International Journal of Scientific Research in Engineering and Management (IJSREM)
Volume: 10 Issue: 10 | Oct - 2026 SJIF Rating: 8.659 ISSN: 2582-3930

Inventory Optimisation and Analytics: A Bibliometric Review with Implications for E-Commerce

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ABSTRACT: Inventory optimisation matters to e-commerce retailers, who face wide assortments, volatile demand and fast delivery promises. This study presents a bibliometric review of the Scopus literature on inventory optimisation and analytics and asks what it implies for e-commerce. The master dataset is a Scopus BibTeX export containing 6,946 records; statistics recomputed for the 6,926 documents of 2018–2026 reproduce the Biblioshiny figures. Annual output grew from 470 documents in 2018 to 1,124 in 2025 (annual growth rate 13.54%, calculated with partial-year 2026), led by China, the USA, India and Iran and by operations and production journals. Optimisation, inventory control, machine learning and sustainability form the main themes. E-commerce terms appear in the title or author keywords of 2.04% of documents and in the title, keywords or abstract of 3.67%; the PRISMA diagram records only the term "inventory optimisation" (the full query is unavailable), so this is a keyword proxy, not a measure of e-commerce coverage. The search history and screening logs were not available, so the reported search and screening stages are not independently verified. The paper closes with seven research directions.

KEYWORDS: inventory optimisation, analytics, e-commerce, bibliometric analysis, machine learning, sustainability, supply chain

1. INTRODUCTION

Inventory optimisation has become a central issue for organisations that compete on item availability and speed of delivery. It is especially important in e-commerce, where retailers serve dispersed customers, manage very wide assortments with volatile demand and must honour delivery promises. Too little stock leads to lost sales, while too much raises storage costs and creates waste for perishable items.

Inventory control has been studied for more than a century; Jackson et al. (2020) show how the field moved from analytical models to optimal control theory, dynamic programming and simulation-based optimisation. Classical models such as the Economic Order Quantity (EOQ) and the Economic Production Quantity (EPQ) still underpin many systems and keep being extended to more realistic conditions (Alfares & Ghaithan, 2019).

Interest in analytics for inventory decisions has recently increased. Choi et al. (2018) explain that big data analytics is changing operations management, Bertsimas and Kallus (2020) show how decisions can be chosen directly from data instead of from demand predictions, and Simchi-Levi and Wu (2018) describe how analytics supports retailers' digital transformation. In the dataset used here, output rose from 470 documents in 2018 to 1,124 in 2025.

Inventory decisions in e-commerce are harder than in traditional retail. Online retailers sell very many products, and demand for many of them is small and irregular. Because customers expect fast delivery, stock is spread over many locations, which raises the risk of imbalance. Data-driven methods are therefore used for assortment, fulfilment and inventory management (Qi et al., 2020), and customer review text can improve ordering decisions(Tian & Zhang, 2023).

However, existing research has limitations. First, it is scattered: earlier reviews usually cover one part of the field, such as deteriorating items (Karimi & Sadjadi, 2025), blood inventory (EL Gharbi et al., 2026), drones in warehouses (Pore et al., 2026) or machine learning (Bergsma et al., 2025), without showing how the parts connect. Second, much of it focuses on techniques rather than applications: (Nayak & Sharma, 2026) note poor reproducibility and interpretability of deep reinforcement learning and a lack of standard benchmarking and real-world validation for newer metaheuristics, and note that drone studies mostly address static environments. Third, studies are spread over many journals and disciplines, so it is hard to see where knowledge is concentrated.

As a result, the overall structure of the literature is unclear. Few studies have used bibliometric methods to show which journals, countries and authors lead the field, which themes are well developed and how optimisation, machine learning and sustainability are linked. Whether e-commerce applications have received less attention than general modelling work is also examined in the results (Section 5.2).

The aim of this study is to give a bibliometric review of the literature on inventory optimisation and analytics and to understand what it means for e-commerce. There are three objectives. The first is to examine how the literature has developed, including output, leading journals, countries, authors, collaboration and citations. The second is to identify the main themes using thematic mapping and keyword co-occurrence analysis. The third is to suggest future research directions from the patterns, clusters and gaps found.

In this paper, "inventory optimisation" means the use of quantitative models and algorithms to decide order quantities, reorder points, safety stock and stock locations so that total cost is minimised while the required service level is maintained. "Analytics" covers descriptive, predictive and prescriptive techniques that turn data into decisions. "Bibliometric analysis" is the quantitative study of academic publications, including their output, citations, collaboration and keywords (Donthu et al., 2021).

Section 2 reviews the literature in four themes, Section 3 explains the data and methods, including how the dataset counts were checked, Section 4 presents the results, Section 5 discusses them, Section 6 sets out the research gaps and future research agenda, and Section 7 concludes.

2. LITERATURE REVIEW

2.1 Overview and Approach

The literature was examined alongside the Scopus records analysed in this study. A keyword co-occurrence network of the Bibliometrix export of 6,941 records (6,715 articles and 226 reviews, including 15 records dated 2027) was used to identify the themes. The review below organises representative studies into four themes: stochastic inventory control; artificial intelligence, machine learning and deep learning; Industry 4.0, digital twins and smart warehouses; and sustainable, perishable and healthcare inventory (Sections 2.2 to 2.5). Section 3.5 explains how the dataset counts used in this paper relate to one another. The studies discussed are representative, not an exhaustive or systematic sample of the dataset.

Following (Guillén-Pujadas et al., 2026) and(Imamoglu et al., 2023), a keyword co-occurrence network was built in VOSviewer (Figure 1). Its five groups are a red group (inventory control, periodic and continuous review, backorders and lost sales), a blue group (robust and multi-objective optimisation, integer programming and logistics), a purple group (supply chain management with machine learning, artificial intelligence and Industry 4.0), a yellow group (life cycle assessment, sustainability and carbon emissions) and a green group of general biomedical terms, such as human, depression and quality of life. The green group was not treated as a theme, and healthcare-related inventory studies are discussed under Theme 4. The literature is therefore organised into four themes (Table 1).

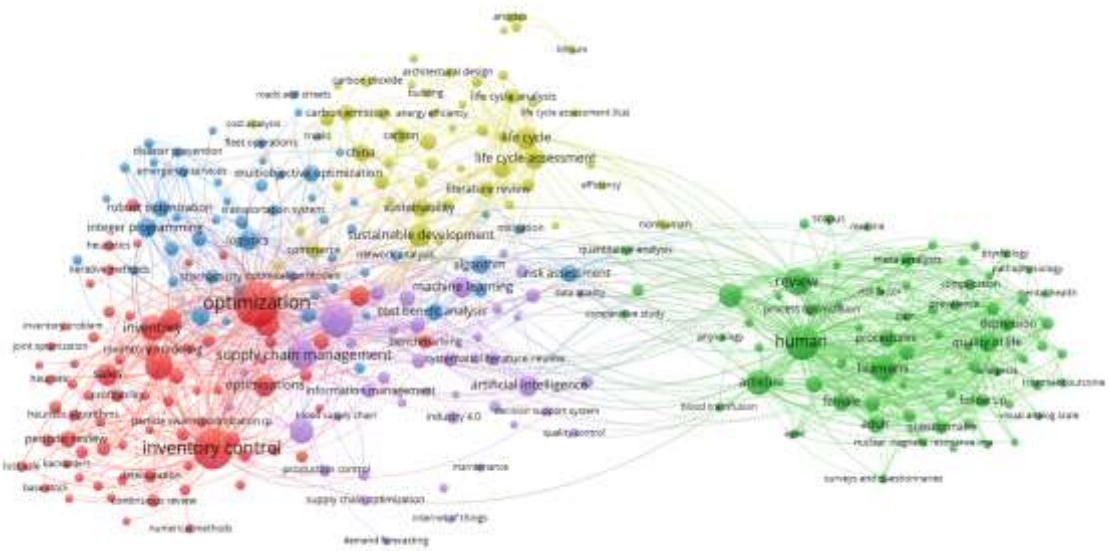


Figure 1. Keyword Co-Occurrence Network Used to Identify the Literature Themes

Note. Node colours show clusters and node size shows keyword frequency. Output generated in VOSviewer.

