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EXPLORING, CATEGORISATION AND USAGE OF ARTIFICIAL INTELLIGENCE ALGORITHMS FOR SUPPLY CHAIN MANAGEMENT

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Abstract: This paper explores the categorisation and usage of Artificial intelligence Algorithms (AIA) in Supply Chain Management (SCM) and discusses the potential benefits and challenges of implementing AI in SCM. The study reviews the literature on the application of AI in SCM. It provides a comprehensive list of commonly used algorithms in different SCM applications, such as vendor selection, production planning, resource allocation, quality control, predictive maintenance, visibility, demand forecasting, inventory optimisation, transportation optimisation, and customer segmentation. The paper highlights the versatility and potential for the cross-functional use of many AI algorithms. It identifies challenges and limitations, including data quality and availability, privacy and security concerns, and a lack of understanding and trust in AI systems. The study concludes that AI has the potential to significantly impact SCM by increasing efficiency, accuracy, and flexibility while reducing costs. However, further research is needed to develop best practices for adopting and implementing AI in SCM and to address ethical implications related to AI in SCM.

Keywords: Artificial Intelligence, SCM, algorithms

Introduction

In the wake of globalisation, companies worldwide have expanded their supply chains, delving into new markets, sourcing raw materials globally, and leveraging cost-effective labour. This interconnectedness, however, presents its own fragilities, as seen from disruptions caused by the COVID-19 pandemic and geopolitical events like the Russia-Ukraine conflict. Such challenges necessitate innovative solutions to ensure the resilience and efficiency of supply chain management (SCM) 1 .

Artificial Intelligence (AI) stands at the forefront of these innovative solutions. As the world strides into the Fourth Industrial Revolution, AI has proven its mettle in transforming supply chains, from enhancing demand forecasting accuracy to streamlining inventory management and fostering informed decision-making. This research paper endeavours to categorise and elucidate the application of AI algorithms in SCM. By examining the historical and current global supply chain scenarios and delving deep into literature reviews on AI's role in SCM, this study aims to offer an invaluable guide for scholars and professionals eager to harness AI's potential in SCM (2), (3).

This paper will also shed light on the common AI algorithms used in the SCM sector, derived from extensive research, academic papers, and publications to offer a holistic understanding. This comprehensive approach aims to give readers a coherent understanding of AI's transformative role in SCM.

Literature Review

Several studies have examined the impact of AI algorithms on supply chain management, highlighting potential benefits and challenges. Some studies have found that AI algorithms can significantly improve SC efficiency, reduce costs, and improve overall performance. For example, AI algorithms can help companies predict demand more accurately, enabling them to optimise inventory levels and reduce the risk of out-of-stocks. AI algorithms can also help companies optimise their logistics and transport operations, which helps to reduce delivery times and costs. In almost all areas of SCM, AI algorithms can be found today (4, 5).

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The articles by Tirkolaee and Hosseinnia et al. provide a comprehensive overview of the areas where AI can be applied in SCM, such as demand forecasting, inventory management, logistics, and supplier selection. The authors discussed various AI techniques that can be used in SCM, including decision trees, artificial neural networks (ANN), and support vector machines (SVM), and they provide examples of how these techniques have been applied, such as using ANN to forecast demand for fashion products and decision trees to select suppliers (6, 7).

The use of deep learning algorithms in SCM, particularly in demand forecasting and inventory optimisation, was the focus of a study by Feizabadi, Allam and Bui Tong et al. The studies found that demand forecasting and inventory management accuracy can be improved using deep learning algorithms such as convolutional neural networks (CNNs) and long short-term memory networks (LSTMNs) (8, 1, 2).

The study by Rolf et al. examined the use of reinforcement learning (RL) algorithms in SCM, particularly in inventory management and production planning. The study found that RL algorithms can optimise decision-making and improve efficiency in these areas (9).

In their systematic literature review, Hangl et al. analysed 44 articles on the barriers, drivers and societal considerations for AI adoption in SCM. The authors identify seven research areas, the most important of which are algorithms. Change management, existing technical limitations, human acceptance of these techniques, understanding and usability of these techniques, existing human knowledge, and high cost are the main barriers to AI adoption in SCM. The main drivers for AI in SCM are cost reduction, efficiency and error reduction. Human-robot collaboration is an essential social driver. The authors make 137 recommendations for future research (10).

Methodology of the research

The research presented in this paper involves a comprehensive review of the literature on AI algorithms in SCM.

