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Sales Forecasting in Relation to Operations Research: A Systematic Literature Review and Bibliometric Analysis

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ABSTRACT: This paper is a systematic literature review combined with a bibliometric analysis of sales forecasting and its relationship with operations research (OR). It asks how far forecasting research has been linked to OR decision making, such as inventory, pricing and assortment planning, and where that link is weak. Data were drawn from the Scopus database and analysed with Biblioshiny, VOSviewer and Microsoft Excel. The final dataset comprises 316 English-language journal articles and reviews. The field has grown rapidly, with 83% of documents published since 2020, and it is dominated by method vocabulary such as machine learning, predictive analytics and deep learning. Six thematic clusters were identified. OR concepts such as inventory and optimisation remain peripheral, so the step from forecast to decision and from decision to outcome is the weakest link in the literature. The paper closes with ten research gaps and a future research agenda.

KEYWORDS: Sales forecasting; Operations research; Machine learning; Bibliometric analysis; Decision support.

1. INTRODUCTION

A sales forecast can be highly accurate on paper and still lead to the wrong business decision. This distinction is becoming increasingly important as businesses rely on forecasting to guide decisions involving inventory, pricing, supply chains and resource allocation. There is a long history of causal and structured models for forecasting retail sales, and evidence on competitors' prices and high-dimensional promotional variables at product level has demonstrated the explanatory power of this information (Huang, Fildes and Soopramanien, 2014; Ma, Fildes and Huang, 2016). Over the past decade, attention has moved towards machine learning (ML) and deep learning (DL). According to Ahaggach, Abrouk and Lebon (2024), the number of articles on ML and DL rose from 10 in 2013 to over 110 in 2023.

As forecasting algorithms have become more sophisticated, the range of data used as inputs has also expanded. Researchers have used sentiment collected from online comments (Lau, Zhang and Xu, 2018), social-network activity (Koren, Perlman and Shnaiderman, 2026) and search-engine data (Wu, Xu and Bach, 2023). However, these gains are not consistent across contexts. Social-network information led to better predictions of demand for fashion products than past sales did, and Google Trends proved useful for predicting demand for conventional but not organic avocados. In some settings additional data is helpful and in others it is not, and there is little guidance on which is which.

The scale of the growth is also evident in the bibliometric data. In our literature review we found 315 English-language Scopus documents, of which 260 (83%) were published from 2020 onwards, while no year before 2020 recorded more than 12 publications. A separate dataset of 255 documents from 179 journals and other sources for 2012–2025 shows that publications grew at an average rate of 35.91% per year, from one in 2012 to 54 in 2025. The authorship pattern is similar: the 255 documents involve 816 authors, only 25 are single-authored, the average is 3.42 authors per paper, and 25.88% of papers are internationally co-authored. These are the statistics of a field that has expanded rapidly and cooperatively. Most of the growth is found in methodological vocabulary such as machine learning (69 documents), predictive analytics (57) and sales forecasting (31) in the 315-document collection.

However, the increasing sophistication of forecasting methods does not necessarily mean that forecasts have become more useful to decision makers, and this is where the OR connection comes in. Wang and Chen (2022) differentiate between demand planning, which optimises internal resources through mathematical programming, and sales forecasting, which captures external market effects through regression, time series and ML. The two areas converge when a forecast becomes an input into a decision model, such as an inventory, pricing or assortment optimisation problem, and the resulting decision produces a measurable operational outcome. Only a few studies follow this full process. Ferreira, Lee and Simchi-Levi (2016) predicted demand for products that had not been sold before and used the prediction in daily price optimisation. Chen, Fan and Sun (2023) linked cross-selling and substitution-based demand estimation to assortment planning. Karami et al. (2026) integrated an LSTM demand prediction model into a continuous-time Markov chain to determine reorder points and order quantities, while Zizi, Chafi and El Hammoumi (2026) combined deep learning forecasts with a multi-objective optimisation based on cost and service levels. Practice shows why this matters: Wahid et al. (2026) found that better forecasts reduced stockouts but also increased stock levels, so an improvement in forecasting carried a cost for the company.