2.2 Theme 1: Stochastic Inventory Control

Continuous-review and periodic-review control under stochastic demand has been studied widely. Jackson et al. (2020) classified a century of inventory control models by how optimal control parameters are obtained, and (Alfares & Ghaithan, 2019) Grouped EOQ and EPQ models with variable holding costs into time-dependent, stock-dependent and multiple-dependence frameworks.(Utama et al., 2022), reviewing 102 papers, reported that integrated procurement-production models support coordinated supply chain decisions. For (Q, r) and (s, Q) systems with backorders, lost sales and uncertain lead times,(Braglia et al., 2018) developed near-optimal procedures for lost-sales and backorder mixtures with controllable lead time,(Keshavarz & Pasandideh, 2018) formulated a multi-objective model for such mixtures, and (Malik & Sarkar, 2018) optimised a multi-product continuous-review model with uncertain demand and variable lead time. For several retailers,found that lateral transshipments reduce long-run average cost, and reported that, in a mobile phone retailer case, their order-capped base-stock methods reached the target service level with 75% to 99% lower store-level inventory.

2.3 Theme 2: Artificial Intelligence, Machine Learning and Deep Learning

Artificial intelligence (AI) and machine learning (ML) are increasingly used for data-driven inventory control. reviewed data-driven research on retail assortment, order fulfilment and inventory management. In a systematic review of 122 articles,(Bergsma et al., 2025) identified three ways of integrating ML into inventory control: separate estimation and optimisation, static ML-integrated optimisation and dynamic reinforcement learning (RL). Reported that ML can improve prediction and replenishment but struggles with high-dimensional data. Deep learning (DL) has been reported to outperform traditional forecasting for intermittent demand (Nabil et al., 2025). For the newsvendor problem, (Tian & Zhang, 2023) proposed an end-to-end DL framework and reported a 28.7% cost reduction from including textual online review data, and also studied the data-driven newsvendor problem with textual reviews through deep learning. Panja et al. (2026) reviewed generative AI applications in logistics and supply chain management, while Nayak and Sharma (2026) reported that deep reinforcement learning has poor reproducibility and interpretability, and that newer metaheuristics outperform genetic algorithms and particle swarm optimisation on large problems but lack standard benchmarking and real-world validation.

2.4 Theme 3: Industry 4.0, Digital Twins and Smart Warehouses

Industry 4.0 technologies have been widely studied for automating factory and warehouse logistics. Soori et al. (2023) reported that Internet of Things (IoT) sensors give real-time inventory visibility and asset tracking in smart factories, and Guillén-Pujadas et al. (2026), in a bibliometric analysis of 7,066 Web of Science articles on warehouse cost optimisation, found that the most cited work focuses on emerging technologies such as blockchain, artificial intelligence and the Internet of Things, automation, sustainability and inventory optimisation. Soori and Arezoo (2025) reported that Autonomous Mobile Robots make warehouse operations more flexible and scalable. Pore et al. (2026) reviewed about 120 studies on drones for inventory counting, mapping and layout optimisation and noted that multi-drone approaches still struggle with coordination and safety. Faqeer and Khajavi (2025) reported that combining digital twins with computer vision can reduce human error and operational bottlenecks, and Alam et al. (2026) reviewed AI-enhanced digital twins and Automated Guided Vehicles (AGVs) in warehouse logistics, noting a lack of return-on-investment analysis. Integrated models have also been proposed for logistics problems: Bertazzi et al. (2019) proposed a matheuristic for multi-depot inventory routing, Liu et al. (2021) a location-inventory-routing model for perishable products, and Ren et al. (2020) a deep learning approach to capacity allocation in cross-border e-commerce logistics.

2.5 Theme 4: Sustainable, Perishable and Healthcare Inventory

Sharma et al. (2025) reviewed sustainable inventory control models published between 2011 and 2023, and Iniya et al. (2026) examined how carbon emission limits can be built into a continuous-review (s, Q) system. Marques and Santos (2025) reported that business intelligence and operations research together contribute to 11 of the 17 UN Sustainable Development Goals, and Salas-Navarro et al. (2026) presented an analytical review of vendor-managed inventory (VMI) models in sustainable supply chains. For deteriorating and perishable items, Karimi (2025) reviewed about 300 articles since 2018 and offered 18 classes and 33 subclasses for classifying deteriorating-item models, constraints and solution methods, and van Donselaar and Broekmeulen (2025) proposed easy-to-use estimators for periodic-review perishable systems, with an average relative cost error of 0.40% in their base setting and below 1% in most other scenarios. In healthcare, Ahmadi et al. (2019) reviewed inventory management of surgical supplies and sterile instruments and pointed to operating-room inventory cost reduction as a direction for future research. Blood inventory is especially demanding because of its short shelf life: Imamoglu et al. (2023) and EL Gharbi et al. (2026) reviewed the blood supply chain and blood inventory management, Wang and Chen (2020) proposed a distributionally robust model for a blood supply network under disasters, and Siriruk and Kotekangpoo (2026) developed a continuous-review (Q, r) model for perishable products.

Theme	Study	Method or policy	Main finding
1	Lowery et al. (2026)	Two-echelon periodic review; stochastic dynamic programming	Order-capped base-stock methods reached target service with 75% to 99% lower store inventory in a real-data case.
2	Bergsma et al. (2025)	Systematic review of 122 studies	Three-tier typology of ML integration, ending in dynamic RL.
2	Tian & Zhang (2023); Zhang & Tian (2024)	End-to-end deep learning newsvendor	Review text in ordering decisions; 28.7% cost reduction reported by Tian & Zhang (2023).
3	Pore et al. (2026); Alam et al. (2026)	Systematic reviews of drones and AI-enhanced digital twins	Drone coordination and safety (Pore); lack of ROI analysis (Alam).
4	Marques & Santos (2025); Iniya et al. (2026)	Review of 56 studies; carbon-constrained (s, Q) model	BI and OR contribute to 11 of 17 SDGs; carbon limits can enter ordering.

Table 1. Representative Studies in the Four Literature Themes

Note. Themes: 1 = stochastic inventory control; 2 = AI, ML and DL; 3 = Industry 4.0 and digital twins; 4 = sustainable, perishable and healthcare inventory.

3. RESEARCH METHODOLOGY

3.1 Research Design

This study uses the Systematic Literature Review (SLR) approach, which brings together existing literature and finds research gaps (Paul & Rialp, 2020). The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) technique (Moher et al., 2010) was used to identify and screen the literature step by step and the bibliometric process followed (Donthu et al., 2021). The work had four stages: identification, screening, eligibility and inclusion.

