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Application of Artificial Intelligence and Machine Learning in Lot Sizing

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Abstract

The purpose of this study is to investigate how artificial intelligence (AI) and machine learning (ML) methods, are being utilized in Lot Sizing and to anticipate future research directions in this area. The approach to conducting this study was through a systematic literature review mainly using the PRISMA framework. This study analyzes the publications available on Web of Science and Scopus associated with AI and ML to Lot sizing with a focus also on the Optimization of order quantities. Initial keyword searches led to a download of 325 papers, which were further reduced to 36 using various filters and eligibility criteria. The included studies are then all listed in tabular format whilst the relevant findings and the main algorithms adopted were discussed. The research found that the use of AI and ML it is still in its infancy, thus providing vast opportunities for different areas of lot sizing. While some authors reported significant improvements in systems performance, hence indicating their efficiency, some stated that system is not fully utilised, while some found that the implementation could significantly reduce the bullwhip effect.Previous research on AI applications in lot sizing has been limited to specific areas such as Demand forecasting which is rather broad. This study offers a unique contribution by providing an in-depth review of AI and ML in Lot sizing.

1. Introduction

Background and Problem Context

In the field of operations and supply chain management, lot sizing is a fundamental concept that plays an important role in optimizing production, inventory, and the distribution process (Silver, Pyke, & Peterson, 1998). Efficient lot sizing strategies are beneficial to businesses looking to minimize costs and improve overall performance (Chopra & Meindl, 2016). Over the years, the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies has revolutionized lot sizing approaches, offering innovative solutions to improve efficiency and decision-making.

Lot sizing is better known as batch sizing or Order quantity determination, this is the process of determining what would be the optimal quantity of items or materials to be ordered or made within a single batch. This is crucial when managing inventory levels, Total costs (Such as ordering costs, holding costs, and miscellaneous costs), and the overall efficiency of the supply chain. Traditional lot sizing techniques such as the Economic Order Quantity (EOQ) are heavily implemented to find a balance between Inventory Carrying Costs (also known as Holding Costs) and Ordering costs. The goal of lot sizing is to minimize the total cost as seen in Figure 1. These methods do have their limitations, especially in more modern supply chains which experience dynamic demand patterns, Variations within Lead times due to various factors and most companies tend to have multiple product lines.

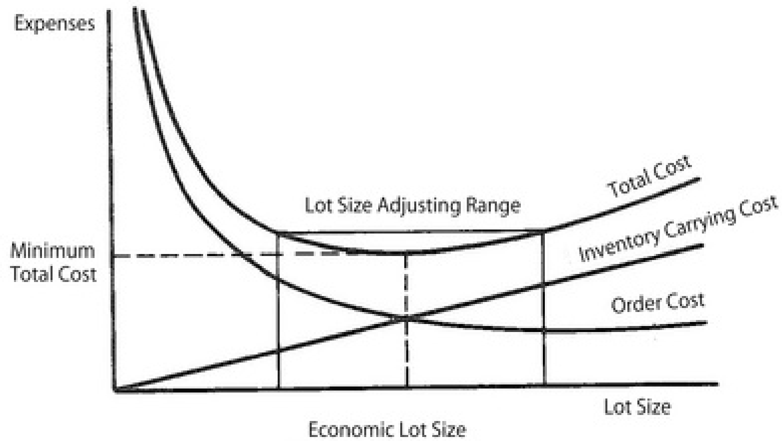

Figure 1. Economic lot size model graph (Mohadaszadeh Bazaz, Lohtander, & Varis, 2020)

Demand forecasting is crucial for lot sizing in supply chain management. Accurate forecasts allow businesses to make informed decisions about production, inventory management, and distribution. By anticipating demand patterns, companies can optimize lot sizes to meet customer needs while minimizing costs. Demand forecasting also reduces excess inventory and associated holding costs, enhances customer service, ensures efficient supply chain planning, and optimizes inventory levels. Integrating demand forecasting with AI and ML technologies enables dynamic lot sizing, adjusting order quantities in real-time based on accurate demand predictions. This fusion of demand forecasting and advanced technologies minimizes costs, meets customer expectations, and enhances overall supply chain efficiency.

Recent developments in lot sizing have made use of the intelligence that computer systems offer and new optimization techniques that help address the challenges traditional systems used to face. Computer systems such as Artificial Intelligence (AI) and Machine Learning (ML) can store and constantly analyze vast amounts of data to adapt at an almost instantaneous level allowing for real-time changes within markets or the supply chain. Through this businesses would be able to make better-informed decisions as they allow for the transition from static, deterministic models to dynamic and data-driven approaches, ultimately reducing costs, improving customer service, and enhancing competitiveness(Silver, Pyke, & Peterson, 1998; Wagner & Whitin 2004).

AL and ML are technology systems that attempt to simulate human intelligence on a computational scale. AI is a rather broad field that encapsulates intelligent software systems capable of performing problem-solving, decision making and reasoning. ML is more focused on the training algorithms that are used to analyze and learn from data to make more accurate predictions and decisions. Implementation and better utilization of information resources such as AI could pose a possible solution to improving some processes. Across manufacturing and Logistics, various companies have been investigating the possible benefits of adding AI to improve workflow. In 2020 the MIT Technology Review insights surveyed 1000 leaders in AI and found that manufacturing was amongst the top adopters of AI as seen in Figure 2. Within manufacturing, industrial engineers were able to get the benefits by enabling dynamic decision-making, improving demand forecasting, and handling complexity. This leads to reduced holding and ordering costs, mitigated risks, enhanced customer service, and increased sustainability. AI is scalable, cost-effective, and offers a competitive advantage, making it a valuable tool for optimizing lot sizes(Patocka 2023).

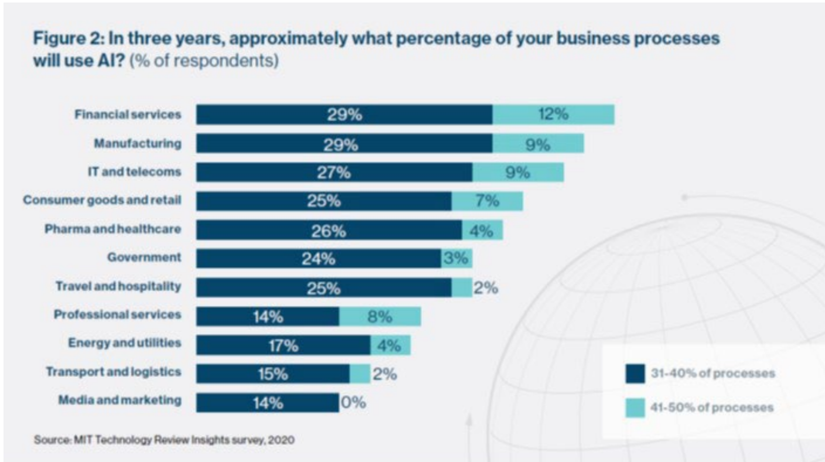

Figure 2. 2020 MIT Technology Review Insights (The global AI agenda: Promise, reality, and a future of data sharing 2020)

The Newsvendor problem is a mathematical model in operations management and applied economics. This model is used to determine the optimal inventory levels in scenarios characterized by fixed prices and uncertain demand for perishable products. This model is a standard formulation in operations management for making optimal capacity or inventory decisions under uncertainty. It plays a significant role in inventory management and has wide-ranging implications for managing inventory decisions in various industries, such as hospitality, airlines, and fashion goods. The model's primary objective is to find the order quantity that maximizes expected profit or minimizes expected loss in a single period with probabilistic demand.

Problem Statement

The current state of research in the field of lot sizing and its integration with artificial intelligence (AI) has witnessed significant advancements in recent years. However, these advancements are contrasted with several notable limitations, creating a need for further investigation and innovation.

Current State of Research

The current state of research on the use of Artificial Intelligence (AI) and Machine Learning (ML) in lot sizing is marked by significant advancements and innovative applications. Recent studies have focused on integrating AI and ML into traditional lot sizing models to enhance their predictive accuracy and efficiency. Researchers have explored how these technologies can optimize inventory levels, particularly in industries with fluctuating demand patterns and periods where uncertainty is faced such as COVID. The methodologies employed often combine computational intelligence with optimization techniques, showcasing a shift from static, rule-based models to dynamic, data-driven approaches. This evolution in lot sizing strategies is primarily driven by the need for more flexible and responsive supply chain operations in the face of increasing market volatility and complexity. AI and ML are doing more than just enhancing current methods; they are establishing new ways to handle inventory, reduce costs, and boost service quality. Recent studies show a move towards more advanced and smart lot-sizing models. These models can deal with the challenges of today's supply chains better than older methods, leading to significant improvements.

Limitation of Extant Research and Motivation for Our Work:

The challenges in current AI research for lot sizing are varied and significant. First, although AI models demonstrate potential in specific situations, issues such as their scalability, clarity, and adaptation to a range of industries and supply chain environments need more investigation. Many existing studies are limited by their narrow focus or lack of real-world applicability, reducing their practical value.

Second, the complex nature of AI-based lot sizing models poses concerns regarding their integration ease and compatibility with existing systems. For AI implementations to be viable and align with business objectives, they must be cost-effective and practical. This necessitates targeted research to address these integration challenges.

Finally, there is a shortcoming in research connecting AI-driven lot sizing with sustainability goals. In today's environment-focused world, understanding how AI can enhance lot sizing decisions with minimal environmental impact is crucial. This gap in research underscores the need for studies that consider both efficiency and ecological responsibility in AI applications.

