufacturers because they often do not have access to downstream demand data in real time. AI-based DP benefits these manufacturers in their production planning; they can be more agile and respond quickly to changes in consumer demand (Falatouri *et al.*, 2022).

Increased supply chain agility also supports resilience by helping to anticipate supply chain disruptions and external shocks (Pereira and Frazzon, 2021). Real-time data analysis using DL models helps manufacturing companies to reduce unplanned downtime and enables planned maintenance windows (Brintrup *et al.*, 2020). Modern supply chains produce millions of data points every day, as reflected by the contingent element of market, consumer and product analysis in this domain. In this environment, decision-making under uncertainty becomes increasingly complex because the processing of this data is beyond human cognitive capabilities. AI-based DP benefits SCM by providing machine-supported decision tools that can analyse the plethora of supply chain data to provide decision support (Lauer and Franke, 2020).

(4) Contingent elements

In Figure 6, contingent elements are considered in two groups: 1) market, consumer and product analysis (Bi *et al.*, 2022; Singha and Panse, 2022); and 2) organisational elements (Lee *et al.*, 2023). Contingent elements such as market (competition) and consumer and product data are key drivers that affect demand and therefore need be considered carefully in the DP process as input parameters for planning. The literature review shows that these input parameters dictate the tools that are selected from the AI toolbox, because market conditions (Jin and Shin, 2020), product life cycles (Kamble *et al.*, 2023) and consumer sentiment (Nguyen *et al.*, 2021; Bi *et al.*, 2022) need to be taken into account. Understanding these elements helps in anticipating and managing dependencies and uncertainties in different scenarios. Using sentiment analysis of consumer or market data can assist supply chain performance by increasing resilience in the case of supply chain disruptions (Nguyen *et al.*, 2021), or aid supply chain agility to react to changes in demand or consumer taste in real time, for example, in the fast fashion industry (Laaziz, 2020).

We included a second contingent, organisational elements, in our framework (it is shown in grey at the bottom), despite it receiving limited attention in the literature. These elements are crucial for AI application in supply chain organisation (Lee *et al.*, 2023; Pournader *et al.*, 2021). Existing technology adoption frameworks, such as TOE (explained in Section 4.1.3), consider organisational elements equally relevant for technology and the environment in the context of technology adoption, including AI (Tornatzky and Fleischer, 1990). These organisational elements, such as resources, associated capabilities and their collaboration, can support AI readiness and appear to improve supply chain performance (Madan and Ashok, 2022; Pournader *et al.*, 2021). SCM is inter-organisational, and a variety of cross-organisational issues, such as trust, collaboration, information security management and data governance, can affect supply chain performance (Lee *et al.*, 2023). Despite the importance of these organisational aspects in established technology adoption theory (DePietro *et al.*, 1990), current research on applying AI in supply chain DP gives it only marginal attention. In the proposed framework for AI adoption in supply chain DP, we conceptually consider organisational elements to provide a comprehensive understanding of AI application in supply chain DP.

In summary, our framework integrates the AI technology domain (AI toolbox) with SCM functional aspects and other contingent elements to enhance supply chain performance in DP. To apply to AI specifically for DP in various supply chain functions, our framework is developed using relevant literature and technology adoption theories such as the TOE framework (mentioned in section 4.1.3). The proposed framework highlights that the AI toolbox is an enabler for conceptualising essential technology elements of AI adoption in supply chain DP. However, there are challenges related to AI tools, among which are selecting and harmonising data, determining appropriate models for specific DP contexts and finding a trusted technology platform (and provider) to integrate the data sources, devices and supply chain functions to enable cohesive decision-making. By incorporating organisational elements of AI adoption, supported by technology adoption theory and AI literature reviews, our framework identifies gaps in the current AI in supply chain DP literature.

Other studies have developed frameworks for big data analytics by focusing on AI tools and techniques (Puneeth *et al.*, 2018) or prevalent AI or ML algorithms for SCM (Ni *et al.*, 2020; Pournader *et al.*, 2021; Aamer *et al.*, 2021; Akbari and Do, 2021). Studies have also explored ML techniques in specific application areas, such as manufacturing (Breitenbach *et al.*, 2021; Aamer *et al.*, 2021), perishable foods (Kaizer *et al.*, 2022), or various supply chain functions (Toorajipour *et al.*, 2021), to add value for SCM (Younis *et al.*, 2021). Unlike other studies, our comprehensive framework elucidates how AI technology, supply chains and organisational and market elements are interconnected to add value to supply chain DP.

*5.3 Identification of research gaps*

The cluster analysis of the literature reveals several research gaps in relation to AI for supply chain DP. To address RQ4, we categorised these gaps into two main areas: 1) research methodology and theoretical foundations; and 2) AI knowledge areas, such as behavioural and organisational research and sustainability. These gaps and associated research questions are summarised in Table 5 to offer valuable insight for future studies.

*5.3.1 Gaps related to research methodology and theoretical foundations.*

*Gaps in research methodology:* Studies that investigated AI in supply chain DP mainly focused on modelling or empirical methods. Although most articles involved modelling, none used pattern matching techniques, which are crucial in this methodology. Future research could explore anomaly detection to identify outliers in datasets, and so help demand planners to manage by exception and by focusing on the most urgent planning problems. Additionally, pattern matching in unsupervised learning could cluster demand based on similar features and so help planners to apply the most suitable forecasting techniques to different demand patterns.