3.2 Data Source and Search

The data come from the Scopus database. The header of the master BibTeX file records only an export date of 11 September 2026. None of the supplied files contains the Scopus query string, the search history, the date on which the search was run, or the initial result count: the figure of 20,772 records appears only in the authors' PRISMA diagram (Figure 2). The diagram labels the search term as "inventory optimisation". The search is therefore incompletely documented, and the full query, including any additional keywords, field codes and limits, cannot be stated here. The authors report that they could not recover the exact query, and that Scopus has since indexed more papers, so a repeated search would return more than the 20,772 records reported and would not reproduce the original count. The master BibTeX file is therefore the fixed dataset for all analyses in this paper, and the initial count and filter steps are reported as the authors' figures only. Scopus is the only database used; it covers a wide range of peer-reviewed research and its exports can be analysed in Biblioshiny.

3.3 Screening

The authors' PRISMA diagram (Figure 2) reports four screening steps. A time-span filter (2018–2027) removed 9,990 records and left 10,782; a document-type filter kept journal articles and reviews and removed 3,396 records, leaving 7,386; a language filter kept English-language records and removed 428, leaving 6,958; and a journal filter removed 12 records, leaving 6,946. The arithmetic is correct ($20{,}772 - 9{,}990 - 3{,}396 - 428 - 12 = 6{,}946$) and the final figure equals the number of entries in the master BibTeX file. The master file is also consistent with the filters: its records are dated 2018 to 2027, 6,719 are typed as articles and 226 as reviews (one entry has no type), and all but one carry the language "English" (one has no language field). These checks show consistency, not reproduction: the records removed at each stage were not supplied, so the stage counts are reported figures and are not independently verified.

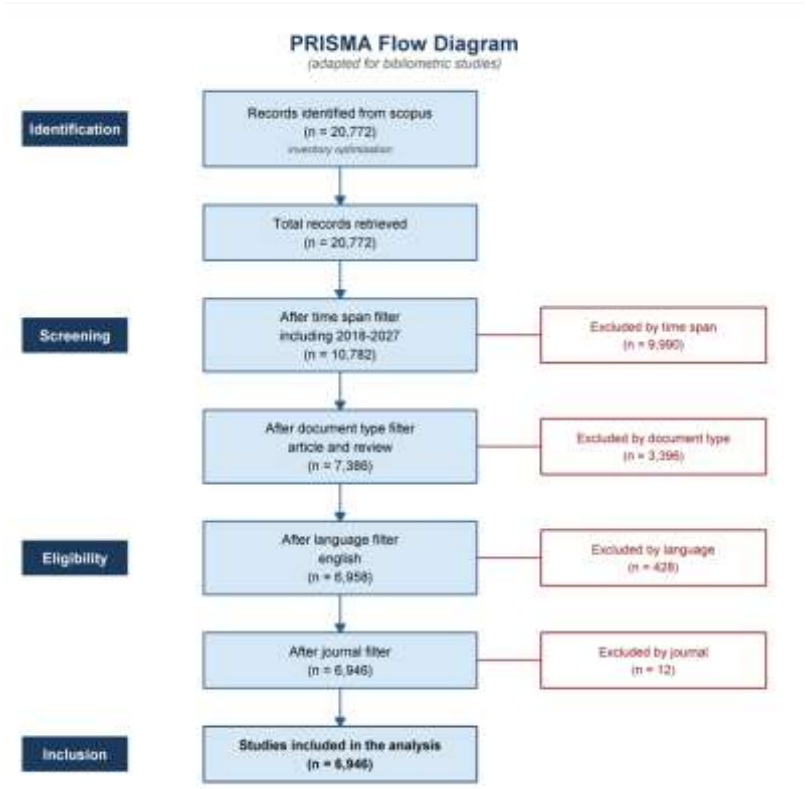


Figure 2. PRISMA Flow Diagram

Note. Adapted for bibliometric studies from the PRISMA flow (Moher et al., 2010). Stage counts are as reported by the authors; the Scopus search history and screening logs were not available.

3.4 Data Processing and Analysis

The master dataset is the 6,946-entry Scopus BibTeX file. The authors report that the records were organised in Mendeley and analysed in Biblioshiny, which runs inside RStudio and is built on the Bibliometrix package (Aria & Cuccurullo, 2017), with VOSviewer used for keyword co-occurrence networks. A reconstructed RIS file derived from the BibTeX file contains the same records and is not an independent export. For this report the BibTeX file and the Bibliometrix export dated 24 September 2026 were parsed with scripts, records were matched by DOI and normalised title, and the main statistics, annual production, sources, author keywords and country counts were recomputed. Figures 3, 7, 8 and 10 and Tables 4 to 6 were produced independently from the data. Figures 1, 4, 5, 6 and 9 (the VOSviewer and Biblioshiny outputs) and the PRISMA diagram (Figure 2) are the authors' original outputs and were not reproduced.

3.5 Dataset Counts and Their Reconciliation

Three dataset counts appear in this paper (Table 2). The master BibTeX file has 6,946 entries. Five titles occur twice in it, so it has 6,941 distinct normalised titles. Only one of the five pairs is an exact duplicate (same DOI, journal and volume); the other four differ in DOI, journal, issue, pages or year and are not treated as established duplicate publications. The Bibliometrix export dated 24 September 2026 has 6,941 rows (6,715 articles and 226 reviews) and no repeated titles; every export record matches a master record by DOI or title. Fifteen records, all articles, are dated 2027. When the export is restricted to 2018–2026 it has 6,926 documents (6,700 articles and 226 reviews), and recomputing the statistics from this subset reproduces the Biblioshiny main-information figures (Table 4). The three counts are therefore related by simple arithmetic: 6,946 − 5 = 6,941 and 6,941 − 15 = 6,926. This is an arithmetic reconciliation, not proof of the filtering that was actually applied: the files do not record how the repeated titles were removed from the master or why the 2027 records were left out of the Biblioshiny run.

Dataset or step	Records	Source	Status
PRISMA final count (reported)	6,946	Authors' screening flow	Arithmetic correct; stages not reproduced
Master BibTeX file	6,946	Scopus export, 11 Sep 2026	Count verified
Distinct normalised titles in master	6,941	Recomputed from the BibTeX file	Verified (5 repeated titles)
Bibliometrix export, 24 Sep 2026	6,941	6,715 articles, 226 reviews	Verified; matches the master by DOI or title
Records dated 2027	15	Master and export	Verified
Analysis set, 2018–2026	6,926	Export restricted to 2018–2026	Reproduces the Biblioshiny statistics; procedure undocumented

Table 2. Dataset Counts and Their Status

Note. The reconciliation 6,946 − 5 = 6,941 and 6,941 − 15 = 6,926 is arithmetic. The exact filtering procedure is not documented in the files.

3.6 The 732-Record Selection

A separate RIS file of 732 records was supplied as a review selection and was examined without being merged with the master. Of the 732 records, 721 match a master record by DOI or title, including all 226 reviews in the master, and 11 match none; the 11 include records from medical and environmental journals that are unrelated to inventory, for example a surgical trial and a landfill leachate study. Its type tags are inconsistent: 622 records are tagged as journal articles, 78 as articles and 32 as reviews, but the master types 226 of the 732 as reviews. The file therefore overlaps the master without being a subset of it, and no document in the project files states how it was selected. It is not used for any count or statistic in this paper.