Research Objectives

The primary goals of this systematic literature review are to thoroughly explore and analyze the application of Artificial Intelligence (AI) and Machine Learning (ML) in lot sizing. This study seeks to deliver an in-depth insight into the current knowledge landscape, pinpointing the most advanced uses of AI and ML in lot sizing across various sectors. We aim to delve into the diverse AI and ML algorithms and techniques utilized, assessing their efficacy in refining lot sizing decisions and their practical significance in supply chain management. The objective is to pinpoint emerging trends, unaddressed areas, and challenges within the existing literature, as well as to highlight prospective avenues for future investigations. The ultimate aim of this review is to provide valuable perspectives on the adoption and impact of AI and ML in lot sizing, contributing significantly to the understanding of their role in enhancing efficiency and decision-making processes in the field of supply chain management.

Methodology

Eligibility Criteria:

Conducting a systematic literature review on the applications of Artificial Intelligence and Machine Learning in lot sizing, it is important to establish specific inclusion and exclusion criteria to determine which studies are eligible for the review. This section outlines the criteria used for the selection of relevant studies and the process of how the studies were grouped for synthesis.

Inclusion Criteria:

1) Relevance to AI and ML in Lot Sizing: Studies must be directly related to the utilization of AI or ML techniques in lot sizing, inventory management, Economic Order Quantity, Demand Forecasting, and related supply chain processes.
2) Publication Date: More recent research was incorporated given how new the field is and earlier content was not as well developed, the time frame that was used was between 2010-01-01 and 2023-08-01.
3) Study Type: The review includes both peer-reviewed journal articles and conference proceedings that meet the relevance criteria.
4) Full-Text Availability: Studies must have their full text available and freely accessible, ensuring that a comprehensive assessment can be conducted.

Exclusion Criteria:

1) Irrelevant to AI and ML in Lot Sizing: Studies that do not specifically address the use of AI or ML in lot sizing or related supply chain processes are excluded.
2) Non-English Publications: To ensure clarity in the assessment and a full understanding of the paper used non-English publications are excluded.
3) Duplicate Publications: In cases where multiple versions of the same study exist, only the most comprehensive or recent version is included and utilized.

Study Grouping for Syntheses:

In this systematic review, the identified studies will be grouped based on common themes and methodologies to facilitate the synthesis of results. The following grouping criteria are applied:

1) AI and ML Techniques: Studies that focus on a specific AI or ML technique, such as neural networks, deep learning, or genetic algorithms, will be grouped. This allows for a detailed examination of the effectiveness of different techniques.
2) Application Domains: Studies are categorized based on the application domain within lot sizing, such as demand forecasting, inventory optimization, or production scheduling. This grouping strategy enables a comprehensive understanding of the specific areas where AI and ML have been applied.

Study Design: Studies are grouped based on their research design, such as empirical studies, case studies, or simulation-based research. This categorization allows for the assessment of the methodological rigour and relevance of each study.

Information Sources

For a comprehensive systematic literature review a meticulous approach to source selection was undertaken. Two primary databases were important in the Systematic literature review. First, the Scopus database, known for its extensive coverage of scientific and technical literature, was utilized. Secondly, the Web of Science, another crucial database known for its academic and scholarly content, was used to enhance the comprehensiveness of the search. The search strategy used in both databases, featured relevant search terms and filters to retrieve pertinent studies encompassing relevant keywords and Boolean operators to identify relevant studies. The last search in both databases was performed on the 15th of October, guaranteeing the incorporation of the latest research.

Scopus and Web of Science served as the primary databases for identifying academic literature, other sources would also be investigated to increase the scope of work found. Additionally, grey literature, including conference proceedings, reports from relevant organizations, and preprints were actively sought to ensure that the review encapsulates both published and unpublished work in the domain.

Search Strategy

Search Strategies:

1) AI and ML in Order Quantity Determination:

- Keywords: "AI," "Artificial Intelligence," "Machine Learning," "ML," "Order Quantity," "EOQ," "Economic Order Quantity."
- Strategy: ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "ML") AND ("Order Quantity" OR "EOQ" OR "Economic Order Quantit*")

2) AI and ML in Lot Sizing:

- Keywords: "AI," "Artificial Intelligence," "Machine Learning," "ML," "Lot Sizing."
- Strategy: ("AI" OR "Artificial Intelligence" OR "Machine Learning" OR "ML") AND ("Lot Siz*")

Filters and Limits:

- Publication Date Range: Studies published between 2010 and 2023 were considered. This range was chosen to incorporate recent developments while encompassing foundational research.
- Language: The search was limited to English-language publications to facilitate understanding and analysis.

Search Strategies Rationale:

The search strategies were designed to capture a wide spectrum of studies related to AI and ML applications in lot sizing. The inclusion of synonyms and related terms for AI and ML ensures that a comprehensive pool of literature is considered, while the specific inclusion of keywords related to lot sizing and order quantity determination hones the focus on the central research themes, thus papers not relating to Lot Sizing as a whole were not included.

Filters and Limits Rationale:

The publication date range was set to include recent research, considering the advancements in AI and ML over the past decade, while still accounting for foundational studies. Limiting the search to English-language publications was chosen for clarity and accessibility, ensuring that the review's audience can readily understand and assess the included studies.

Selection Process

The screening process was conducted by one reviewer, this allowed the reviewer to assess the records whilst maintaining consistency and streamlining the selection process. This independent assessment does increase the possibility of any bias but allows for future researchers to better find possible gaps.

Automation tools were not utilized in the initial screening process but will be used in later stages. Automation tools, such as bibliographic reference management software, were utilized to efficiently manage and organize the records and reports. These tools facilitated the removal of duplicate records and aided in the systematic categorization of studies based on their relevance and applicability to the research objectives.

Data collection process

In cases where data clarification was needed to enhance the accuracy of the data collected, attempts at contacting the study investigators were made. This was initiated via email and available direct communication channels. Automation tools, such as data extraction software such as Atlas.ti and Microsoft Excel, were employed in the data collection process. Given how context-specific the data within the selected reports, manual extraction was used to capture all relevant information accurately.

Data items

Outcomes of Interest:
For this literature review specific outcomes of interest were identified and defined. These outcomes relate to the effectiveness of AI and ML in lot sizing and related supply chain processes. The outcomes are the following:

- Order Quantity Optimization: This relates to the extent to which AI and ML techniques contribute to optimizing order quantity, including the calculation of the Economic Order Quantity (EOQ) and variants. The aim was to collect data on the various methods, models, and approaches used to achieve this optimization.
- Inventory Management Efficiency: Data were sought concerning the impact of AI and ML on improving overall inventory management efficiency. This encompasses data on inventory turnover rates, safety stock levels, and inventory carrying costs, among other relevant measures.
- Supply Chain Performance: The data collection process focused on understanding how the application of AI and ML influences broader supply chain performance. This outcome includes data on order fulfilment rates, lead times, and supply chain cost reduction.
- Decision-Making Accuracy: Data is collected to understand the extent to which AI and ML enhance the accuracy of decision-making in lot sizing and supply chain processes. This involves data on forecasting accuracy, demand prediction, and the reduction of forecasting errors.
- Cost Savings: The review sought data on cost savings and reductions achieved through the implementation of AI and ML in lot sizing, which may include data on reduced carrying costs, improved demand forecasting, and decreased order processing expenses.

Data was sought on other variables as well such as the following:

- Participant Characteristics: This variable includes data related to the characteristics of the case studies. Such data includes demographic information, industry field, and geographic location, among others.
- Intervention Characteristics: Data on the specifics of the AI and ML interventions or methodologies employed in the included studies were sought. This includes details on the type of AI or ML techniques used, the implementation context, and the duration of the intervention.
- To address missing or unclear information, assumptions were made cautiously and transparently. Any assumptions made were documented, and the potential impact of these assumptions on the overall analysis was considered during data synthesis and interpretation.

Study Risk Bias

For this report no specific study risk bias assessment tools were used, this decision is based on the nature and scope of the research and topic as it does not necessitate the need for mitigating potential biases in the studies that are being reviewed. While study risk bias tools are valuable in certain contexts for identifying and addressing systematic biases in research, the research being conducted now relies on established methodologies relevant to our research objectives.

• Effect Measures

For each outcome considered in the review, specific effect measures were selected based on the nature of the outcome and the characteristics of the included studies. The choice of effect measure was guided by the following considerations:

1) Order Quantity Optimization: Mean Difference or Ratio (e.g., Mean Order Quantity in AI group vs. Control group or Ratio of Order Quantity in AI group to Control group).
2) Inventory Management Efficiency: Inventory Turnover Rate or Reduction in Carrying Costs (e.g., Mean Difference in Inventory Turnover Rate or Carrying Costs between AI and Control groups).
3) Supply Chain Performance: Supply Chain Performance Metrics (e.g., Risk Ratios for meeting order fulfilment targets, Mean Differences in lead times).
4) Decision-Making Accuracy: Accuracy Metrics (e.g., Percentage Reduction in Forecasting Errors, Risk Ratios for Improved Decision-Making).

5) Cost Savings: Cost Reduction Ratios (e.g., Mean Difference in Cost Savings between AI and Control groups).

Synthesis Methods

In synthesizing findings on the implementation of AI-driven lot sizing systems, a systematic approach was employed. Eligibility for synthesis was determined by comparing study intervention characteristics against planned groups. Results were presented through tables and visual displays for clarity. Given how diverse the data is a narrative synthesis will be used. These are the possible type of studies that may be used:

1. Analytical Studies: In the systematic review, analytical studies would be essential for understanding the relationships between the implementation of AI in lot sizing and various outcomes. This could include assessing the impact of AI on order quantity optimization, inventory management efficiency, supply chain performance, decision-making accuracy, and cost savings.
2. Categorical Studies: Categorical studies could involve grouping the literature based on different AI applications, industries, or types of lot sizing problems. This categorization would help in identifying patterns, similarities, and differences across various contexts of AI implementation in lot sizing.
3. Thematic Studies: Thematic studies, especially in the qualitative domain, might be valuable for extracting and understanding recurring themes related to challenges, benefits, or best practices in the implementation of AI in lot sizing. Qualitative thematic analysis could reveal insights not easily captured by quantitative approaches.
4. Meta-Analysis: In the systematic literature review, a meta-analysis could be employed if there are quantitative outcomes reported in multiple studies. For example, if several studies report the impact of AI on order quantity optimization, a meta-analysis could be conducted to pool and analyze these quantitative results, providing a more robust estimation of the overall effect.