Empirical research often focuses on specific datasets, resulting in a narrow perspective on SCM performance in a single case that lacks transferability or generalisability (Shenton, 2004). Future empirical studies could conduct longitudinal or in-depth case studies of early AI adopters in DP, to obtain a comprehensive understanding of the drivers, challenges and success factors of AI adoption.

Conceptual studies, which are typically theory building, are less common in the literature. Future studies could concentrate on developing theory by focusing on organisational elements that affect the successful application of AI in supply chain DP. By employing theory exploration or theory extension approaches (Ketokivi and Choi, 2014), transferability and the creation of generalisable models that link AI adoption in DP to SCM performance could be enhanced.

*Research without theoretical underpinning:* Overall, we noticed that few studies used theory to explain AI adoption in supply chain DP. This shortcoming relates to the previously identified gap in conceptual studies. Given that using AI in supply chain DP considers technology adoption in a multifunctional supply chain context, we found few studies that used technology adoption theories. Future research on using AI in DP could investigate theories, such as technology affordance and constraints theory (Markus and Silver, 2008) or the technology acceptance model (Davis *et al.*, 1989). These theories emphasise perceived utility of a particular technology for the user in the form of affordances (Gibson, 1979) for the former and perceived usefulness for the latter that affect adoption. Other relevant theories, such as socio-technical systems theory (Clegg, 2000), or the TOE framework (Tornatzky and Fleischer, 1990), make technology and organisational elements focal aspects of technology adoption. The TOE framework, in particular, has proven very useful for investigating technology adoption on a cross-functional organisational level because it considers technical, environmental and organisational contexts to be of equal importance (DePietro *et al.*, 1990).

*5.3.2 Research gaps in the knowledge area of artificial intelligence.* This section lists gaps in technology, AI application in DP and organisational issues that offer opportunities for further research on AI adoption in supply chain DP.

**Table 5.** Gaps identified in this literature review and future research agenda

| Gap category | Gap description | Research questions or future research agenda |
|---|---|---|
| (1) *Gaps related to methodology and theoretical foundations* | | |
| Research methodology | Lack of modelling research on pattern matching | - How can pattern matching techniques detect outliers in large datasets for exception based DP?<br>- How can unsupervised learning techniques assist in establishing clusters in demand patterns? |
| | Empirical research focusing on longitudinal studies | - How can longitudinal case studies help identify drivers, challenges, and success factors in AI adoption for demand planning |
| | Conceptual case studies to increase transferability of findings | - How do drivers and challenges of AI adoption change over time as companies navigate through digital transformation processes? |
| Lack of research with theoretical underpinning | Lack of research underpinned by theory | - How can AI adoption for DP be explained through the lens of established technology adoption theories?<br>- What are the drivers and challenges of AI adoption based on existing technology adoption theory? |
| (2) *AI knowledge area gaps* | | |
| Research in AI technology tools | Inter organisational technology platforms | - How can collaborative approaches affect SC outcomes when using AI based predictive planning tools? |
| | Intra organisational technology platforms | - What are the success factors for building integrated data platforms that drive AI based planning tools within organisations?<br>- What are the challenges related to data quality and availability that organisations face when integrating AI into supply chain DP? |
| | Cloud platforms | - Which factors should organisations consider when using predictive planning tools on external cloud platforms?<br>- How does the existing IT infrastructure of an organisation influence its readiness to adopt AI in DP? |
| | Cognitive AI – DP foundation models | - How can the use of foundation models alleviate the barriers to AI adoption for SME?<br>- How can data sharing in foundation model enable supply chains mitigate the BWE?<br>- How can firms maintain data security and protect data proprietary in foundation model powered big data supply chain planning? |
| | Cost benefit considerations of ML models | - Which factors impact planning cost in ML driven AI demand planning and how can these factors help determine the true efficiency of the model in terms of cost-benefit implications? |

(*continued*)

**Table 5.** Continued

| Gap category | Gap description | Research questions or future research agenda |
|---|---|---|
| Human behavioural research | | - How does human behaviour and trust in AI affect planning outcomes using AI based supply chain DP?<br>- How can companies build trust in (black box) machine predictions within their DP teams?<br>- Which factors affect collaboration between domain experts in DP and data scientists to improve model calibration that optimises planning outcomes? |
| Organisational research | | - Which are the organisational elements that affect digital transformation for DP?<br>- How does SC organisational capacity, willingness, or resource availability influence AI implementation in DP?<br>- How does leadership, culture, and inertia influence AI in DP?<br>- What role does leadership play in fostering a culture that supports AI adoption in DP?<br>- Which resources are pertinent in driving digital transformation in supply chain DP?<br>- What are the differences in resources pertinence affecting AI adoption comparing SME and larger organisations in supply chain DP? |
| AI skills and talent shortage | | - What skills and competencies will be in demand due to digital transformation of supply chain DP through AI?<br>- What specific skills and competencies are required by demand planners to effectively use AI tools in DP?<br>- What training programs or educational initiatives are most effective in preparing supply chain teams for AI integration? |
| SC sustainability and reverse logistics | Impact of AI DP on SC sustainability | - How can real time predictive DP affect SC sustainability? |
| | Apply AI based planning in reverse logistics | - How can AI driven DP be deployed to predict product return volumes in supply chains?<br>- Can big data enabled ML models be deployed to predict the quality of returns to improve the efficiency of reverse supply chains? |
| | Application of AI based DP in SC functions in warehousing and shipping/distribution | - How can AI based DP be deployed to predict parcel volumes for distribution or sorting centres to improve resource allocation efficiency in these facilities?<br>- How can AI based DP assist vehicle routing and distribution network planning to maximise vehicle utilisation? |