Item	Status	Basis
Master BibTeX count (6,946)	Verified	Parsed from the supplied file
6,941 export and 6,926 analysis set	Verified by recomputation	Export matches the master; 2018–2026 subset reproduces Biblioshiny statistics
Search date 11 Sep 2026	Export date verified; search date unresolved	BibTeX header; no search history
Search query and 20,772 initial records	Not recoverable	Appear only in the PRISMA diagram, which labels the term "inventory optimisation"; authors cannot recover the exact query and a re-run would return more records
PRISMA stage counts	Arithmetic verified; stages unresolved	Screening logs not available
Country map, three-field plot, thematic map, networks	Reported, not reproduced	Original Biblioshiny and VOSviewer outputs
Reference details	Checked against Scopus; two checked by authors at publisher pages	See note

Table 3. Evidence Status of Key Items

Note. Reference details were compared with the Scopus records for the 39 cited works that are in the master dataset. The authors report that they checked Zhang & Tian (2024) and EL Gharbi et al. (2026) against the publisher DOI pages and found the reference-list details to be the same. This was done by the authors and was not independently repeated in this analysis, because the publisher pages could not be opened here.

4. RESULTS AND FINDINGS

This section reports statistics recomputed from the data, and the original Biblioshiny and VOSviewer outputs where recomputation was not possible. Unless stated otherwise, results refer to the 6,926 documents of 2018–2026.

4.1 Main Information of the Bibliometric Dataset

The dataset covers 6,926 documents from 1,850 sources written by 16,963 authors between 2018 and 2026 (Table 4), with a compound annual growth rate of 13.54%, calculated from 470 documents in 2018 to 1,298 in 2026; because 2026 is a partial year, the rate is probably overstated or at least not comparable with full-year rates. The numbers of sources and authors show that the research is spread over many journals and a large community. The average of 4.03 authors per document and 392 single-author documents indicate that most work is done in teams. Documents average 17.06 citations and are 3.17 years old on average. All values in Table 4 were recomputed from the export except the international co-authorship rate, which is the Biblioshiny value and was not reproduced: recalculations from the affiliation and corresponding-author fields gave between 29.1% and 31.3% depending on the definition and

denominator, and none matched 29.95% exactly. The recalculations are not equivalent to the software statistic, and the exact Bibliometrix definition was not available for checking.

Description	Result	Check
Timespan	2018–2026	Reproduced
Sources	1,850	Reproduced
Documents	6,926	Reproduced
Articles	6,700	Reproduced
Reviews	226	Reproduced
Annual growth rate	13.54%	Reproduced; uses partial-year 2026 (470 to 1,298 over 8 years)
Document average age	3.17 years	Reproduced
Average citations per document	17.06	Reproduced
Authors	16,963	Reproduced
Co-authors per document	4.03	Reproduced
International co-authorship	29.95%	Biblioshiny value; not reproduced

Table 4. Main Information About the Dataset (2018–2026)

Note. Source: Bibliometrix export of 24 September 2026, restricted to 2018–2026, and Biblioshiny main information. International co-authorship is the software value, not a recalculation.

4.2 Annual Production

Figure 3 shows the annual output. Output was lowest in 2018 with 470 documents and rose each year to 543 in 2019, 580 in 2020, 626 in 2021, 681 in 2022 and 742 in 2023. It then increased sharply to 862 in 2024 and 1,124 in 2025. The figure for 2026 is 1,298, which is the highest, but 2026 is a partial year and should be read with care. No year shows a decline. Fifteen further records dated 2027 are in the master dataset and were excluded from this 2018–2026 analysis; although the screening flow in Figure 2 includes 2027, the files do not document why or by what procedure these records were left out of the Biblioshiny run.

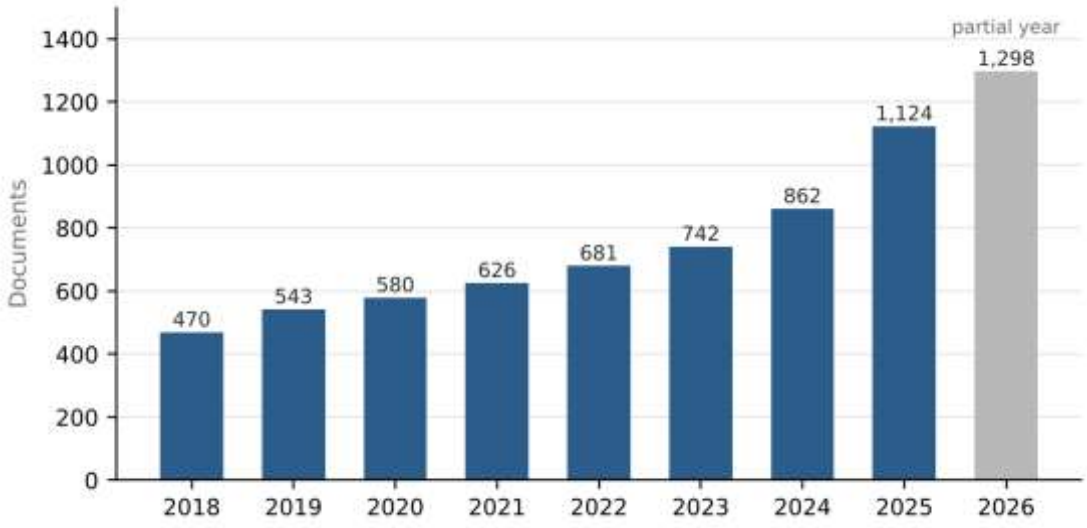


Figure 3. Annual Scientific Production, 2018–2026

Note. Recomputed from the Bibliometrix export (n = 6,926). 2026 is a partial year and is shown in grey.

4.3 Country Scientific Production

Table 5 counts the documents with at least one author affiliated in each country, using a simple parse of the affiliation strings. China (1,907 documents), the USA (1,099), India (1,002) and Iran (530) lead, followed by Canada, the United Kingdom, Germany, France, Turkey and South Korea. This agrees with the Biblioshiny map in Figure 4, which shades China darkest, with the USA, India and Iran next. The two measures are not identical and the map was not reproduced, so Table 5 is a separate count from the affiliation field and is not equivalent to the map.

Country	Documents	Share of 6,926
China	1,907	27.5%
United States	1,099	15.9%
India	1,002	14.5%
Iran	530	7.7%
Canada	351	5.1%
United Kingdom	341	4.9%
Germany	254	3.7%
France	249	3.6%
Turkey	218	3.1%
South Korea	205	3.0%

Table 5. Documents by Author-Affiliation Country (Top 10)

Note. A document counts once for each country in its affiliations, so shares do not sum to 100%. Six documents have blank affiliation data and 14 have no recognisable country in their affiliations.

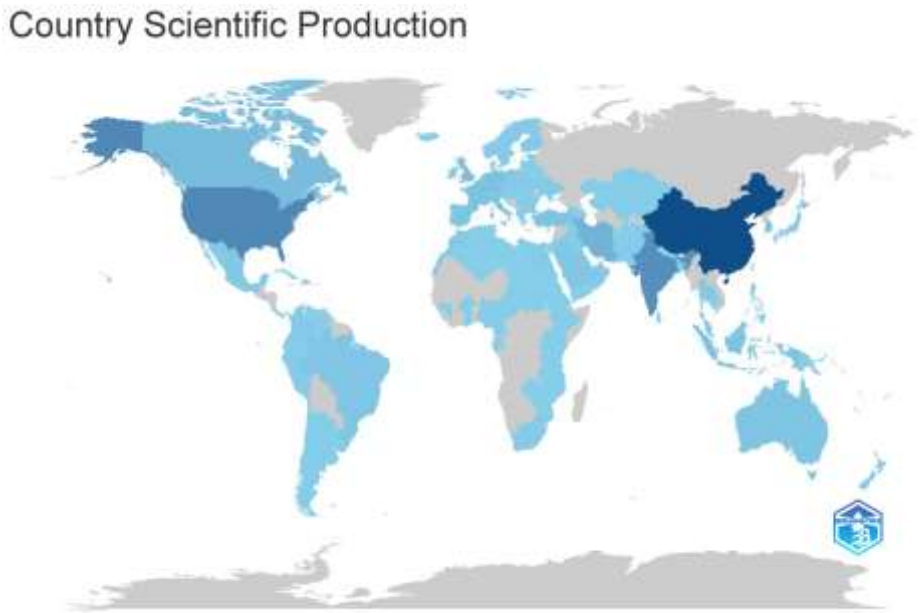


Figure 4. Country Scientific Production

Note. Darker colours show higher production and grey shows no recorded publications. Original Biblioshiny output, not reproduced.