The research involves a systematic literature review, focusing on published articles, reports, and case studies examining AI algorithms usage on SCM. In addition, the review includes a critical literature analysis, identifying key themes and issues related to adopting and implementing these algorithms in SCM. To ensure the validity and reliability of the research findings, the paper employs a rigorous methodology, including a comprehensive search of multiple databases, a rigorous screening process to select relevant articles, and a systematic literature analysis to identify key themes and issues. Finally, by examining the practical applications of these technologies in SCM, the paper aims to provide insights and guidance for businesses and the scientific community (11, 12).

The literature search used several electronic databases, including Scopus, Google Scholar and Web of Science. The search terms were identified based on the research questions. The search was conducted in January 2023 and included articles published between January 2000 and May 2022. The following search strings were used:

((Artificial Intelligence OR AI or intelligent algorithms) AND (Supply Chain Management OR SC)) AND (technique OR tool OR framework)

In addition, To evaluate which algorithms are mainly used in publications, a Google Scholar search for each algorithm was executed to understand the number of publications per algorithm. Each extracted algorithm out of the literature research where individually explored with the following search string:

(("Algorithm") AND (Supply Chain Management OR SC))

The inclusion and exclusion criteria were established to select relevant studies for the review. Studies were included if they met the following criteria: (1) reported original research findings, (2) focused on SCM or AI, and (3) were published in English between 2000 and 2022. Studies were excluded if they were (1) not original research (e.g., editorial, letter, review article), (2) not related to SCM or AI, and (3) published before 2000.

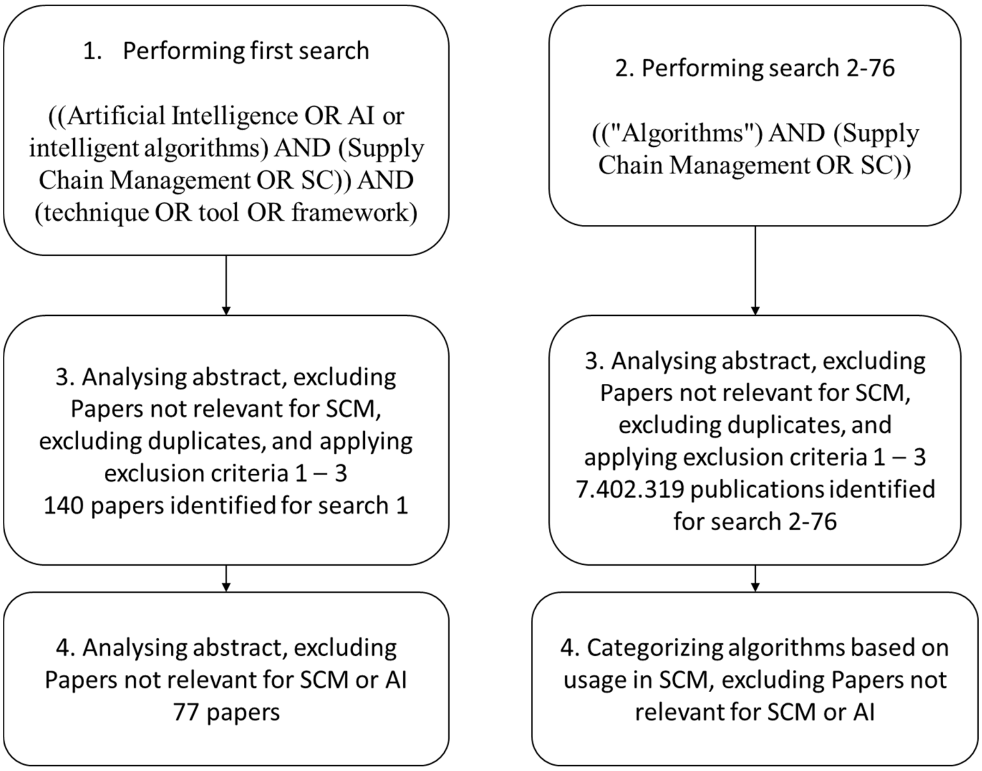

Figure . Search Strategy

Source: Own study

Three independent reviewers screened the titles and abstracts of the search results to determine their relevance to the research questions and eligibility for full-text review. Two independent reviewers reviewed full-text articles using MaxQDA to tag the text and summarise the results.

To categorise the algorithms in the area of SCM. The papers were analysed based on the specific keywords which are used. MaxQDA has been used to tag the papers and summarise them in categories.