**Source(s):** Authors' own work

*Research gaps in AI technology tools:* Supply chain DP research in relation to AI focuses mostly on optimising ML models and using software technology that is related to ML models and has an inward-looking approach to organisational planning. Given that the bullwhip effect, in general, causes poor outcomes because of inadequate supply chain coordination, further research could explore collaborative AI-based DP across the supply chains and effective data and planning interfaces between partners. Additionally, expanding research to include intra-organisational interfaces for integrating data into AI models and optimising predictive ML models on shared cloud platforms could enhance understanding and efficiency.

Cognitive AI is underexplored in the literature, despite the development of large language foundation models in various fields. Currently, no foundation model for DP exists that requires minimal training, although progress is promising (Magistretti *et al*., 2019). Such models could offer accessible, cost-effective and accurate DP for SCM, which would be of particular benefit for small and medium-size enterprises (Kazakova *et al*., 2020; Han and Trimi, 2022). The potential impact on demand volatility and the bullwhip effect on the supply chain depends on whether these models are used independently or whether they are adopted as integrated foundational models for DP. Questions remain regarding funding of integrated models and how to address privacy and security concerns, which highlight the need for further research in cognitive AI for DP.

The forecasting approaches we reviewed emphasise accuracy, which should be supported by empirical evidence. However, to add real value to SCM, models need to improve the efficiency of the forecasting approach, including cost–benefit considerations. Training and operating ML models can be expensive, which affects efficiency. The literature largely overlooks these cost-benefit factors when model performance is assessed. Future research should assess model efficiency for AI in DP by incorporating cost and sustainability aspects of training and running large computationally intensive ML models.

*Behavioural research for AI in DP:* It appears that the current research focus leans heavily on tools and techniques, with less emphasis on human behavioural aspects of AI in DP. Perera *et al*. (2019) argue that modelling research often overlooks behavioural aspects, such as user acceptance, trust or collaboration and the human element in decision-making processes. This issue also applies to AI-based DP in supply chains, for which humans frequently process and act on machine-generated forecasts. The literature reviewed here shows little focus on the human–machine interface, and many researchers assume that forecasts are automatically trusted and used. This may not always be true in practice, which results in performance implications for AI-based DP tools that are not fully utilised because of trust issues. Hence, we emphasise that future behavioural research should explore why and how teams can effectively develop and trust forecasting models (Cluster 3 – decision-making) and resulting links to supply chain performance.

*Research on organisational aspects of AI in DP:* Research on organisational elements as they relate to AI adoption is limited. Only a few articles touched on these organisational aspects. While practical applications often use specific datasets or case studies, crucial elements for applying AI in DP as part of digital transformation, such as collaboration, organisational learning, data governance and readiness, are often overlooked. Frameworks such as the TOE framework (Tornatzky and Fleischer, 1990) and resource orchestration theory (Sirmon *et al*., 2007) could provide valuable insights into the underlying elements that enable organisations to develop the relevant resources needed for adopting AI technology platforms. The conceptual framework for AI adoption proposed in this review highlights these organisational elements as integral to linking with the technology dimension in AI adoption for supply chain DP. Future research could explore how supply chain organisations structure resources to facilitate digital transformation and establish AI-based DP processes.

*Research gap in AI skills and talent shortages:* While some AI literature highlights talent as a barrier to adoption (Ransbotham *et al*., 2017), this topic was notably absent from the reviewed publications. AI application in DP may require demand planners to upgrade their skills, or organisations may need to employ new talent to work on new technology as part of the digital transformation of supply chains. Considering the issues, future research can be conducted on the types of competencies that are required in AI based DP roles. Future research should investigate the competencies needed for AI in DP, the skills required for demand planners, and how the global shortage of AI talent (data scientists, ML engineers) affects AI adoption and the value of DP (MHI, 2022).

*SC sustainability and reverse logistics:* AI research in supply chain DP explores impacts such as agility, resilience and operations costs in SCM, although sustainability impacts have not been well studied. Future research could examine how real-time DP could enhance environmental sustainability by reducing waste in excess inventory. DP is essential in SCM at all levels of value creation, from components to finished products, which may eventually become returns in closed-loop supply chains. For example, if return rates are high like in e-tail, effective planning is crucial (Ahsan and Rahman, 2021). Future studies could explore AI applications in DP for predicting product returns and developing closed-loop, sustainable supply chains.