4.4 Three-Field Plot

The three-field plot in Figure 5 connects authors (left column, AU), countries (middle column, AU_CO) and author keywords (right column, DE). It shows who conducts the research, where, and on which topics. The authors shown include wang z, li y, zhang h, wang x, zhang y and wang y, linked mainly to China, India and the USA. China has the largest block in the middle column, followed by India, the USA and Iran, and Canada, the United Kingdom, Indonesia, Turkey, Korea and Germany also appear. These countries connect to the keywords optimization, inventory, inventory management, machine learning, supply chain management, supply chain and inventory control. The order of India and the USA differs from Figure 4, and the outputs do not state how countries are counted in each, so this is not interpreted.

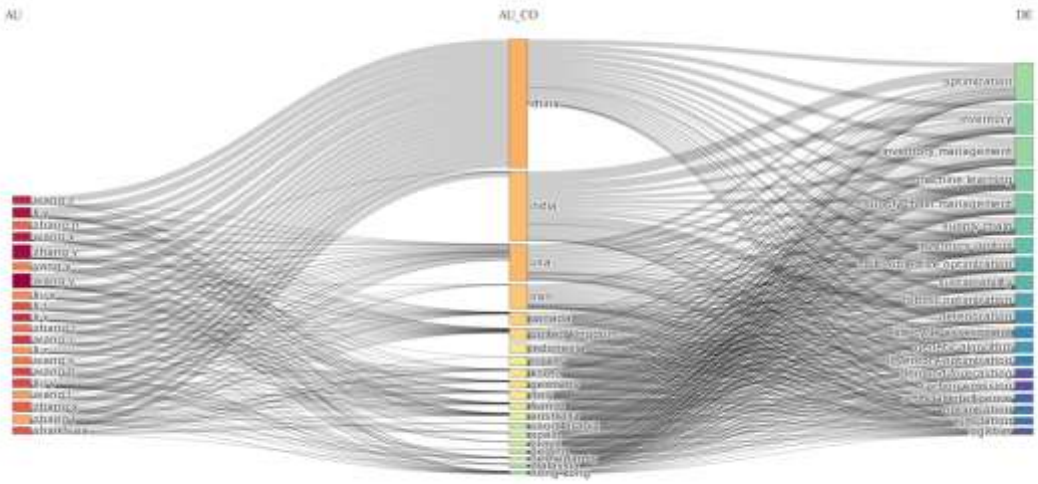


Figure 5. Three-Field Plot of Authors, Countries and Keywords

Note. AU = authors; AU_CO = countries; DE = author keywords. Original Biblioshiny output, not reproduced.

4.5 Thematic Map

The thematic map in Figure 6 places the main themes by their centrality (relation to the overall research area) and density (degree of development), and themes appear in all four quadrants. Motor themes, with high centrality and density, are inventory management, supply chain management and machine learning, together with sustainability, multi-objective optimization and life cycle assessment, so they are well developed and central. Basic themes, with high centrality and low density, are optimization, inventory, deterioration, robust optimization, production planning and stochastic programming, which are important but less developed internally. Niche themes, with low centrality and high density, include supply chain, optimisation, simulation, depression and anxiety and are well developed internally but weakly linked to the overall area. Emerging or declining themes, with low centrality and low density, include genetic algorithm, particle swarm optimization, simulated annealing, inventory control, dynamic programming and perishable products; the map shows only their position, not whether they are emerging or declining.

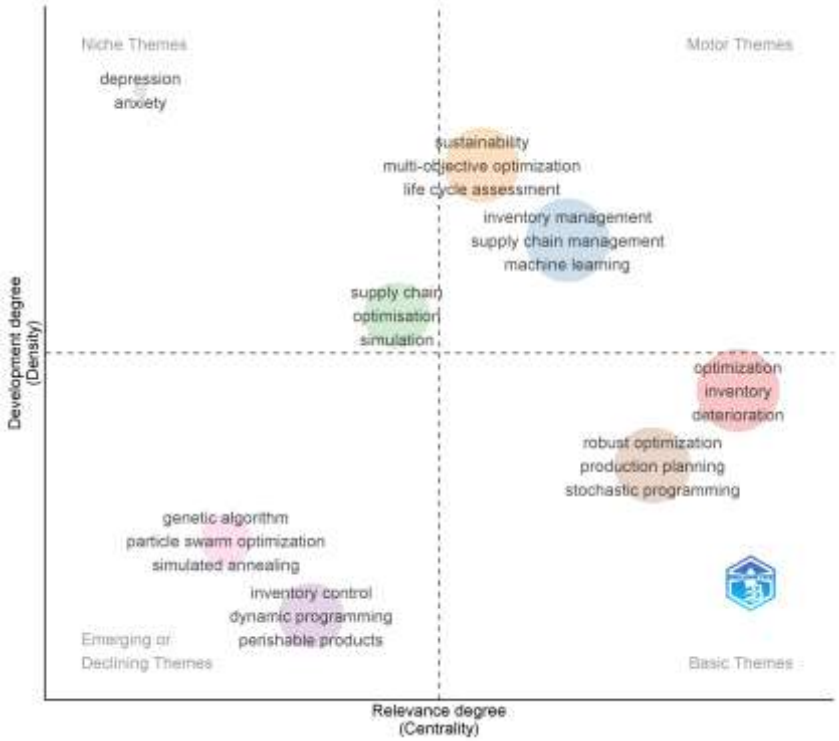


Figure 6. Thematic Map

Note. Original Biblioshiny output, not reproduced.

4.6 Most Relevant Sources

Figure 7 shows the journals with the most documents. *Computers and Industrial Engineering* leads with 191, followed by the *European Journal of Operational Research* (165) and the *International Journal of Production Research* (144). The *International Journal of Production Economics* has 118, *Sustainability* and the *Journal of Cleaner Production* 98 each, *Mathematics* 91, *Computers and Operations Research* 81, *Annals of Operations Research* 79 and *IEEE Access* 78. Operations and production journals hold the largest share.