Reporting Bias Assessment

To address possible reporting biases in the synthesis, various methods were applied:

1) Gray Literature and Unpublished Studies: Actively searching and including Gray literature and unpublished studies to minimize the impact of publication bias.
2) Contacting Study Authors: Directly contact study authors to request missing data or results, reducing the risk of bias from selective reporting.

Certainty Assessment

To understand the certainty in studies for each outcome only expert Consultation was used. Consultation with subject matter experts would be conducted to obtain additional insights and perspectives on the certainty of evidence. In this case, Lecturers, as well as experienced professionals in the industrial sense, will be engaged. This collaborative approach aimed to enhance the robustness of the certainty assessment.

Findings

Study Selection

The study selection process made use of the PRISMA framework, this meticulous structure ensured a comprehensive and relevant collection of studies to be used. As depicted in Figure 3, the initial Identification phase involved a thorough search of the selected databases from section 2 and theses were Web of Science and Scopus and they both yielded 320 papers combined and 274 after duplicate records were identified. Thereafter a screening phase was performed based on the predefined eligibility criteria based on relevance to the topic and methodological rigor to name a few. A majority of 207 studies were excluded as a result of being an Unrelated Topic as even though there were relevant to the subtopics being investigated, they did not relate in any capacity to lot sizing thus were excluded. 27 Papers were unrelated papers that did not meet the search criteria and passed through filters. Studies that met all criteria progressed to the final phase and resulted in 36 papers being used for the study.

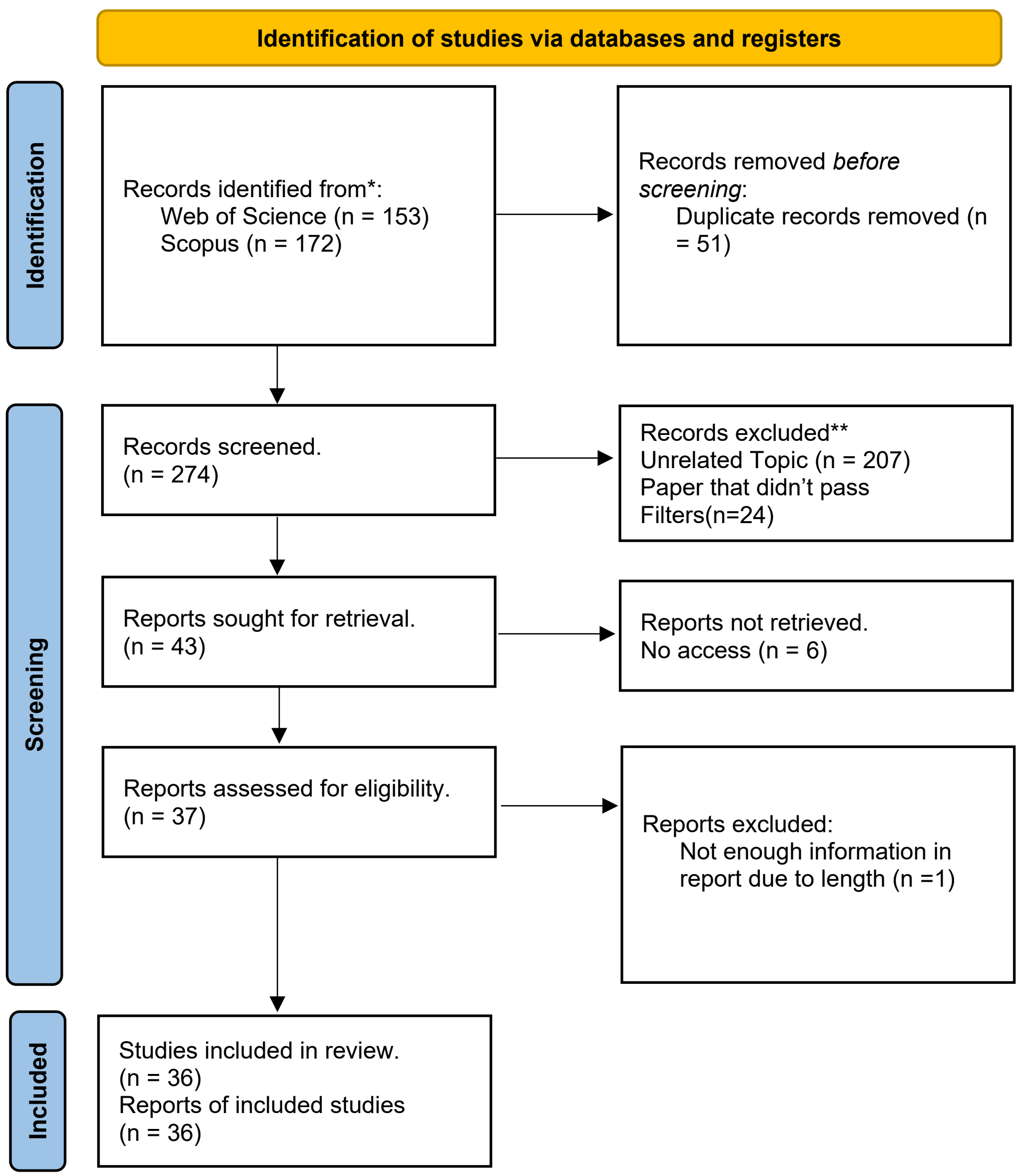

Figure 3. Prisma flow diagram for the Identification of studies via databases and registers

Bibliometric Analysis

Overview

In this section, we will investigate a bibliometric analysis of the reports that will be included in the study. Insights into the geographical distribution of research on AI and ML in lot sizing (Regions), explore the primary subject areas that have attracted scholarly attention (Subject Area), categorize the diverse types of documents contributing to the body of knowledge (Document Type), and employ keyword network visualization to visualize the interconnectedness of research themes and concepts.

Distribution by Region

The analysis of research regions shows there is a diverse and global landscape of contributions by scholars. Leaders in research were found to be China, India, Canada, and the United States of America. However, when analyzed by region we can observe that Asia leads the statistic marginally as seen in Figure 4. Studies in the Middle East, Africa and South America are still developing and open a research avenue to investigate for future researchers.

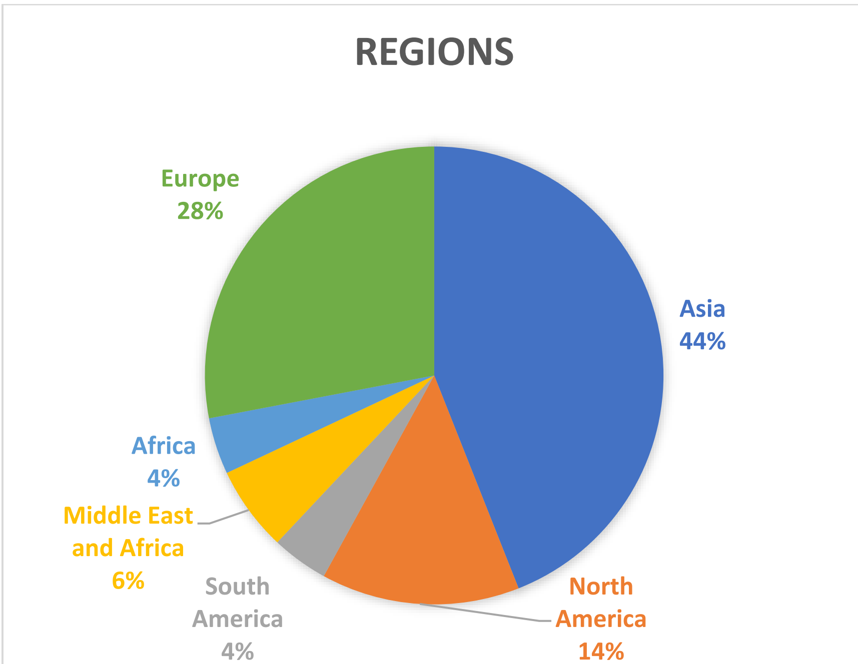

Figure 4. Classification based on region.

Distribution by Subject Area

The distribution of studies was well spread out, shown in Figure 5, with the highest occurring subject area being Computer science indicating the technological core and basis of the field. This is closely followed by Engineering (namely industrial) and Decision Sciences which show the application in problem solving. Business Management and Accounting follows with 10 papers, highlighting the commercial implications of lot sizing. Operations Research Management Science is represented by 6 papers, focusing on the optimization aspect. It's important to note that papers can be classified into more than one field, reflecting the interdisciplinary nature of the research. The summarized data lumps the remaining fields into an 'Other' category, totalling 13 papers.