The literature mainly addresses SCM functions (Figure 4), such as procurement (Jonás *et al*., 2016), inventory planning (Benhamida *et al*., 2021), sales and finished goods in SCM (Zhuang *et al*., 2022), with less focus on distribution and intralogistics warehouse applications for DP. Further exploration is needed by research into warehousing, distribution and shipping functions related to AI based DP.

## 6. Conclusion

The application of AI in DP is still emerging, but has, in recent years, attracted increasing attention to improve SCM performance. By reviewing 141 relevant academic articles, this study identified the key elements of AI adoption in the supply chain DP context. We identified three emerging knowledge clusters in the literature around AI tools and techniques, applications of AI-based DP in supply chains, and impacts of AI-based DP, with 22 associated themes. These themes and key knowledge elements of the reviewed literature were applied through the lens of established technology adoption theory to develop a conceptual AI application framework for supply chain DP. This review also highlights several gaps that should be considered for future research. Considering these contributions, this review has several theoretical and practical implications.

### *6.1 Theoretical implications*

This study makes four key contributions to the emerging literature on AI in supply chain DP. First, this study summarises and conceptualises literature on AI in DP in supply chains, by providing a comprehensive overview that extends beyond previous related literature reviews (Table 3), thereby highlighting the novelty of our study. Second, this study categorises the evolution of AI in DP into three knowledge domains: 1) AI tools and techniques, 2) AI applications in the supply chain and 3) the impacts of AI-based DP. Notably, current research focuses largely on technology and its impacts and often overlooks organisational and inter-organisational aspects that are essential in SCM, which represent significant blind spots regarding AI in supply chain DP research.

Third, this study synthesises the literature on AI in supply chain DP, identifies gaps and presents a conceptual framework that outlines the key elements of AI application in DP. It charts the enablers, processes and impacts and emphasises technical, intra-organisational and inter-organisational issues. By amalgamating the existing research and incorporating existing technology adoption theory into the identified knowledge clusters, the framework offers a strong basis for future empirical research. The organisational elements in the conceptual framework are specifically emphasised in demand planning for SCM, as the DP function impacts every other aspect of the supply chain. Whilst most SC functions have a single upstream and downstream connection, DP is a cross-functional SC activity that directly or indirectly affects all SC functions (Table 5). Organisational elements and organisational structure serve as enablers for cross-functional change in supply chains (Lee, 2004; Ketchen and Hult, 2007). Therefore, our conceptual framework makes an important theoretical contribution by integrating both technical and organisational aspects which are essential for technology adoption, such as application of AI in DP. Finally, this study contributes to the literature by identifying several research gaps in methodology, theory use, organisational and behavioural elements, value creation and sustainability and the AI taxonomy framework. Addressing these gaps will help advance this emerging field of research.

### *6.2 Practical implications*

This review offers a conceptual framework for AI application in supply chain digital transformation, with a focus on DP. It connects theory and practice by identifying key elements and their interactions in AI adoption, including data, model and technology platform selection and training, to enhance supply chain performance. The framework helps practitioners understand critical aspects of AI implementation. We also highlight that an emphasis focusing solely on technology is insufficient when AI is adopted in DP; the incorporation of organisational factors such as trust, capabilities, collaboration and governance is essential. Many companies face challenges because of an inadequate understanding of AI, integration issues and unclear impacts of AI in DP, which makes this framework a valuable contribution to practice. This framework can guide industries with low AI adoption rates (MHI, 2020) by detailing enablers, processes and impacts and emphasising both technical and organisational issues. Managers often find it challenging to navigate the extensive literature on this topic and may rely on a few articles that fail to capture the full scope of the topic. This review saves time for practitioners by providing a comprehensive overview and offering more insight than any single empirical study does.

### *6.3 Limitations and future research directions*

Like any literature review, this study has limitations. The scope of the study was limited by the literature search procedures, which considered only publications in English. Additionally, the time horizon for the search was limited to publications after 2012, thereby excluding potentially relevant earlier research. However, analysis shows that the topic gained significant momentum only after 2019, which mitigates this limitation. The study is also confined to the Scopus database supplemented by Google Scholar. Scopus is one of the most comprehensive scientific databases available and contains over 20,000 peer-reviewed journals. We therefore argue that the inclusion of other databases, such as the Web of Science, would not have significantly altered the resulting article pool of this literature review. Further limitations include the large number of articles, which necessitated aggregation techniques that might have skewed findings. Additionally, the conceptual framework of AI application is tailored specifically to DP and may not apply to other SCM areas. The framework has limitations too because it is, at this stage, conceptual regarding both domains and their links. The connection between the domains, in particular, could be aided by empirical validation to confirm their direction and strength.

Despite these limitations, the study provides timely insights into AI applications in DP, which is a key area of SCM. Despite the extensive literature, challenges persist regarding AI adoption for DP, leaving numerous unanswered questions that were highlighted in this study. Scholars can address the identified gaps and explore the research questions highlighted in this study.