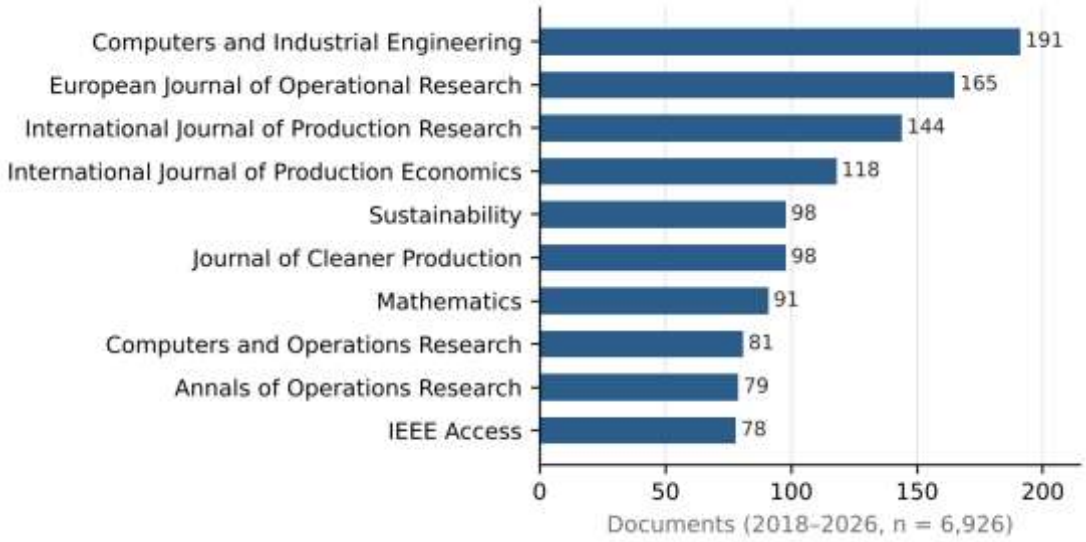


Figure 7. Most Relevant Sources

Note. Recomputed from the Bibliometrix export (n = 6,926).

4.7 Author Keywords and the Keyword Co-Occurrence Network

Figure 8 shows the most frequent author keywords. “Optimization” (482), “inventory management” (389), “inventory” (385), “machine learning” (230) and “supply chain management” (228) lead. Spelling variants such as “optimization” (482), “optimisation” (103) and “inventory optimization” (110) are counted separately and were not merged, and 329 of the 6,941 export records have no author keywords.

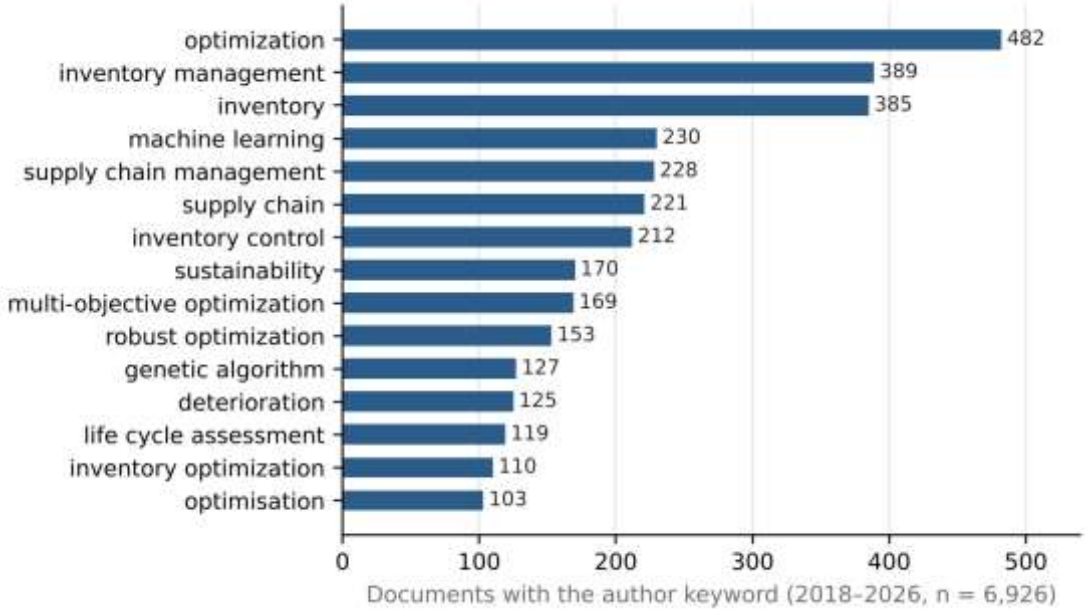


Figure 8. Most Frequent Author Keywords

Note. Recomputed from the Bibliometrix export (n = 6,926). Keyword variants are not merged.

Figure 9 shows how keywords occur together in the same publications. Larger nodes are the most frequent keywords, lines show relations between keywords and colours show clusters. The red cluster is the largest and is built around optimization, inventory control, supply chains, inventory, costs, sales and stochastic models. It also includes integer

programming, robust optimization, sensitivity analysis, warehouses and vehicle routing, so this part of the research focuses on optimisation models for inventory and supply chains. Electronic commerce appears only as a small node in this cluster. The green cluster includes sustainable development, sustainability, multiobjective optimization, life cycle assessment, environmental impact, carbon emissions, climate change and greenhouse gases, which represents the environmental side of the topic. The blue cluster includes decision making, inventory management, machine learning, forecasting, deep learning, reinforcement learning and Markov processes, which links decision making with learning methods. The yellow cluster includes general terms such as human, humans, article, controlled study, female, male, adult, questionnaire and major clinical study. It lies on the right with few links to other clusters, and its terms are not inventory optimisation themes, so it is peripheral. The red, green and blue clusters are strongly connected: optimization and inventory control link with decision making, machine learning, sustainability and multiobjective optimization.

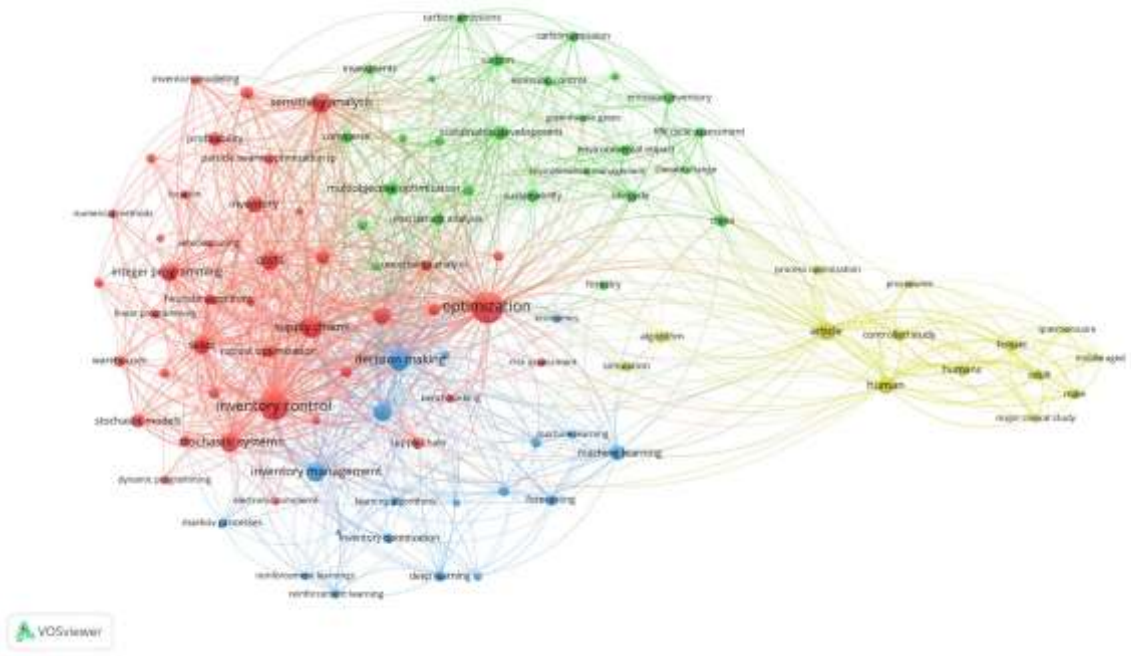


Figure 9. Keyword Co-Occurrence Network

Note. Node colours show clusters and node size shows keyword frequency. Original VOSviewer output, not reproduced.