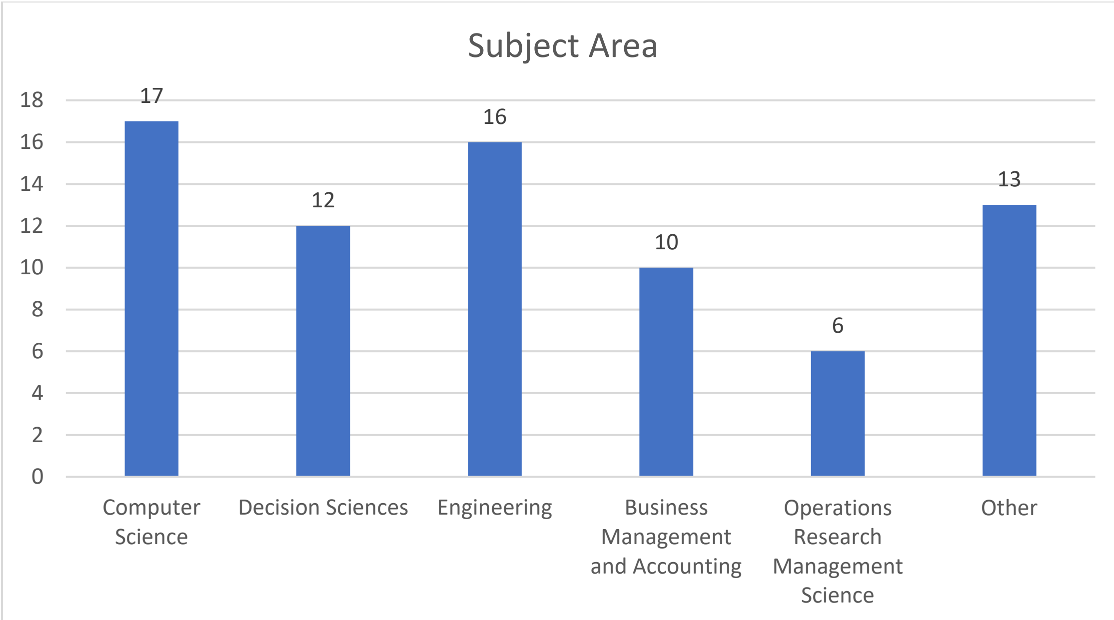

Figure 5. Classification based on Subject Area

Distribution by Year

The unusual distribution of research papers on AI and ML in lot sizing reveals an interest in the field over the last decade as seen in Figure 6. The years 2012 and 2016 saw an early increase with two papers published each year, indicating the initial recognition of AI and ML's potential in lot sizing. However, it wasn't until 2020 that a noticeable increase in publications occurred, with five papers, suggesting a turning point in research attention and perhaps a response to technological advancements of the market demands. This upward trend continued, with 2021 matching the previous surge and both 2022 and 2023 sustaining the momentum with five publications each. The consistency in these recent years underscores a solidifying interest and a continued commitment to exploring the capabilities of AI and ML in optimizing lot sizing processes.

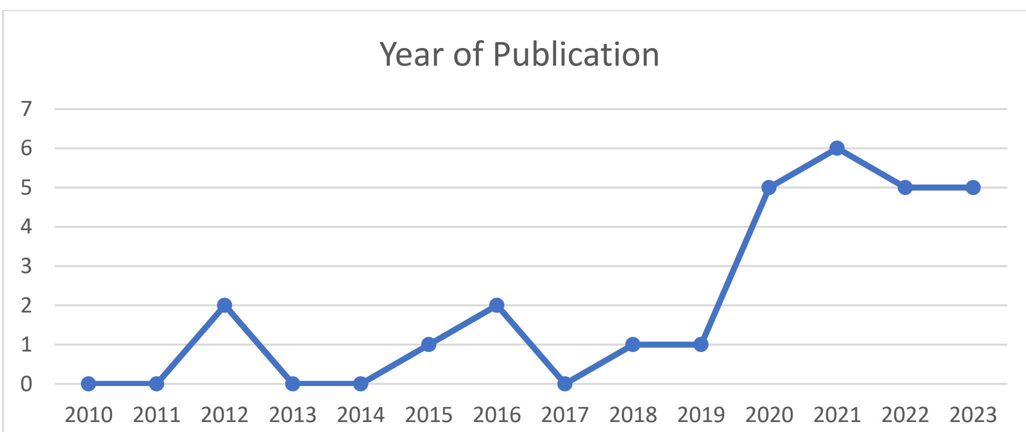

Figure 6. Publication by Year

Document Type

In the review conducted, the types of publications used are predominantly journal articles and conference papers. Journal Articles substantially accounted for the portion of the papers with 25 entries, whilst Conferences papers only contributed with 11 entries.

Keyword Network Visualization

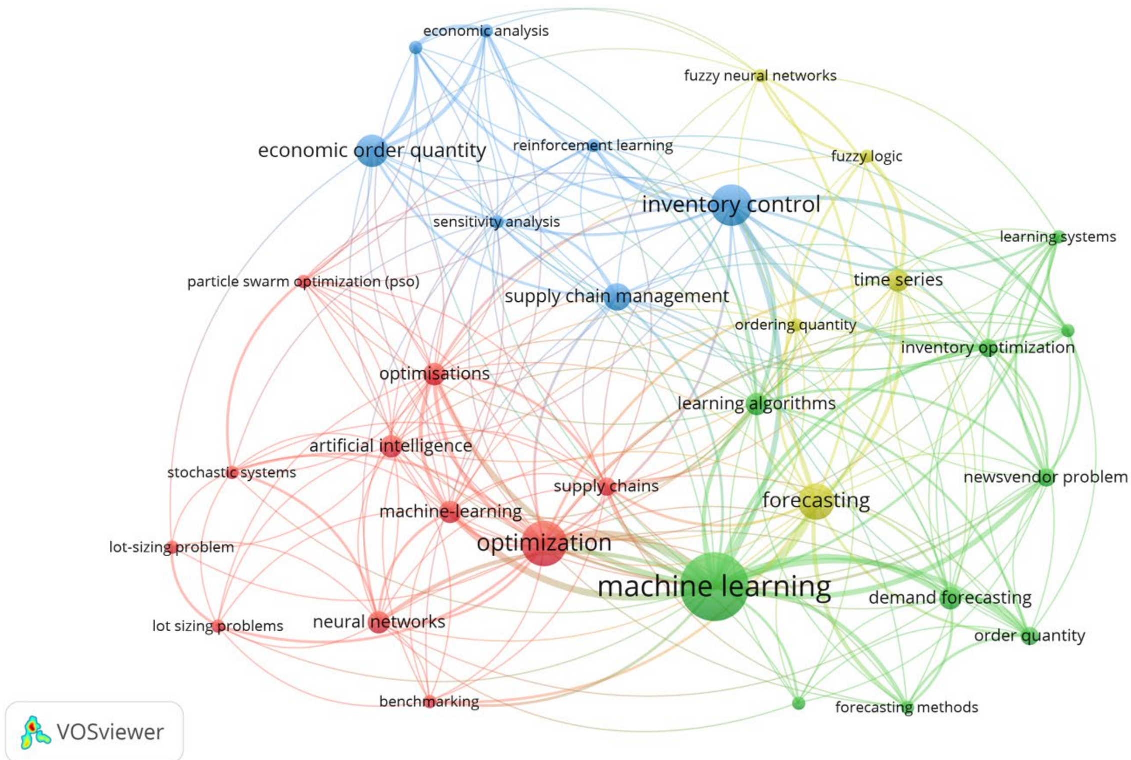

Figure 7. Visualization of the bibliometric network (n=36)

For the bibliometric analysis of the collected studies, VOSviewer was utilized to investigate the bibliometric network established within the sources used. The dataset was made up of 36 sources of literature. There is a strong interconnection between various keywords because of the focus on the specified field. Keywords were filtered to include those only that appeared in a minimum of 3 documents.

The bibliometric analysis provides a visual representation of the 33 keywords and how they are connected as seen in Figure 7. The is a correlation between the size of nodes and frequency with bigger and brighter nodes denoting higher frequency in the appearance of the word within the abstracts and titles of the sources.

To categorize these keywords, they are segmented into four principal clusters for analysis:

1. Foundations of AI and Optimization (Cluster 1):
    - Artificial Intelligence: This cluster includes terms such as 'artificial intelligence', 'machine-learning', 'neural networks', and 'particle swarm optimization', emphasizing the technological backbone of the research.
    - Supply Chain Optimization: Encompassing 'benchmarking', 'lot sizing problems', 'optimisations', 'optimization', 'stochastic systems', and 'supply chains', this category highlights the focus on enhancing supply chain efficiency through AI and ML.
2. Predictive Analytics and Inventory Management (Cluster 2):
    - Predictive Techniques: Here, 'deep learning', 'demand forecasting', 'forecasting methods', and 'learning systems' signify the role of AI in predicting market and supply chain behaviours.
    - Inventory and Order Optimization: This group includes 'inventory optimization', 'machine learning', 'newsvendor', and 'newsvendor problem', pointing to the application of AI in managing inventory levels and order quantities.

3. Economic Assessment and Strategic Management (Cluster 3):

    - Economic Evaluation: Keywords like 'economic analysis', 'economic order quantity', and 'economic ordering quantity' reflect the financial aspects of lot sizing.
    - Strategic Decision-Making: Incorporating 'inventory control', 'reinforcement learning', 'sensitivity analysis', and 'supply chain management', these terms indicate the strategic use of AI for decision-making in supply chains.

4. Forecasting and Computational Methods (Cluster 4):

    - Advanced Forecasting: The focus here is on 'forecasting', and 'time series', along with 'fuzzy logic' and 'fuzzy neural networks', representing sophisticated approaches to predicting future trends.
    - Quantitative Methods: 'Ordering quantity' falls into this category, relating to the calculation of optimal stock levels in supply chains.