**Notes**

1. https://chat.openai.com
2. APICS—Association for Supply Chain Management (https://www.ascm.org/learning-development/certifications-credentials/dictionary/)
3. www.kaggle.com

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(The Appendix follows overleaf)

## Appendix

**Table A1.** Contributing authors to AI in demand planning knowledge clusters

| Cluster | Theme | Articles represented |
|---|---|---|
| Cluster 1 | Machine Learning approaches | Agatic *et al.* (2021), Agbemadon *et al.* (2023), Ahmed Marta *et al.* (2023), Akande *et al.* (2022), Alsanad (2020), Andersson and Siminos (2023), Alqatawna *et al.* (2023), Benhamida *et al.* (2021), Bi *et al.* (2022), Bibaud-Alves *et al.* (2019), Bousqaoui *et al.* (2021), Brintrup *et al.* (2020), Brau *et al.* (2023), Buttner and Rabe (2021), Cadavid *et al.* (2018), Chapados (2014), Dellino *et al.* (2018), Demizu *et al.* (2023), Dong (2022), El Garrab *et al.* (2020), Eldred *et al.* (2023), El Garrab *et al.* (2023), El Haoud and Bachiri (2019), Falatouri *et al.* (2022), Etebari *et al.* (2023), Feizabadi (2020), Filali *et al.* (2022c), Gaur *et al.* (2015), Gonçalves *et al.* (2021), Grygor *et al.* (2022), Hamdan *et al.* (2023), Ho *et al.* (2023), Hodzic *et al.* (2019), Ji *et al.* (2019), Joseph *et al.* (2022), Kantasaard *et al.* (2019), Karthikeswaren *et al.* (2021), Khosrowabadi *et al.* (2022), Kilimci *et al.* (2019), Koç and Türkoğlu (2021), Lin *et al.* (2019), Lingitz *et al.* (2018), Mariappan *et al.* (2023), Martins and Galegale (2022), Mbonyinshuti *et al.* (2022), Mediavilla *et al.* (2022), Mitra *et al.* (2023), Mittal *et al.* (2019), Moroff *et al.* (2021), Nassibi *et al.* (2023), Nguyen *et al.* (2022), Nita (2015), Pandey *et al.* (2023), Pereira and Frazzon (2021), Praveen *et al.* (2019), Punia *et al.* (2020), Rožanec *et al.* (2022), Sanjay Raja *et al.* (2023), Shang *et al.* (2023), Saraogi *et al.* (2021), Sarhani and El Afia (2014), Seyedan and Mafakheri (2020), Singh *et al.* (2023), Singha and Panse (2022), Tang and Ge (2021), Tawde and Jaswal (2017), Terrada *et al.* (2022), Vairagade *et al.* (2019), Van Belle *et al.* (2021), Venkateswaran *et al.* (2020), Wanchoo (2019), Wibowo (2023), Xia *et al.* (2023), Yani and Aamer (2023), Zhu *et al.* (2021), Zhuang *et al.* (2022), Zohdi *et al.* (2022) |
| | Supervised learning | Akande *et al.* (2022), Basljan *et al.* (2021), Bi *et al.* (2022), Bibaud-Alves *et al.* (2019), Bottani *et al.* (2019), Bousqaoui *et al.* (2021), Buttner and Rabe (2021), Chapados (2014), Dey and Ghose (2020), Dong (2022), Dowie and Grothmann (2021), El Filali *et al.* (2022), Falatouri *et al.* (2022), Fan and Cai (2019), Filali *et al.* (2022b, c), Gaur *et al.* (2015), Grygor *et al.* (2022), Innuphat and Toahchoodee (2022), Islek and Oguducu (2015), Jayant *et al.* (2021), Hodzic *et al.* (2019), Jonás *et al.* (2016), Kandananond (2012), Joseph *et al.* (2022), Kantasaard *et al.* (2019), Karthikeswaren *et al.* (2021), Khosrowabadi *et al.* (2022), Kilimci *et al.* (2019), Koç and Türkoğlu (2021), Lingitz *et al.* (2018), Martins and Galegale (2022), Mediavilla *et al.* (2022), Mittal *et al.* (2019), Moroff *et al.* (2021), Nikolopoulos *et al.* (2016), Pacella and Papadia (2021), Pandey *et al.* (2023), Punia *et al.* (2020), Rožanec *et al.* (2022), Saraogi *et al.* (2021), Sarhani and El Afia (2014), Singh and Challa (2016), Slimani *et al.* (2015b, 2017), Slimani *et al.* (2016), Sohrabpour *et al.* (2021), Stoll *et al.* (2021), Singha and Panse (2022), Tang and Ge (2021), Tawde and Jaswal (2017), Turrado García *et al.* (2012), Terrada *et al.* (2022), Vairagade *et al.* (2019), Villegas and Pedregal (2018), Weng *et al.* (2020), Yuan *et al.* (2018), Zhao *et al.* (2023), Zheng *et al.* (2014), Wanchoo (2019), Zhuang *et al.* (2022) |
| | Unsupervised learning | Islek and Oguducu (2015), Mediavilla *et al.* (2022), Nita (2015) |
| | Deep learning | Agbemadon *et al.* (2023), Bibaud-Alves *et al.* (2019), Bousqaoui *et al.* (2021), Demizu *et al.* (2023), Dowie and Grothmann (2021), El Filali *et al.* (2022), Erol and Inkaya (2023), Filali *et al.* (2022b, c), Innuphat and Toahchoodee (2022), Jung and Park (2020), Karthikeswaren *et al.* (2021), Kilimci *et al.* (2019), Kim *et al.* (2023), Koç and Türkoğlu (2021), Ma *et al.* (2023), Mediavilla *et al.* (2022), Moroff *et al.* (2021), Nasseri *et al.* (2023), Naveen Parthasarathy *et al.* (2023), Sanjay Raja *et al.* (2023), Pacella and Papadia (2021), Panda and Mohanty (2023), Punia *et al.* (2020), Tang and Ge (2021), Terrada *et al.* (2022), Vallés-Pérez *et al.* (2022), Wen and Yan (2019), Weng *et al.* (2020), Yuan *et al.* (2018), Wanchoo (2019) |