Various papers used the following terms: vendor selection, production planning, resource allocation, quality control, predictive maintenance, visibility, demand forecasting, inventory optimisation, transportation optimisation, and customer segmentation.

These terms were put forward and analysed if they use specific algorithms.

The studies' quality in the review was assessed using a standardised quality assessment tool. The tool was developed based on the guidelines outlined in the by Kitchenham. Three reviewers assessed each study independently, and disagreements were resolved through discussion and consensus (11, 12).

The data extracted from the studies were synthesised using a narrative approach. Then, the results were organised according to the research questions and presented in a tabular format. Finally, the findings were summarised, and conclusions were drawn based on the available evidence.

Several limitations should be considered when interpreting the results of this paper. First, the search strategy was limited to three electronic databases and may have missed relevant studies. Second, the inclusion criteria were restricted to studies published in English, which may have introduced language bias. Third, not every algorithm used will be published as a paper; therefore, the latest development cannot be shown. Finally, the quality assessment tool used in this review was developed based on the PRISMA guidelines and may not capture all aspects of study quality.

Results

The following section presents the study's results on categorising and using AI algorithms for SCM. The study aimed to explore the different types of AI algorithms and their applications in SCM to help practitioners choose the appropriate algorithm for their specific use case.

Algorithms in supply chain

To evaluate which algorithms are mainly used in publications, a Google Scholar search for each algorithm was executed to understand the number of publications per algorithm.

The table below shows the number of results that appear in Google Scholar when searching for commonly used algorithms in SCM. Each algorithm is listed along with the number of results that occur when the algorithm is searched in Google Scholar.

The algorithms are ordered by the number of search results in descending order, starting from the algorithm with the highest results.

This table indicates the popularity of these algorithms in supply chain research, as measured by the number of publications that reference these algorithms.

The commonly used algorithms include linear regression, dynamic programming, robust optimisation, decision trees, clustering, and many others. These algorithms effectively solve complex supply chain problems and have been extensively researched and tested. As such, they are essential tools for supply chain professionals to improve operational efficiency and reduce costs. Moreover, the use of these algorithms is likely to continue to increase as supply chains become more complex and demand for efficiency and cost savings continues to grow.

Table 1. Publications per algorithm (only the Top 15 showed)

Commonly used Algorithms	Number of results in Google Scholar
Linear regression	747000
Dynamic programming	670000
Robust optimisation	577000
Decision Trees	517000
Rough set theory	427000
Column Generation	409000
Clustering	394000
Differential Evolution (DE)	336000
Stochastic programming	332000
Random Forest	289000
Fuzzy logic	239000
Logistic Regression	203000
Heuristic	168000
Association Rules	159000
Dynamic pricing algorithm	139000

Source: own study

Usage of algorithms per supply chain function

The algorithms were categorised based on their type and usage in different supply chain management aspects, such as demand forecasting, vendor selection, and inventory optimisation. The algorithms included ANN, swarm intelligence algorithms, artificial immune systems, rule-based systems, mathematical optimisation algorithms, unsupervised learning algorithms, RL algorithms, evolutionary algorithms, time series analysis algorithms, and support vector machines.

Vendor selection is an essential process in SCM. Decision Trees, Gaussian Processes Classifier, Vendor selection, Generalised Regression neural network (GRNN), Gradient Boosting, RL, and SVM are commonly used algorithms to optimise this process (13–16).

Production planning is another crucial process in SCM, and it can be optimised using Integer Linear Programming (ILP), Linear Programming (LP), Mixed Integer Linear Programming (MILP), Nonlinear Programming (NLP), RL (RL), and Stochastic programming (17–20).

Resource allocation is an essential aspect of SCM, and the optimisation of this process is possible using ILP, LP, MILP, NLP, RL, and Stochastic programming (21–25).

Quality control is critical to ensure that the products and services meet the required standards. The commonly used algorithms in SCM for quality control include Decision Trees, Gaussian Processes Classifier, Generalized Regression neural network (GRNN), Gradient Boosting, RL, and SVM (16) (13, 26).

Predictive maintenance is another crucial process in SCM, and it can be optimised using Long Short Term Memory (LSTM), RL, ANN, Convolution Neural Network (CNN), and Feedforward neural network (27–29).

Visibility is an essential aspect of SCM, and it can be optimised using ANN, Convolution Neural Networks (CNN), Hidden Markov Models (HMM), Long Short Term Memory (LSTM), RL (RL), SVM, Decision Trees, and Naive Bayes (30–33).