1.1 Findings

Table 1. Literature findings

Authors	Title	Findings	Algorithm
(Fallahi, Amani Bani, & Niaki, 2022)	A constrained multi-item EOQ inventory model for reusable items: Reinforcement learning-based differential evolution and particle swarm optimization	The research demonstrates the effectiveness of the proposed EOQ model in managing reusable item inventories under realistic operational constraints. The integration of reinforcement learning with DE and PSO algorithms (DEQL and PSOQL) significantly improves their performance in handling the model's nonlinearity. In Small, medium, and large size examples DEQL did take longer on average CPU time but had the better best solution and average solution	Differential Evolution (DE), Particle Swarm Optimization (PSO) boosted by Q-Learning
(Oroojlooyjadid et al., 2022)	A Deep Q-Network for the Beer Game: Deep Reinforcement Learning for Inventory Optimization	The DQN algorithm is efficient in handling the complexities of the Beer Game, including decentralized decision-making and limited information. It outperforms traditional base-stock policies, especially when agents do not behave optimally. The approach does not require knowledge of demand distribution, unlike classical inventory management methods. The average cost gap between DQN and Base Stock policies across all agents was 5.56%. Transfer learning was used to train new agents more efficiently. The approach resulted in an average training time reduction by a factor of 15 compared to training from scratch.	Deep Q-Network (DQN), Transfer Learning
(Gonçalves et al., 2021)	A multivariate approach for multi-step demand forecasting in assembly industries: Empirical evidence from an automotive supply chain	The multivariate approach outperforms univariate models in forecasting and inventory management. ARIMAX model predicts early life-cycle demand signals better, but ML models excel in later stages. MLP most accurate forecasting, NAIVE least accurate, ERNN best total inventory cost, ARIMA highest cost. The approach addresses the challenge of managing high inventories and safety stocks while maintaining high service standards.	ARIMAX Various ML models
(Corsini et al., 2022)	A new data-driven framework to select the optimal replenishment strategy in complex supply chains	The paper emphasizes the challenges in supply chains dealing with perishable products, where supplier dispatch times and product shelf life are variable and uncertain. The framework combines predictive abilities with optimization techniques to enhance supply chain economics while accounting for uncertainties.	Artificial Neural Networks (ANNs), Particle Swarm Optimization (PSO)
(Hoque et al., 2021)	A novel dynamic demand forecasting model for resilient supply chains using machine learning	Bullwhip Effect is influenced by factors like ordering policies and lead times, resulting in production swings and increased inventory and transportation costs. The proposed Data Driven Weighted Moving Average (DDWMA) algorithm bypasses traditional time series modelling and optimizes forecast weights to minimize forecast error sum of squares (FESS).	Data Driven Weighted Moving Average (DDWMA)
(Hajek & Abedin, 2020)	A Profit Function-Maximizing Inventory Backorder Prediction System Using Big Data Analytics	A profit function-maximizing model is proposed, modifying the Clustering-Based Under-Sampling (CBUS) method with the Random Forest classifier. The empirical evaluation demonstrated the model's economic effectiveness and prediction performance. The Random Forest classifier outperformed other classifiers in both Receiver Operating Characteristics and profit measures. A genetic algorithm optimized the decision cut-off, increasing the average expected profit to 4.14%.	Random Forest Classifier
(Yang, Zhang, & Ieee, 2015)	Adaptive Inventory Control and Bullwhip Effect Analysis for Supply Chains with Non-stationary Demand	The adaptive inventory control models developed in this study prove to be effective in managing non-stationary demand and reducing the bullwhip effect, thus improving the supply chain performance. Further research could focus on refining the models and exploring their applicability to different types of demand patterns, particularly fuzzy demands. Exponential smoothing for demand forecasting and Reinforcement learning for selecting safety stock levels.	Q learning, Reinforcement learning.

(Liu et al., 2023)	AI vs. Human Buyers: A Study of Alibaba's Inventory Replenishment System	The AI algorithms significantly outperformed human buyers in terms of reducing the out-of-stock (OOS) rates and days-in-inventory (DII), The AI's performance was especially notable during the COVID-19 pandemic, where it managed to mitigate the bullwhip effect and panic buying behaviours that were, observed with human buyers. on average, the Single Agent Reinforcement Learning (SARL) and Single Agent Reinforcement Learning (MARL) methods resulted in a 26.75% reduction in DII rates and a 1.5% reduction in OOS rates across the three cases.	Single-agent reinforcement learning (SARL) method. multi-agent reinforcement learning (MARL) method.
(Yung et al., 2023)	An autonomous, multi-agent, IoT-empowered space logistics system for mission-critical inventory packing	Space logistics differs significantly from commercial logistics, with higher operation costs, limited payload capacity, and a longer replenishment cycle.The system comprises three independent agents focusing on order-up-to levels, optimizing space chunk loading, and performing 3D object scanning for quality control .On average, the Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values in the proposed system are significantly lower (5.97% and 5.52% less, respectively) , This indicates that Interval type-2 fractional fuzzy inference systems can predict demand more accurately, supporting inventory replenishment decisions.	Interval Type-2 Fuzzy Logic for chaotic time-series demand forecasting. Differential Evolution
(Yu, Wang, & Shi, 2023)	Analytics for multiperiod risk-averse newsvendor under nonstationary demands	The transformed methods provide competitive predictive performance compared to more complex approaches like ARIMA. Prescriptive analytics develops dynamic risk-averse newsvendor models for each transformation method, revealing distinct behaviour in optimal order quantities based on the newsvendor's risk aversion. Case study findings suggest varying performance of the models based on the manufacturer's risk aversion level.	Detrending (DET), Differencing (DIT), Percentage Change Transformations (PCT)
(Shekarian et al., 2016)	Analyzing optimization techniques in inventory models: The case of fuzzy economic order quantity problems	Adaptation of EOQ models using fuzzy set theory leads to FEOQ models, providing more precise policies in imprecise environments.	GP, GRG, FNLP, GA, PSO
(Sremac et al., 2018)	Anfis model for determining the economic order quantity	The ANFIS model effectively determines EOQ in complex logistics scenarios. Combines fuzzy logic and neural networks, leveraging their individual strengths. Model shows high accuracy in imitating expert decision-making in supply chain management. Flexible and applicable to various good types in supply chain contexts. Sensitivity analysis indicates the model's validity across different membership function forms. Average relative error in EOQ determination: 3.28%	ANFIS
(Guimaraes et al., 2020)	Application of data-based prediction methods in newsvendor problems subject to purchase price uncertainty	The hybrid model, integrating machine learning models with traditional time series forecasting methods, outperforms both SARIMA and Prophet models in aiding decision-making for optimal order timing. The model enhances the decision-making process regarding both the order quantity and the timing for replenishment in fluctuating purchase price scenarios. The hybrid model provides a more effective solution to the newsvendor problem by anticipating fluctuations in supply prices, particularly in the context of perishable goods. Cost Avoidance 1,2084% improvement	SARIMA, Prophet, Multi-Layer Perceptron's (MLP), Hybrid Forecasting Model
(Shi, 2022)	Application of the model combining demand forecasting and inventory decision in feature-based newsvendor problem	Successful integration of a one-step machine learning algorithm for the newsvendor problem, enabling demand forecasting with multiple characteristic variables. Random Forest Regressor model shows the best performance across all metrics compared to Linear and Lasso Regression models. RFR was on average 53.09% better in RMSE and 3.8% better MAE than other Algorithms.	Linear Regression, Lasso Regression, Random Forest Regressor
(Oroojlooyjadid, Snyder, & Takáč, 2020)	Applying deep learning to the newsvendor problem	Deep Neural Networks (DNN-1), Stochastic Optimization (SEO-2), Primal Stochastic Optimization (PSEO), Equal Quantile (EQ), Kernel Regression (KR), and k-Nearest Neighbours (KNN) are the top-performing algorithms. These algorithms showed roughly equal performance across 99 test datasets. SEO methods excel with normally distributed demand but underperform with other distributions. This underperformance is due to the inherent assumption of normal distribution within SEO methods.	Linear Regression, Lasso Regression, Random Forest Regressor

(Yang, Chen, & Ieee, 2021)	Bullwhip Effect Analysis for Supply Chains using a Fuzzy Forecast Approach	The fuzzy forecast approach helps stabilize service levels and mitigates the bullwhip effect in supply chains. Two types of demand processes are considered: known and unknown demand distribution. The proposed model effectively deals with non-stationary random demand by adapting the service level to the target volume. fuzzy adaptive inventory model's mean service level was 98.02%, deterministic inventory model at 98.04%.	Fuzzy Inference System, Q-learning Algorithm
(Aengchuan & Phruksaphanrat, 2018)	Comparison of fuzzy inference system (FIS), FIS with artificial neural networks (FIS plus ANN) and FIS with adaptive neuro-fuzzy inference system (FIS plus ANFIS) for inventory control	FIS+ANFIS_Gauss model outperforms other models in reducing total inventory costs. Incorporating ANN and ANFIS into FIS leads to more accurate order quantity predictions. The FIS+ANFIS_Gauss model achieved a total inventory cost saving of over 75% when compared to the stochastic EOQ model.	Fuzzy Inference System (FIS), Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS)
(de Sousa Junior et al., 2019)	Economic lot-size using machine learning, parallelism, metaheuristic, and simulation	The study introduced an optimization algorithm that significantly reduced processing time by 95% compared to the serial GRASP method. Decision Trees Regressor was identified as the most effective machine learning method The parallel machine learning GRASP achieved a solution that was 94% as effective as the best local optimum. The integration of parallelism and machine learning within a metaheuristic framework was shown to be an effective approach for large-scale industrial problem-solving.	OMP, PR, LDA, MNB, DTC,DTR,RFC, RFR,ETC, GTBR
(Chang, 2016)	Forecasting production quantity by integrating time series forecast technologies and artificial intelligence methods	The IMA and IMF methods outperform traditional methods, with lower RMSE values, indicating higher prediction accuracy. The IMA method resulted in an RMSE value lower than that of pure ANN, and IMF achieved better results than pure FNN.	Artificial Neural Network (ANN), Fuzzy Neural Network (FNN)
(Punia, Singh, & Madaan, 2020)	From predictive to prescriptive analytics: A data-driven multi-item newsvendor model	A novel quantile-regression and machine learning-based approach is developed to find optimal order quantities, integrating demand estimation with inventory optimization. A heuristic is created for multi-item inventory optimization under capacity constraints, utilizing top-down hierarchies of products. The data-driven approach significantly reduces total inventory costs compared to traditional newsvendor models. Quantile regressing with RF resulted in the minimum inventory cost in 3 of the 4 product groups, RF had a forecast accuracy of 91.22%	Random Forest (RFR), Feed-Forward Neural Network (FFNN), Deep Neural Network (DNN):
(Rohaninejad, Janota, & Hanzálek, 2023)	Integrated lot-sizing and scheduling: Mitigation of uncertainty in demand and processing time by machine learning	The study proposes a predictive and periodic reactive strategy for rescheduling dynamic Capacitated Lot-Sizing Problem (CLSP) in job shop environments.It employs machine learning to predict safety reserves (safety stock and safety slack) for upcoming periods based on historical data, integrated into the scheduling process.Neural networks are used to estimate safety stock and slack, considering factors like market demand, period number, and past demands.The study uniquely applies SMT formulations for CLSP and introduces safety slack as a time-based safety measure. 102% reduction in shortage cost.	Neural Networks, K-means Clustering, SMT (Satisfiability Modulo Theories) Formulations
(Singh & Mishra, 2023a)	Inventory model using Machine Learning for demand forecast with imperfect deteriorating products and partial backlogging under carbon emissions	The model accounts for products that deteriorate over time and may be partially imperfect due to manufacturing or handling issues. Incorporating carbon emission costs into the inventory model emphasizes environmental responsibility and sustainability.	Decision Tree Classifier