(*continued*)

**Table A1.** Continued

| Cluster | Theme | Articles represented |
|---|---|---|
| | Forecasting approaches | Abdollahi *et al.* (2023), Alqatawna *et al.* (2023), Andersson and Siminos (2023), Bi *et al.* (2022), Brau *et al.* (2023), Cadavid *et al.* (2018), Erol and Inkaya (2023), Etebari *et al.* (2023), Fan and Cai (2019), Grygor *et al.* (2022), Jonás *et al.* (2016), Ji *et al.* (2019), Kamal *et al.* (2023), Kantasaard *et al.* (2019), Karthikeswaren *et al.* (2021), Kilimci *et al.* (2019), Koç and Türkoğlu (2021), Mamede *et al.* (2023), Mbonyinshuti *et al.* (2022), Mediavilla *et al.* (2022), Mobarakeh *et al.* (2017), Moroff *et al.* (2021), Nasseri *et al.* (2023), Naveen Parthasarathy *et al.* (2023), Panda and Mohanty (2023), Pandey *et al.* (2023), Punia *et al.* (2020), Quiñones-Rivera *et al.* (2023), Sanjay Raja *et al.* (2023), Shang *et al.* (2023), Slimani *et al.* (2016), Sohrabpour *et al.* (2021), Stoll *et al.* (2021), Singha and Panse (2022), Suresh and Suresh (2023), Turrado García *et al.* (2012), Terrada *et al.* (2022), Vairagade *et al.* (2019), Villegas and Pedregal (2018), Wanchoo (2019), Wang (2023), Zhao *et al.* (2023), Zietsman and van Vuuren (2023) |
| | Data analytics | Agatic *et al.* (2021), Bala (2012), Brintrup *et al.* (2020), Cao *et al.* (2021), El Haoud and Bachiri (2019), Fan and Cai (2019), Gaur *et al.* (2015), Grygor *et al.* (2022), Joseph *et al.* (2022), Nguyen *et al.* (2021), Nita (2015), Pereira and Frazzon (2021), Seyedan and Mafakheri (2020), Stoll *et al.* (2021), Tawde and Jaswal (2017), Wang and Chen (2020), Weng *et al.* (2020), Zohdi *et al.* (2022) |
| | Predictive analytics | Brau *et al.* (2023), Brintrup *et al.* (2020), Falatouri *et al.* (2022), Fan and Cai (2019), Naveen Parthasarathy *et al.* (2023), Punia *et al.* (2020), Saraogi *et al.* (2021), Shang *et al.* (2023), Singh *et al.* (2023), Slimani *et al.* (2016), Xia *et al.* (2023) |
| Cluster 2 | Supply Chain management | Akande *et al.* (2022), Alsanad (2020), Bala (2012), Basljan *et al.* (2021), Bi *et al.* (2022), Bibaud-Alves *et al.* (2019), Boru *et al.* (2019), Bottani *et al.* (2019), Bousqaoui *et al.* (2021), Brintrup *et al.* (2020), Buttner and Rabe (2021), Cadavid *et al.* (2018), Cao *et al.* (2021), Chapados (2014), Dellino *et al.* (2018), Dong (2022), Dowie and Grothmann (2021), El Garrab *et al.* (2020), El Haoud and Bachiri (2019), Falatouri *et al.* (2022), Fan and Cai (2019), Filali *et al.* (2022b, c), Fu and Chien (2019), Gaur *et al.* (2015), Gonçalves *et al.* (2021), Grygor *et al.* (2022), Hamdan *et al.* (2023), Islek and Oguducu (2015), Jaipuria and Mahapatra (2019), Hodzic *et al.* (2019), Ji *et al.* (2019), Kandananond (2012), Joseph *et al.* (2022), Kantasaard *et al.* (2019), Karthikeswaren *et al.* (2021), Khosrowabadi *et al.* (2022), Kilimci *et al.* (2019), Laaziz (2020), Lauer *et al.* (2020), Koç and Türkoğlu (2021), Lin *et al.* (2019), Lingitz *et al.* (2018), Mascle and Gosse (2014), Mamede *et al.* (2023), Martins and Galegale (2022), Mediavilla *et al.* (2022), Mobarakeh *et al.* (2017), Monteleone *et al.* (2015), Mittal *et al.* (2019), Nasseri *et al.* (2023), Nassibi *et al.* (2023), Nguyen *et al.* (2021), Moroff *et al.* (2021), Nikolopoulos *et al.* (2016), Nita (2015), Pacella and Papadia (2021), Pandey *et al.* (2023), Praveen *et al.* (2019), Punia *et al.* (2020), Rožanec *et al.* (2022), Sanjay Raja *et al.* (2023), Saraogi *et al.* (2021), Sarhani and El Afia (2014), Shang *et al.* (2023), Silva and Rupasinghe (2017), Seyedan and Mafakheri (2020), Slimani *et al.* (2017), Slimani *et al.* (2015a, b), Slimani *et al.* (2016), Sohrabpour *et al.* (2021), Singha and Panse (2022), Suresh and Suresh (2023), Tang and Ge (2021), Tang *et al.* (2023), Tawde and Jaswal (2017), Turrado García *et al.* (2012), Terrada *et al.* (2022), Vallés-Pérez *et al.* (2022), Vairagade *et al.* (2019), Villegas and Pedregal (2018), Venkateswaran *et al.* (2020), Watanabe *et al.* (2019), Weng *et al.* (2020), Wibowo (2023), Yani and Aamer (2023), Zheng *et al.* (2014), Wanchoo (2019), Zietsman and van Vuuren (2023), Zohdi *et al.* (2022) |
| | Inventory management | Agbemadon *et al.* (2023), Bala (2012), Demizu *et al.* (2023), Eldred *et al.* (2023), Fu and Chien (2019), Gaur *et al.* (2015), Grygor *et al.* (2022), Innuphat and Toahchoodee (2022), Jaipuria and Mahapatra (2019), Jin and Shin (2020), Ji *et al.* (2019), Mascle and Gosse (2014), Monteleone *et al.* (2015), Naveen Parthasarathy *et al.* (2023), Omar *et al.* (2023), Panda *et al.* (2019), Saraogi *et al.* (2021), Singha and Panse (2022), Zietsman and van Vuuren (2023) |