Demand forecasting is a crucial process in SCM, and it can be optimised using Gaussian Processes Classifier, Gradient Boosting, Generalized Regression neural network (GRNN), LSTM, RL, Seasonal auto-regressive integrated moving average (SARIMA), Singular spectrum analysis (SSA), and SVM (34–38).

Inventory optimisation is essential in SCM, and it can be optimised using ILP, LP, MILP, NLP, RL, and Stochastic programming (39–42).

Transportation optimisation is another critical process in SCM, and it can be optimised using ILP, LP, MILP, NLP, RL, Stochastic programming, Ant Colony Optimization (ACO), and Artificial Bee Colony (ABC) (43–46).

Customer segmentation is crucial to understanding and targeting customer needs and preferences. The commonly used algorithms in SCM for customer segmentation include K-means clustering, RL, SVM, Clustering, Fuzzy Logic, K-Naive Bayes, K-Nearest Neighbors (KNN), and Latent Dirichlet Allocation (LDA) (47, 48, 6, 49–51).

Fraud detection is essential to identify and prevent fraud in SCM. The commonly used algorithms in SCM for fraud detection include Decision Trees, Gaussian Processes Classifier, GRNN, Gradient Boosting, RL, SVM, and HMM (52–56)

The study found that AI algorithms have a wide range of applications in supply chain management, and each algorithm has unique features and limitations. The appropriate algorithm for a specific use case depends on the problem's nature and data availability. Moreover, the study results provide a high-level overview of how different algorithms can be used in various aspects of SCM and help practitioners understand which algorithms are suitable for specific problems.

Discussion

This study demonstrates that various AI algorithms are employed across various Supply Chain Management (SCM) areas, including vendor selection, production planning, resource allocation, quality control, predictive maintenance, visibility, demand forecasting, inventory optimisation, transportation optimisation, and customer segmentation.

Reinforcement Learning (RL) is the most frequently used AI algorithm, valued for its ability to learn from experience and optimise decision-making over time. Support Vector Machine (SVM) is another common algorithm used for its capabilities in handling both linear and nonlinear data with high accuracy in classification tasks. Gradient Boosting is popular for vendor selection, demand forecasting, quality

control, and fraud detection, as it improves prediction accuracy by combining multiple weak models into a robust model. Other popular algorithms include General Regression Neural Network (GRNN), Long Short-Term Memory (LSTM), and Mixed Integer Linear Programming (MILP).
The study shows that these AI algorithms are versatile and can be applied in multiple SCM areas. However, challenges such as data availability and quality, and the need for human oversight in interpreting AI-generated results remain. Despite these challenges, there is a growing trend of AI applications in SCM, as shown by the increasing number of relevant studies and publications.
In conclusion, while AI algorithms show potential to improve efficiency, accuracy, and decision-making in SCM, their adoption is not without challenges and limitations. Further research is necessary to understand AI's opportunities and challenges in SCM and to develop best practices for its adoption and implementation.

Conclusion

This paper delves into the classification and utilisation of AI in Supply Chain Management (SCM), reviewing relevant literature and presenting an extensive list of AI algorithms applied in diverse SCM contexts. AI has the potential to greatly improve SCM by boosting efficiency, accuracy, and flexibility while also decreasing costs. However, the paper identifies obstacles to AI's adoption in SCM, such as lack of understanding, data quality and availability issues, concerns about privacy and security, and a lack of trust in AI systems. AI has been applied in various SCM areas, including vendor selection, production planning, resource allocation, quality control, predictive maintenance, visibility, demand forecasting, inventory optimisation, transportation optimisation, and customer segmentation. Different algorithms are used based on the specific requirements of each application. Despite its potential, there are limitations to the study. It heavily relies on past research, which may not accurately represent the current state of AI in SCM.

Furthermore, the listed algorithms may not be suitable for every SCM scenario and might require customisation. Potential biases and errors exist in the data used for training and testing AI algorithms, and AI adoption requires substantial investment, which could be challenging for smaller organisations. The ethical implications of AI in SCM, including privacy, security, and transparency issues, also need to be considered. Overreliance on technology could lead to reduced human oversight and accountability, emphasising the need for ethical guidelines for AI in SCM. Further research is recommended to explore AI's potential benefits and challenges in specific SCM applications and develop hybrid AI algorithms that merge different AI techniques to enhance SCM. Despite the limitations and challenges, AI's application in SCM can lead to better decision-making, increased efficiency, and reduced costs.

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