4.8 E-Commerce Terms in the Dataset

The only search term recorded in the authors' PRISMA diagram is "inventory optimisation" and the full query is unavailable, so the presence of e-commerce work in the dataset was checked directly. Table 6 counts documents whose title, author keywords or abstract contain e-commerce terms. Under the narrow term set, 141 documents (2.04%) have such a term in the title or author keywords, and 254 (3.67%) have one in the title, author keywords or abstract. The broader set, which adds omnichannel, multichannel, online platform, drop-shipping, last-mile and similar terms, gives 215 (3.10%) and 331 (4.78%). The percentages use all 6,926 documents as the denominator and describe the matching of the listed terms, not the share of research about e-commerce. The author keyword "e-commerce" occurs 51 times and ranks 43rd among author keywords, and "cross-border e-commerce" occurs 11 times. By year, the share of documents with a narrow-term hit in the title or author keywords was 0.9% in 2018 and 2.4% in 2026, with a peak of 2.9% in 2024 (Figure 10).

Fields searched	Narrow terms	Broad terms	Narrow / broad share
Title	103	179	1.49% / 2.58%
Author keywords	111	165	1.60% / 2.38%
Title or author keywords	141	215	2.04% / 3.10%
Title, author keywords or abstract	254	331	3.67% / 4.78%

Table 6. Documents With E-Commerce Terms (n = 6,926)

Note. Narrow terms: e-commerce, ecommerce, electronic commerce, online retail(ing), online shopping, e-retail, online marketplace, online store. Broad terms add online sales, online channel, online platform, omnichannel, multichannel, dual-channel, drop-shipping, quick commerce, click-and-collect, last-mile, fulfilment centre and dark store. Case-insensitive substring matching on the title, author keywords and abstract fields; all percentages use the 6,926 documents of 2018–2026 as the denominator.

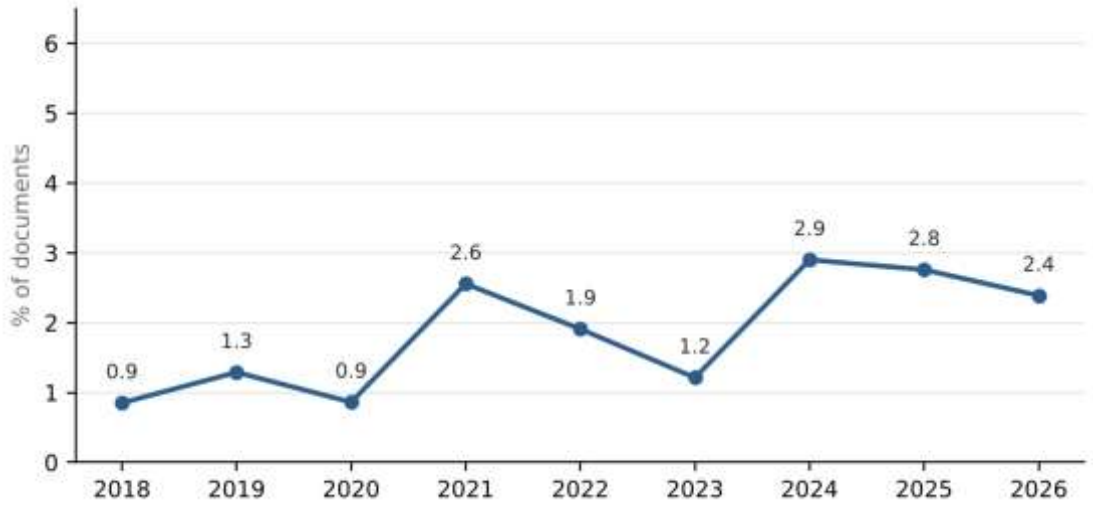


Figure 10. Share of Documents With Narrow E-Commerce Terms in the Title or Author Keywords, by Year

Note. Recomputed from the Bibliometrix export (n = 6,926). 2026 is a partial year.

These figures are a keyword proxy. A term in an abstract can be a passing mention, and relevant studies that use other words are missed, so the counts are neither the number of e-commerce studies nor a measure of how well e-commerce is covered. No manual classification of the documents was carried out.

5. DISCUSSION

5.1 Findings and the Literature

The results agree with the literature in several ways. The annual growth rate of 13.54% (affected by the partial year 2026) and the sharp rise from 2024 are consistent with the argument that big data, machine learning and digital technologies have increased interest in analytics-based inventory decisions. The author keywords "inventory control", "robust optimization" and "deterioration" and the red cluster of the keyword network (inventory control, stochastic models, integer programming, robust optimization) match Theme 1 and show that classical stochastic models remain the base of the field (Jackson et al., 2020; Keshavarz & Pasandideh, 2018).

Machine learning is a motor theme, and the blue cluster links it with forecasting, deep learning and reinforcement learning, which matches Theme 2 (Bergsma et al., 2025). However, a well-developed theme is not a solved problem, because the review also reported poor reproducibility and interpretability of deep RL and a lack of benchmarking and real-world validation(Nayak & Sharma, 2026). Sustainability, also a motor theme, forms the green cluster linked with multiobjective optimization, which matches Theme 4, where carbon limits and waste are built into inventory models (Iniya et al., 2026; Marques & Santos, 2025; Sharma et al., 2025).

Theme 3 is less visible. Industry 4.0 appeared in the network of the literature review (Figure 1) but is not among the labelled keywords in Figure 9, where warehouses appears only in the red cluster.

5.2 E-Commerce in the Literature

The main finding for the topic of this paper is that e-commerce is a small part of the dataset. No e-commerce theme appears on the Biblioshiny thematic map and "electronic commerce" is only a small node in the keyword network. The direct count in Section 4.8 agrees: about 2% of documents have an e-commerce term in the title or author keywords, and about 4% when abstracts are included, although the share is higher in recent years than in 2018. The PRISMA diagram records only the term "inventory optimisation" and the full query is unavailable, so the dataset should not be treated as a sample of e-commerce research, and these shares describe this dataset, not e-commerce literature as a whole. The most developed themes are generic. The literature does contain e-commerce work, such as omnichannel base-stock policies(Lowery et al., 2026), (review-based ordering(Tian & Zhang, 2023) and cross-border e-commerce logistics, but it is small compared with general modelling work. The methods are mature, but evidence of their application to e-commerce is limited in this dataset.

5.3 Practical Implications

For managers in online retail, the results suggest combining ML forecasting with optimisation models for stock decisions (Lowery et al., 2026)(Bergsma et al., 2025)and testing such policies in the firm's own setting first. Environmental objectives should be weighed with cost and service level, and firms adopting IoT sensors, drones or digital twins need good-quality data and models that planners can understand.