(*continued*)

**Table A1.** Continued

| Cluster | Theme | Articles represented |
|---|---|---|
| | Production planning | Brintrup *et al.* (2020), Cao *et al.* (2021), Filali *et al.* (2022c), Fu and Chien (2019), Lingitz *et al.* (2018), Nita (2015), Silva and Rupasinghe (2017), Venkateswaran *et al.* (2020), Zheng *et al.* (2014) |
| | Production control | Basljan *et al.* (2021), Lingitz *et al.* (2018) |
| | Logistics | Alqatawna *et al.* (2023), Bala (2012), Basljan *et al.* (2021), Kim *et al.* (2023), Nikolopoulos *et al.* (2016), Slimani *et al.* (2017), Yuan *et al.* (2018) |
| | Product analysis | Andersson and Siminos (2023), Fu and Chien (2019), Jonás *et al.* (2016), Watanabe *et al.* (2019) |
| | Demand forecasting | Agatic *et al.* (2021), Ahmed *et al.* (2020), Akande *et al.* (2022), Alsanad (2020), Andersson and Siminos (2023), Bala (2012), Basljan *et al.* (2021), Benhamida *et al.* (2021), Bi *et al.* (2022), Bibaud-Alves *et al.* (2019), Boru *et al.* (2019), Bottani *et al.* (2019), Brau *et al.* (2023), Brintrup *et al.* (2020), Buttner and Rabe (2021), Cadavid *et al.* (2018), Cao *et al.* (2021), Dellino *et al.* (2018), Dey and Ghose (2020), Dong (2022), Dowie and Grothmann (2021), El Filali *et al.* (2022), El Garrab *et al.* (2020), Etebari *et al.* (2023), Falatouri *et al.* (2022), Fan and Cai (2019), Feizabadi (2020), Filali *et al.* (2022b, c), Fu and Chien (2019), Gaur *et al.* (2015), Gonçalves *et al.* (2021), Grygor *et al.* (2022), Innuphat and Toahchoodee (2022), Islek and Oguducu (2015), Jaipuria and Mahapatra (2019), Jayant *et al.* (2021), Hodzic *et al.* (2019), Jin and Shin (2020), Jonás *et al.* (2016), Ji *et al.* (2019), Kandananond (2012), Joseph *et al.* (2022), Kantasaard *et al.* (2019), Karthikeswaren *et al.* (2021), Khosrowabadi *et al.* (2022) Kilimci *et al.* (2019), Laaziz (2020), Lauer *et al.* (2020), Lauer and Wieland (2021), Kim *et al.* (2023), Koç and Türkoğlu (2021), Lin *et al.* (2019), Lingitz *et al.* (2018), Ma *et al.* (2023), Mascle and Gosse (2014), Martins and Galegale (2022), Mediavilla *et al.* (2022), Mitra *et al.* (2023), Mobarakeh *et al.* (2017), Monteleone *et al.* (2015), Mittal *et al.* (2019), Nguyen *et al.* (2021), Moroff *et al.* (2021), Nikolopoulos *et al.* (2016), Nguyen *et al.* (2022), Omar *et al.* (2023), Pacella and Papadia (2021), Panda and Mohanty (2023), Nita (2015), Punia *et al.* (2020), Rožanec *et al.* (2021, 2022), Saraogi *et al.* (2021), Sarhani and El Afia (2014), Silva and Rupasinghe (2017), Seyedan and Mafakheri (2020), Slimani *et al.* (2015a, b, 2016, 2017), Sohrabpour *et al.* (2021), Singha and Panse (2022), Tang and Ge (2021), Tang *et al.* (2023), Tawde and Jaswal (2017), Terrada *et al.* (2022), Vallés-Pérez *et al.* (2022), Vairagade *et al.* (2019), Van Belle *et al.* (2021), Villegas and Pedregal (2018), Venkateswaran *et al.* (2020), Wang and Chen (2020), Watanabe *et al.* (2019), Wen and Yan (2019), Weng *et al.* (2020), Yani and Aamer (2023), Yuan *et al.* (2018), Wanchoo (2019), Zhu *et al.* (2021), Zhuang *et al.* (2022), Zohdi *et al.* (2022) |
| | Supply chain performance | Ahmed *et al.* (2020), Mobarakeh *et al.* (2017), Moroff *et al.* (2021), Nguyen *et al.* (2022) |
| | Artificial Intelligence | Agatic *et al.* (2021), Ahmed *et al.* (2020), Alsanad (2020), Bala (2012), Boru *et al.* (2019), Cadavid *et al.* (2018), Cao *et al.* (2021), Chapados (2014), Dellino *et al.* (2018), Dey and Ghose (2020), Dong (2022), Fan and Cai (2019), Fu and Chien (2019), Gaur *et al.* (2015), Jaipuria and Mahapatra (2019), Jonás *et al.* (2016), Laaziz (2020), Lauer and Franke (2020), Lin *et al.* (2019), Lingitz *et al.* (2018), Mariappan *et al.* (2023), Mascle and Gosse (2014), Mediavilla *et al.* (2022), Mobarakeh *et al.* (2017), Monteleone *et al.* (2015), Mittal *et al.* (2019), Nguyen *et al.* (2021), Nikolopoulos *et al.* (2016), Nita (2015), Rožanec *et al.* (2021, 2022), Saraogi *et al.* (2021), Sarhani and El Afia (2014), Silva and Rupasinghe (2017), Singh *et al.* (2023), Slimani *et al.* (2015b, 2016, 2017), Sohrabpour *et al.* (2021), Tang *et al.* (2023), Tawde and Jaswal (2017), Turrado García *et al.* (2012), Terrada *et al.* (2022), Villegas and Pedregal (2018), Yuan *et al.* (2018), Zheng *et al.* (2014) |