(Islam, Amin, & Wardley, 2021)	Machine learning and optimization models for supplier selection and order allocation planning	This research is pioneering in integrating demand forecasting with supplier selection and order allocation planning, a critical aspect previously overlooked in this research domain.The RRC method, considering interrelationships between product consumptions for similar periods, is a novel approach and demonstrates higher precision in demand forecasting compared to traditional methods.The choice of forecasting method is shown to significantly impact both supplier selection and order allocations, demonstrating the importance of accurate demand forecasting in supply chain decisions.RRC method outperforms SVR and PR methods with reductions in forecasting errors by 77.82% and 59.1%. RRC method lowers the forecasting errors by 98.5% and 73% for HLT and ARIMA, respectively	Relational Regressor Chain (RRC), Holt's Linear Trend (HLT), Auto-Regressive Integrated Moving Average (ARIMA)
(Singh & Mishra, 2023b)	Machine learning based fuzzy inventory model for imperfect deteriorating products with demand forecast and partial backlogging under green investment technology	The study highlights the significance of accurately forecasting seasonal demand, especially for deteriorating products, to optimize inventory levels and improve customer service, leading to greater profitability. The paper demonstrates the effectiveness of using machine learning, specifically a Decision Tree-based Classifier method, for predicting seasonal demand, which is more suited for handling random fluctuations in demand.	Decision Tree Classifier
(Seubert et al., 2020)	Making the newsvendor smart - order quantity optimization with ANNs for a bakery chain	The integration of ANNs in inventory decision-making significantly improves forecast quality and reduces costs and food waste. Both data-driven models outperform traditional human-based planning methods. Sequential Approach resulted in 30% savings; Integrated Approach resulted in 27% cost savings.	Artificial Neural Networks
(Metzker et al., 2021)	Optimization for Lot-Sizing Problems Under Uncertainty: A Data-Driven Perspective	The study underscores the significance of managing uncertainty in LSP models and how data-driven approaches can enhance decision-making quality. It finds that DRO offers a balance between RO's conservatism and SP's requirement for accurate probability distribution, making it sufficiently flexible for unforeseen events.	Stochastic Programming (SP), Robust Optimization (RO), Distributionally Robust Optimization (DRO)
(Kalaiarasi et al., 2021)	OPTIMIZATION OF THE AVERAGE MONTHLY COST OF AN EOQ INVENTORY MODEL FOR DETERIORATING ITEMS IN MACHINE LEARNING USING PYTHON	Deterioration in inventory models, particularly for items like food and medicine, significantly impacts the average total cost or profit. The paper references various prior works on optimal ordering policies, deterioration models, and the economic order quantity (EOQ) concept, which combine time-dependent demand under inflation with deteriorating items.Fuzzy sets and fuzzy linear programming are used to find optimal solutions to these inventory problems, with the inclusion of fuzzy non-linear programming for problems with inequality constraints. Proposed model had 98% accuracy forecasting accuracy.	Fuzzy Sets, Fuzzy Linear Programming, Graded Mean Integration Representation Method, Lagrangian Method
(Wu, 2022)	Predictive Search for Capacitated Multi-Item Lot Sizing Problems	The predictive search method offers a novel approach to solving complex lot sizing problems by integrating data-driven insights with optimization techniques. The method enhances decision-making by predicting optimal setup patterns, leading to more efficient and cost-effective production plans. MAPE is 46.2% better and RMSE is 48.73% better than base ARIMA technique.	ARIMA, DET, DIT, PCT, Ensemble Random Forest Neural network
(Galli et al., 2021)	Prescriptive analytics for inventory management in health care	Hospitals traditionally maintain small drug inventories in wards and rely on regular replenishment orders to meet demand. Emergency orders are issued in case of potential stock-outs. Lack of attention in the literature to the management of internal ward inventories and the integration of machine learning models in internal hospital logistics. Traditional methods, such as Sample Average Approximation (SAA), have	K-Nearest Neighbours (KNN), Decision Trees, Random Forests, XGBoost

		limitations when only demand history is considered. using additional information like disease profiles and patient needs for more accurate demand estimation.	
(Kosasih & Brintrup, 2022)	Reinforcement Learning Provides a Flexible Approach for Realistic Supply Chain Safety Stock Optimisation	RL can simultaneously optimize both safety stock level and order quantity, unlike classical models which only optimize safety stock level. RL allows for more realistic problem settings by treating the supply chain as a black-box simulation environment. The main drawbacks in Reinforcement learning include longer time for solution convergence and higher computational complexity. While RL has been used in other domains, its application in safety stock optimization remains limited. There is 95% better Continuous inventory level across all algorithms.	Q-Learning, Advantage Actor-Critic, Multi-agent Advantage Actor-Critic.
(Tanizaki et al., 2020)	Restaurants store management based on demand forecasting	The forecasting ratios for customer order quantity and inventory order quantity ranged between 30% to 70%, indicating moderate accuracy. Random Forest Regression was used for forecasting, which provided varying levels of success across different stores. While the forecasting accuracy was not consistently high, the approach shows potential for practical implementation in restaurant management.	Random Forest Regression
(Wang et al., 2023)	Single-Site Perishable Inventory Management Under Uncertainties: A Deep Reinforcement Learning Approach	The RL4LS algorithm enhances the decision-making process for perishable inventory management by incorporating various uncertainties. It outperforms traditional algorithms in terms of effectiveness (44% improvement) and efficiency (significantly faster). The paper includes a theoretical analysis of the best possible competitive ratio for online algorithms tackling the LS-PMU problem. Demonstrates practical applicability through extensive experiments with both real and synthetic datasets.	Parameterized Deep-Q Network (P-DQN)
(Wang, Peng, & Yang, 2022)	Solving Inventory Management Problems through Deep Reinforcement Learning	The DRL method shows flexibility in handling different cost parameter settings, overcoming limitations of traditional heuristics. The approach is effective in managing lost sales scenarios, which are typically challenging in inventory management. The research highlights the potential of DRL in multi-echelon inventory models, enhancing collaborative decision-making among different supply chain levels. Sharing parameters among different echelons leads to significant improvements in performance, especially under high fixed cost scenarios. The DRL approach, particularly the DDLS algorithm, matches or outperforms most traditional heuristic algorithms in terms of cost efficiency and optimal ordering behaviour. There were 4.3% improvement lost sales.	Double Deep Q-network (DDQN)
(Piperagkas et al., 2012)	Solving the stochastic dynamic lot-sizing problem through nature-inspired heuristics	The paper employs a two-stage optimization process: determining optimal replenishment quantities and identifying the sequence of replenishment periods . The uniform selection scheme in HS were most effective.	Particle Swarm Optimization, Differential Evolution, Harmony Search
(Wong, Su, & Wang, 2012)	Stochastic dynamic lot-sizing problem using bi-level programming base on artificial intelligence techniques	The paper highlights the need for efficient methods to manage non-deterministic raw materials and demands in supply chains.The proposed model involves upper-level decision variables for adjusting raw material quantity and deterioration rate, and lower-level variables for replenishment policy.The methodology integrates ANN for learning simulation results and a real-valued modified ACO algorithm to find optimal decision variables.The paper utilizes simulation to estimate the expected total cost, addressing the challenges of solving an NP-hard problem.The neuro-DM&ACO approach showed better performance compared to Response Surface Methodology (RSM) in finding optimal decision variables. The approach was effective in handling the complexity of the stochastic dynamic lot-sizing problem, as evidenced by the simulation results.	Artificial Neural Network, Ant Colony Optimization

(van Hezewijk et al., 2023)	Using the proximal policy optimisation algorithm for solving the stochastic capacitated lot sizing problem	The Stochastic Capacitated Lot Sizing(S-CLSP) involves managing multiple products with limited capacity, set-up times, and stochastic demand. The main challenge is to specify near-optimal replenishment and production policies.The paper explores the application of the PPO algorithm to the S-CLSP, noting its scalability and potential to offer more efficient solutions than existing methods.The problem is formulated as an Multi-Dimensional Problem with multi-dimensional state space, considering inventory positions, set-up carryover indicators, and production quantities.Adjustments to the standard PPO algorithm were made, including reducing the action space based on observed characteristics from optimal solutions in smaller instances and using eligibility and feasibility masks to improve efficiency. The algorithm finds solutions that outperform the benchmark (an aggregate modified base-stock heuristic) by ~7%. PPO requires on average 16% fewer iterations to converge to a solution PPO 7 percent lower costs. PPO algorithm results in an average gamma service level of 91.3%	Proximal Policy Optimisation (PPO), Generalised Advantage Estimation, Mini-Batch Gradient Descent

Themes

AI and ML

The use of AI and ML in Supply Chain Management covers a wide spectrum of applications and industries. The applications of AI and ML range from enhancing decision-making processes to optimizing operational efficiencies. These technologies are most efficient when analyzing large and complex datasets to make informed decision making in uncertain scenarios at an almost real-time level. Work done by (Fallahi, Amani Bani, & Niaki, 2022) and (Oroojlooyjadid et al., 2022) show how well AI and ML can be used to improve traditional supply chain systems. Work done by (Hajek & Abedin, 2020) and (Yang, Zhang, & Ieee, 2015) explore the different aspects of AI within supply chains and show its versatility in various industries. The methodologies used showcase the shift in supply chain management as a majority of the implementation has occurred in the last few years.