5.4 Limitations

This study has several limitations. It uses only Scopus, so records found only in other databases, such as Web of Science, are not included. The reported search covered English-language journal articles and reviews from 2018 to 2027, so conference papers, book chapters and non-English studies were excluded. Because the search history and screening logs were not available, the query, the search date, the initial count and the screening stage counts could not be verified, and the PRISMA diagram labels the search term as "inventory optimisation" only, so the full query is not established. The three dataset counts are related only arithmetically (Section 3.5). The analysis covers 2018–2026, so the 15 records dated 2027 are not analysed, and 2026 is a partial year. Some unrelated records remain, as the medical and survey terms in the network and the niche theme of depression and anxiety show, and keyword variants are counted separately. The thematic map, three-field plot, country map and networks are original software outputs that were not reproduced. The international co-authorship rate is the Biblioshiny value and could not be reproduced. The e-commerce counts are a keyword proxy without manual classification, calculated over all 6,926 documents. A thematic map cannot show whether a theme is growing or declining, and bibliometric analysis does not judge study quality. The narrative review covers representative studies and is not a systematic synthesis, and its reference details were checked against Scopus records, not publisher pages. These limitations concern the study. The practical limits of the methods themselves, such as poor reproducibility and interpretability of deep reinforcement learning and the lack of real-world validation, are discussed in Section 6.1.

6. RESEARCH GAPS AND FUTURE RESEARCH AGENDA

6.1 Research Gaps

Three gaps come from the literature review. First, deep learning and reinforcement learning are flexible but have poor reproducibility and interpretability, and newer metaheuristics lack standard benchmarking and real-world validation(Nayak & Sharma, 2026). Second, drone studies mostly address static rather than dynamic warehouse environments (Pore et al., 2026), and AI-enhanced digital twin studies lack return-on-investment analysis. Third, in the Theme 4 studies reviewed here, sustainable and healthcare models appear to assume centralised decision making and to focus on economic and carbon trade-offs; decentralised settings are rarely modelled (authors' reading). The bibliometric results add the e-commerce gap (Section 5.2) and the unclear direction of low-centrality, low-density themes.

6.2 Future Research Agenda

Table 7 turns these gaps into seven directions, each with research questions and suggested contexts and methods.

Direction	Research questions	Suggested contexts and methods
1. E-commerce inventory policies. Design policies for wide assortments, irregular demand and stock spread over many nodes, using lateral transshipment (Zhou & Wang, 2023) and intermittent-demand forecasting (Nabil et al., 2025).	Which forecasting-plus-optimisation pipelines work best for long-tail, intermittent-demand products? How should safety stock be spread over fulfilment centres when delivery promises are tight?	Indian online marketplaces, D2C brands and quick-commerce dark stores. ML forecasting feeding stochastic dynamic programming or two-echelon models, tested on transaction data against (Q, r) and base-stock policies.
2. From simulation to real operations. Run live pilots of Industry 4.0 tools in operating warehouses and report accuracy, stockouts, service level, cost and return on investment (Alam et al., 2026; Pore et al., 2026).	Do digital-twin-guided storage assignment and AGV or AMR coordination (Soori & Arezoo, 2025) improve throughput in live operations? What is the return on investment of AI-enhanced digital twins and drones for inventory counting?	E-commerce fulfilment centres and third-party logistics providers. Pilots, A/B tests between similar warehouses or periods, longitudinal case studies and design-science research.
3. Interpretable, reproducible and benchmarked AI and RL. Turn RL or deep learning policies into rules planners can check, and test newer metaheuristics on shared benchmarks and practical problems (Nayak & Sharma, 2026).	How much cost performance is lost when an RL policy is replaced by an interpretable approximation? Which level of the Bergsma et al. (2025) typology suits larger networks?	Explainable RL, surrogate or metamodel optimisation (Jackson et al., 2020), comparison with classical analytical policies, and experiments with more echelons, SKUs and lead-time variability.
4. Returns and reverse flows. Treat returns as a source of supply, not only a cost. This is a deduction from the literature review, where no theme covers return-aware models; it was not tested against the dataset.	When return rates can be predicted from customer or product features, how should order quantities change? Does a data-driven newsvendor model with return forecasting outperform one without?	Fashion and electronics online shopping, where return rates are high. End-to-end newsvendor models (Tian & Zhang, 2023; Zhang & Tian, 2024) with return and review data as extra input.
5. ML with sustainability in replenishment. ML and sustainability are both motor themes, but it is unknown whether learning-based replenishment can cut waste and carbon without raising cost; carbon-constrained work (Iniya et al., 2026) is mostly analytical.	Can multi-objective RL find better cost–emission trade-offs than carbon-constrained EOQ and (s, Q) models? How do replenishment rankings change under different carbon policies?	Online grocery, quick commerce, and consumer packaged and fast-moving goods. Multi-objective optimisation with Pareto analysis (Keshavarz & Pasandideh, 2018) using life cycle assessment data.
6. Perishable inventory and low-density themes. Run a thematic evolution analysis for sub-periods (for example 2018–2021, 2022–2024 and 2025–2026), and extend perishable models (Siriruk & Kotekangpoo, 2026; van Donselaar & Broekmeulen, 2025) with real-time freshness data from IoT sensors (Soori et al., 2023).	Are perishable products, dynamic programming and metaheuristics emerging, declining or stable over time? Does real-time shelf-life information improve perishable replenishment?	Online grocery, quick commerce and hospital blood banks. Period-wise thematic evolution in Biblioshiny and hybrid simulation-optimisation.
7. Decentralised and socially conscious optimisation. Model independent actors (platform, sellers, logistics providers, hospitals, suppliers) with social goals such as fair access to essential goods; vendor-managed inventory (VMI; Salas-Navarro et al., 2026) is one possible coordination mechanism.	How do contracts or information sharing between a marketplace and its sellers affect seller inventory and waste? Can distributionally robust models (Wang & Chen, 2020) be extended to multi-party settings?	Game-theoretic and distributionally robust formulations for platform marketplaces, humanitarian logistics and healthcare networks, validated with real-time hybrid simulation-optimisation.

Table 7. Future Research Agenda

Note. D2C = direct-to-consumer; SKU = stock-keeping unit.

7. CONCLUSION

This study gave a bibliometric review of the literature on inventory optimisation and analytics and examined its implications for e-commerce. The master dataset is a Scopus BibTeX export containing 6,946 records. Statistics recomputed for the 6,926 documents of 2018–2026 reproduce the Biblioshiny figures, and the 6,946, 6,941 and 6,926 counts are related by simple arithmetic, with the underlying search and screening records unavailable.

Three main findings came from the analysis. First, the field has grown strongly: the annual growth rate is 13.54% (calculated with partial-year 2026), and output rose from 470 documents in 2018 to 1,124 in 2025, with 1,298 in the partial year 2026. Second, the research community is global and collaborative, with China, the USA, India and Iran as

the leading countries, and operations and production journals, led by *Computers and Industrial Engineering* (191 documents), as the main outlets. Third, optimisation, inventory control, machine learning and sustainability are closely connected: machine learning and sustainability are motor themes, and the keyword network shows strong links among the modelling, sustainability and decision-making clusters.

E-commerce is a small part of this literature. E-commerce terms appear in the title or author keywords of 2.04% of documents and in the title, keywords or abstract of 3.67%, and e-commerce is not a labelled theme on the thematic map. These shares are a keyword proxy for a dataset whose recorded search term was "inventory optimisation" (the full query is unavailable), so they suggest that applications to e-commerce are thinly represented in this dataset, not that e-commerce research is rare. The agenda in Section 6 gives seven directions, with research questions and methods, for these areas. Verifying the search history and screening logs would allow the reported search and screening stages to be confirmed.

AUTHOR CONTRIBUTIONS

The contributions are stated according to the roles provided by the authors.
Nihar Thakkar: Data analysis.
Nishtha Joshi: Research methodology.
Naisha Almeida: Future research agenda.
Nayanika Harde: Literature review.
Ojas Garg: Introduction and conclusion.

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