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**Table A1.** Continued

| Cluster | Theme | Articles represented |
|---|---|---|
| Cluster 3 | Market analysis | Akande *et al.* (2022), Bi *et al.* (2022), Bibaud-Alves *et al.* (2019), Bottani *et al.* (2019), Buttner and Rabe (2021), Cadavid *et al.* (2018), Cao *et al.* (2021), Dellino *et al.* (2018), Dong (2022), Falatouri *et al.* (2022), Jonás *et al.* (2016), Ji *et al.* (2019), Joseph *et al.* (2022), Lauer *et al.* (2020), Mascle and Gosse (2014), Martins and Galegale (2022), Mittal *et al.* (2019), Nguyen *et al.* (2022), Moroff *et al.* (2021), Punia *et al.* (2020), Saraogi *et al.* (2021), Slimani *et al.* (2015b, 2016), Sohrabpour *et al.* (2021), Singha and Panse (2022), Tang and Ge (2021), Tawde and Jaswal (2017), Vairagade *et al.* (2019), Venkateswaran *et al.* (2020), Weng *et al.* (2020), Wanchoo (2019) |
| | Consumer analysis | Akande *et al.* (2022), Basljan *et al.* (2021), Bi *et al.* (2022), Dowie and Grothmann (2021), El Garrab *et al.* (2020), Filali *et al.* (2022c), Lauer *et al.* (2020), Lauer and Wieland (2021), Saraogi *et al.* (2021), Singha and Panse (2022) |
| | Decision making | Abdollahi *et al.* (2023), Ahmed Marta *et al.* (2023), Bottani *et al.* (2019), Dong (2022), Lauer *et al.* (2020), Lin *et al.* (2019), Monteleone *et al.* (2015), Nassibi *et al.* (2023), Singha and Panse (2022), Suresh and Suresh (2023), Terrada *et al.* (2022) |
| | Supply Chain planning | Ahmed Marta *et al.* (2023), Chapados (2014), Lauer *et al.* (2020), Lauer and Wieland (2021), Moroff *et al.* (2021) |
| | Cost | Abdollahi *et al.* (2023), Akande *et al.* (2022), Basljan *et al.* (2021), Dong (2022), El Garrab *et al.* (2020), Fan and Cai (2019), Monteleone *et al.* (2015), Tang and Ge (2021), Turrado García *et al.* (2012), Venkateswaran *et al.* (2020) |
| | Retail | Akande *et al.* (2022), Bi *et al.* (2022), Martins and Galegale (2022), Slimani *et al.* (2015b), Suresh and Suresh (2023) |
| | SC digital transformation | Brau *et al.* (2023), Brintrup *et al.* (2020), Cadavid *et al.* (2018), Hodzic *et al.* (2019), Lauer *et al.* (2020), Lauer and Wieland (2021), Moroff *et al.* (2021), Rožanec *et al.* (2022), Vairagade *et al.* (2019) |

**Source(s):** Authors' own work

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