Within reinforcement learning, there are limitations with existing models and algorithms within the beer game as older models had the preference and focus more on human decision-making as a pose to finding the most optimal solutions, efforts made to optimize inventory actions using genetic algorithms or reinforcement learning (RL) faced challenges as a result of unrealistic assumptions like full observability of processes and manageable state spaces (Oroojlooyjadid et al., 2022) . The model structure of reinforcement learning can be seen in Figure 8. Classical RL algorithms and supervised machine learning approaches are not fully applicable due to the beer game's complexity and lack of historical data.

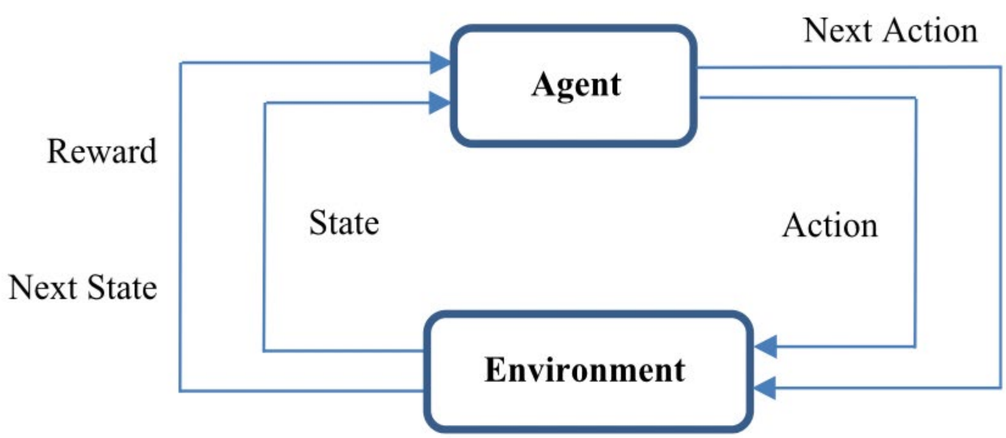

Fig. 3. The model structure in reinforcement learning.

Figure 8. Reinforcement learning model structure (Fallahi, Amani Bani, & Niaki, 2022)

During periods where uncertainty was faced such as the pandemic, AI had superior performance in the supply chain management processes. Firstly, it noted that humans tend to overreact to disruptions, to behaviours like panic buying and overstocking. This was evident when comparing manual ordering methods with AI-driven ones; for example, in Guangzhou, manual order quantities surged by 260% after outbreaks, whereas those managed by AI only increased by 150%. Secondly, AI proved more adept at handling changes in suppliers' behaviour during the pandemic, such as increased lead times. The use of Multi-Agent Reinforcement Learning (MARL) allowed for stable and accurate predictions of lead times and fill rates, even during periods of lockdown, showcasing AI's ability to adapt to rapidly changing environments (Liu et al., 2023).

Lot sizing

Lot sizing is predominantly challenged by challenges such as balancing inventory levels when there is unpredictable demand, and this is where AI and ML excel. Studies by (Corsini et al., 2022) and (Shekarian et al., 2016) both highlight the impact of intelligent computing especially in the Retail and Manufacturing field. This is achieved through a more real-time and dynamic approach to inventory management. Specified data and variables were often used in optimizing the economic lot size problem faced when simulating the theoretical shop floor scenario. This included variables such as order arrival times, order demand, service times, and replenishment times (de Sousa Junior et al., 2019). Stochastic distributions were often used to help ensure a more realistic environment for simulation.

Popular ML methods such as Decision Tree Regressor and Random Forest were often used to help make more informed decisions using a mix of historical demand and prediction of unknown order processes. The focus of the machine learning (ML) approach was on identifying the ideal lot size, the threshold for initiating new orders, and the appropriate interval for reviewing inventory levels. These elements are critical to the function aimed at maximizing net revenue in solving the economic lot-sizing issue. The ML algorithms offered valuable insights and suggestions on these aspects, contributing to more precise and cost-efficient decision-making in production and inventory management.

With Multi-Feature newsvendor problems, there are found to be typical 5 approaches used. The most common is Estimate-As-Solution, which entails forecasting the expected demand and then just using it as the order quantity using algorithms such as ARIMA or Deep Neural Networks. This approach is widely used in practical applications and academic studies even given its basic manner. (Oroojlooyjadid, Snyder, & Takáč, 2020)

Demand Forecasting

Using AI and ML drastically improves demand forecasting as so much more data can be used for analysis and even real-time market trends and sentiments which play a big role in purchasing behaviours (Singh & Mishra, 2023a). Improved demand forecasting has significant implications for supply chain dynamics, as better predictions lead to more aligned production schedules, efficient inventory management, and optimized logistics. This results in cost savings, increased operational efficiency, and improved customer satisfaction as seen by studies by (Seubert et al., 2020) and (Metzker et al. 2021).

In Analyzing the effectiveness of demand forecasting across various industries, a notable observation is its predominantly high efficiency in most sectors like manufacturing, with an exception in the restaurant and catering industries. This could be the result of several unique factors specific to the food service sector. Firstly, the restaurant industry is subject to high variability in customer preferences and random demand fluctuations, often influenced by factors such as weather, local events, and trends among people, which are challenging to predict accurately. Additionally, the perishable nature of food items adds a layer of complexity, as inventory decisions must account for limited shelf life and potential waste, this was not extensively studied according to literature. Restaurants also face challenges in accurately forecasting demand due to the influence of social factors, such as reviews and dining trends, which can rapidly shift consumer behaviour. This data is not easily mined and accessible, especially on businesses of a smaller scale. These aspects add to the difficulty of applying demand forecasting models improved by AI and ML effectively in the restaurant and catering sector, highlighting the need for more tailored and responsive forecasting approaches in this industry.

Algorithms Used

There is a broad range of algorithms that were observed as seen in Table 2 and it highlights the various challenges and contexts experienced within the field of AI and ML within Lot sizing. This then underscores the necessity of choosing the right algorithm for each unique situation. This comprehensive synthesis reveals the significant role of AI and ML in revolutionizing supply chain management, offering advanced, precise, and adaptable solutions for diverse industry requirements. The insights from this analysis lay a solid foundation for future research and practical implementations in the field.

Table 2. Distribution of articles by algorithm used

Category	Count
Classifiers	10
Optimization	10
Deep Learning	8
Time Series Analysis	6
Reinforcement Learning	6
Fuzzy Systems	5
Evolutionary Algorithms	4

Regression	4
Random Forest	3
Decision Tree	3
Policy Optimization	3
Forecasting Models	2
Linear Regression	2
Other Machine Learning	2
XGBoost	1
k-Nearest Neighbour	1
Adaptive-neuro-fuzzy classifier	1
Clustering	1

Within the best-performing studies, Random Forest Algorithms consistently produced great results when forecasting. This could be due to its ability to capture complex interactions and nonlinear relationships, robustness against overfitting, and speed in handling missing values. It can process various data types and requires less pre-processing compared to other algorithms. Random Forest is effective with large datasets, making it a versatile and reliable choice for predicting demand across different scenarios. However, its effectiveness can vary depending on the characteristics of the forecasting problem.

Another trend noticed was the common adoption of the use of Q Learning especially with newer studies after 2018. It was found to perform when supplemented with an existing algorithm or heuristic used and varied from case to case. ARIMA and ARIMAX were very often observed used within the manufacturing and Production space already. This could be due to ARIMA models being extremely suitable with time series data which is prevalent in the industry.

Data Analytics

During the data and preparation process data was often collected from various data sources and data types that would be relevant. This data would be often sourced from ERP and CRM systems and sometimes made use of real-time data in more modern manufacturing contexts. Data would go through processing to ensure it fits the format and structure needed for analysis. Lastly, data cleaning would be done to ensure all data is aligned. Severe outliners were often removed to not heavily skew the data used for training and analysis and to ensure reliability.

As previously stated in modern systems data collection has evolved to include small and more frequent updates, significantly increasing data volume and velocity. This detailed data, often captured through IoT devices, is stored in big data warehouses for efficient processing and analysis. The primary focus is on big data analytics for backorder prediction, making use of a blend of predictive and prescriptive analytics. This approach involves using machine learning algorithms to predict backorders and devise optimal strategies, with training data carefully selected to balance item classes (Hajek & Abedin 2020).

Text Coding Analysis

Introduction

The primary objective of this section is to extract, visualize, and interpret valuable information from a collection of text data from the selected studies. Atlas.ti is used to uncover hidden connections, themes, and trends to help understand the documents. Word frequency analysis, co-occurrence analysis, and code-document analysis will be conducted.

Word Frequency

In the word frequency analysis section of the study, we focused on words that appeared more than ten times across 36 studies. This analysis was conducted by extracting text codes from specifically chosen word groups. In Figure 9, the visualization illustrates the prevalence of these words as larger-sized words indicate higher frequency in the documents. We meticulously filtered out words irrelevant to ML, AI, or lot sizing to accurately represent the distribution and occurrence of key terms within the research collection. The pattern revealed a transition from older systems to more recent technologies. While traditional models like Fuzzy systems were still prevalent, there was a clear emergence of advanced algorithms such as Deep Q-Networks (DQN), Fuzzy Inference Systems (FIS), Deep Neural Networks (DNN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Proximal Policy Optimization (PPO). This trend indicates a shift towards more sophisticated, AI-driven approaches in the domain of lot sizing and supply chain optimization.

Figure 8. Word Frequency visualization of code

Co-Occurrence Analysis

Table 3 provides an insightful visualization of the connection between key code groups that were formulated. A majority of the computational code groups linked back to forecasting, cost and Profit. This could suggest a focused research interest in cost-reduction techniques through algorithmic optimization. The table serves as a roadmap, charting out the intersections of various research domains that contribute to the advancement of lot sizing and supply chain optimization.

Table 3. Code Co-Occurrence of selected codes

	○Algorithms Gr=144	○Artificial Intelligence Gr=280	○Data Gr=196	○Fuzzy logic Gr=68	○Heuristics Gr=34	○ML techniques Gr=42	○Models Gr=90	○Nonlinear programming Gr=18	○Optimization Gr=232	○Optimization algorithms Gr=31	○Q-learning Gr=24	○Regression Gr=54	○Reinforcement learning Gr=55	○Stochastic Gr=63
○Cost Gr=119	13	17	9	4	7	3	3	0	18	1	2	2	4	5
○Demand Gr=39	3	9	10	4	1	4	6	1	6	2	0	3	1	2
○Demand fluctuations Gr=44	1	11	6	2	0	2	4	0	4	0	0	0	0	2
○Forecasting Gr=162	7	53	17	7	0	13	14	4	20	1	0	10	0	6
○Lot-sizing problem Gr=36	3	5	6	4	6	2	5	4	12	2	0	0	5	13
○Ordering Gr=61	9	15	5	5	2	4	5	1	11	3	1	1	6	2
○Profit Gr=52	10	21	16	2	0	8	3	0	8	6	2	5	1	3
○Replenishment Gr=32	5	13	4	4	1	3	5	1	13	3	1	0	1	9
○Supply chain Gr=150	8	20	10	3	3	1	0	1	19	3	2	0	8	15

Code-Document Analysis

In Figure 10 we investigate the occurrence of themes and concepts across various studies as visualized. This column chart reveals the frequency and distribution of specific topics within the body of literature examined. A group of papers could not be fully analyzed due to software constraints, which may include compatibility issues or data processing limitations. Shorter studies inherently generated fewer codes, indicating a lower occurrence of key terms. Two papers emerged as particularly significant: "Applying deep learning to the newsvendor problem" and "Using the proximal policy optimization algorithm for solving the stochastic capacitated lot sizing problem". These studies stood out for their frequency of coded terms, indicating a dense concentration of relevant themes.

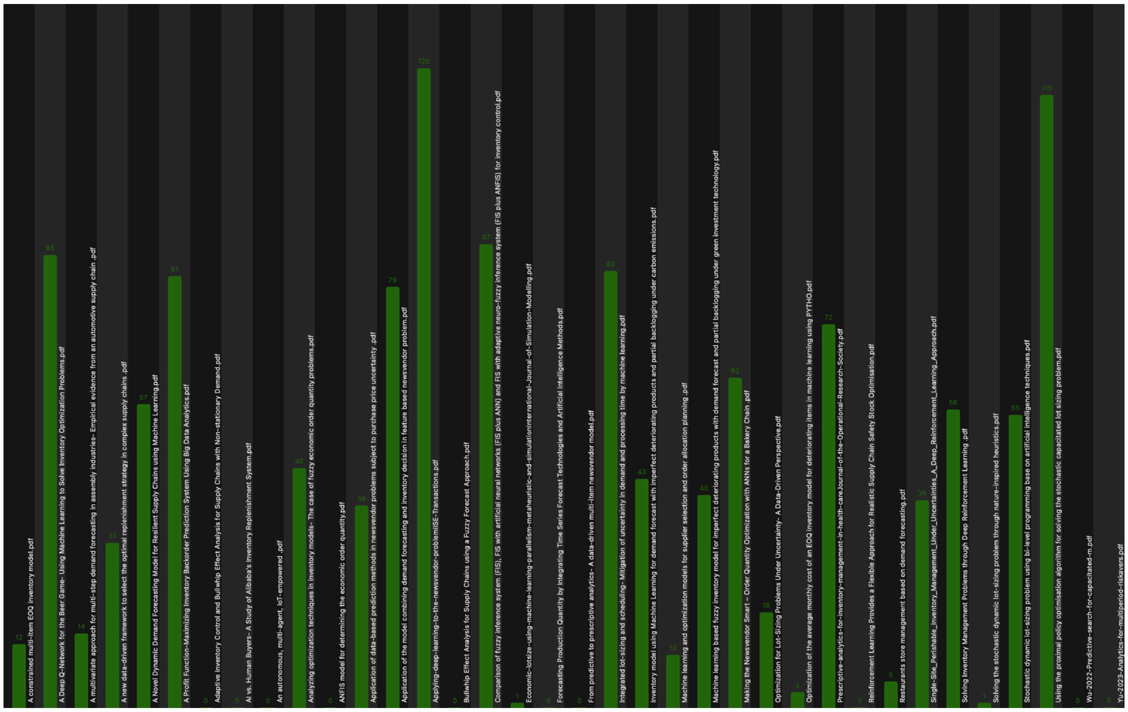

Figure 9 . Column chart Analyzing the Code-Occurrence within Documents

Conclusions

The objective of this research was to investigate how AI and ML are used within Lot sizing and its associated fields more specifically focused on the supply chain. Two databases namely Web of Science and Google Scholar were used to find papers based on the selected keyboards and filters used resulting in 36 documents being used for analysis. Key findings were then taken for every document and listed within a table along with a thorough analysis of other factors such as algorithms used, industries and other relevant information. All this information was used to draw conclusions to help gain an understanding of the field and its future which could be used as a reference point for any other researchers in the field.

Theoretical Contributions

Comprehensive Analysis and review of the literature found that models from Mathematical modeling and Empirical studies that employed AI or ML techniques to refine lot sizing practices were important in showcasing the practical applications and benefits of the use of these technologies to optimize processes. The research collected provided evidence of AI and ML making a difference in supply chains through cost savings by improved accuracy of forecasting methods, reaffirming the notion of these theoretical models being able to work in the real world and providing value. There is a consensus that these technologies are still within early adoption and there is still a lot of potential in making full use of their capabilities.

Practical contributions

The research highlighted a group of practical contributions of AI and ML across diverse fields, extending well beyond the traditional realms of retail and manufacturing. These contributions have been particularly impactful in specialized sectors like healthcare and space logistics, demonstrating the versatility and potential of these technologies.

In the healthcare industry, a notable innovation involves the optimization of medicine inventory management. A model, that made use of patient history, environmental conditions, and patterns observed in similar patient cases, was developed to ensure the availability of essential medicines. This approach not only minimizes the risk of inventory shortages but also plays a crucial role in patient care, potentially saving lives by ensuring timely access to medications (Galli et al., 2021).

The field of space logistics also witnessed significant advancements through the application of AI and ML. In this domain, the integration of AI and ML facilitated both order quantity forecasting and the optimization of space utilization for the inventory storage (Yung et al., 2023). This dual approach exemplifies how AI and ML can be tailored to address unique challenges in highly specialized environments, where both resource allocation and space management are critical.

Furthermore, AI and ML have made substantial inroads in environmentally conscious sectors. One ground-breaking development is the incorporation of environmental metrics into inventory optimization models. Such an approach was seldom seen in traditional SCM practices. By considering environmental impacts alongside traditional inventory metrics, these AI and ML-driven models contribute to more sustainable and responsible supply chain management, aligning operational efficiency with ecological considerations.

These examples highlight the broad range and significant impact of AI and ML applications in various industries. They demonstrate not just the technological abilities of AI and ML but also their capacity to address complex, industry-specific challenges, leading to more efficient, sustainable, and life-saving outcomes in diverse sectors.

Limitations

There were multiple limitations within the study. The selection of only 36 studies though insightful possibly did not fully represent the Applications of AL and ML in lot sizing as other related topics of potentially emerging trends and innovations such as Industry 4.0, IoT and Big data were not included. There were a bunch of papers which were not used because of inaccessibility content through issues with platforms or struggles with contacting researchers for access to papers and thus further insights could've been missed. Important considerations such as job displacement, privacy, and algorithmic bias are not extensively explored and could play a critical role in the responsible application of these technologies.

Future Research Directions

An area for future research is the categorization of specific AI and ML algorithms to particular problems or sectors within Supply Chain Management. This categorization would involve analyzing which algorithms are most effective for different types of challenges or industry-specific needs. For example, certain algorithms may be more suited to perishable goods inventory management, while others might excel in high-variability demand forecasting. Systematic categorization could lead to a more targeted and efficient application of AI and ML in SCM, ensuring that the chosen algorithms are optimally aligned with the specific characteristics and requirements of different sectors.

Further in-depth analysis in the area of lot sizing combined with lot scheduling is another crucial research direction. While significant work has been done in lot sizing, lot scheduling—concerning the timing and sequencing of production lots—presents its unique challenges. Future research could focus on how AI and ML can optimize lot scheduling processes, considering factors like production capacity, lead times, and various production activities. Such research would be instrumental in enhancing the efficiency and responsiveness of SCM operations.

Lastly, an exciting prospect for future research is the application of Deep Reinforcement Learning (DRL) algorithms in developing new heuristics for complex SCM problems. Future studies could focus on translating the findings from DRL algorithms into practical, well-performing heuristics that are easier to understand and implement. This research would not only contribute to the advancement of theoretical knowledge in the field but also provide people involved in supply chains with more accessible and applicable tools for managing complex supply chain challenges.

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