Such integrated applications remain the exception, which points to a central limitation of the existing literature. Most studies evaluate models using error metrics such as RMSE and R^2 and stop before the model is applied, and the few that go further sit apart from the field's main keywords. Reported accuracy also varies substantially across studies using similar methods. Khani et al. (2026), with 844,275 transactions, report an R^2 of just 0.536, whereas Manoj, Baby and Devaraj (2025) report an R^2 of 0.999895 for a random forest on restaurant sales. Hobor et al. (2026) found that tree-based models outperformed deep architectures for intermittent retail demand, while Lingkon, Hossain and Chakrabortty (2026) found that hybrid deep models beat standard LSTM networks. Such results are difficult to compare because of differences in datasets and validation, which supports the call by Fildes, Ma and Kolassa (2022) for caution before drawing conclusions about ML. These differences should not be read as evidence that one family of methods is universally superior. They show that accuracy is hard to interpret and that the model with the smallest error is not necessarily the one that improves inventory, service or profit outcomes. Kuhlmann and Pauly (2023) make a related point by proposing a dynamic

systems model that incorporates the cost of overstocking and shortages, and Hajek and Abedin (2020) set a decision threshold to maximise expected profit instead of predictive accuracy. Accuracy is still essential, because a poor forecast cannot support a good decision. But it is not enough, and there is not necessarily a strong correlation between forecasting results and measurable business outcomes.

The literature also reveals several research gaps. Forecasting and marketing prediction are largely examined separately, so the impact of a forecast on pricing, promotion, customer targeting and inventory decisions is rarely studied together. Many recent models are black boxes, yet as Bohanec, Kljajić Borštnar and Robnik-Šikonja (2017) argued, decision makers need explanations of ML predictions before they will accept them. Historical data also offers little insight into whether a rise in sales came from a discount or from a campaign. Taken together, these gaps indicate that the weakest link in the literature is the step from forecast to decision and from decision to result, and not the production of forecasts.

The analysis reveals six thematic areas: commercial and marketing applications, advanced algorithmic methodologies, strategic data use and big data, logistics and supply chain operations, deep learning and sequential forecasting, and customer classification and churn prediction. Two features stand out. Method-related terms dominate the keyword maps, while OR-related terms such as inventory and optimisation are not prominent. The field therefore appears relatively mature in predictive modelling but less developed in linking forecasts to operational decision making.

The contribution of this study is small but useful. Academically, it brings together a fast-expanding body of research that is spread across computing, engineering and management journals, and it highlights the lack of evaluation of forecasts based on their decision consequences. For practitioners, it shows the importance of considering the decisions made and the outcomes achieved by a forecasting system, rather than looking only at the error figure.

The paper is organised as follows. The next section presents the literature review, followed by the research objectives and the research methodology. The data analysis and results are then presented, followed by the research gaps and future research agenda, the discussion and implications, and finally the conclusion and limitations.

2. LITERATURE REVIEW

Sales forecasting has evolved from a tool for OR decision models into their input, because its outputs define the parameters of inventory, pricing and supply chain problems. Forecasts have traditionally formed the foundation for planning and executing supply chain activities (Boone et al., 2019), and in retail they run from strategic location decisions to store-level operational decisions (Fildes, Ma and Kolassa, 2022). A large and growing body of literature has examined how sales can be predicted more accurately. Over the past decade, most of this research has emphasised ML and DL. Ahaggach, Abrouk and Lebon (2024) analysed 516 articles from 2013 to 2023 and reported that ML and DL articles rose from 10 in 2013 to over 110 by 2023. Accuracy alone, however, is not the end point. Wahid et al. (2026) argue that a more accurate forecast matters only if it leads to a better decision on the warehouse floor, which is where forecasting meets OR. This review therefore maps the field bibliometrically, synthesises the forecasting methods used, examines how forecasts relate to OR decision models, and identifies research gaps. It draws on titles, abstracts and keywords from a 315-document Scopus export and a 26-paper review file; full texts were not examined.

The corpus comprises 315 English-language Scopus documents (310 articles and 5 reviews) exported through Bibliometrix. Publication is recent and accelerating: 260 documents (83%) appeared in 2020 or later, including 54 in 2025 and 60 in 2026 (a partial year), whereas no year before 2020 exceeds 12. The documents are distributed among computational, engineering and management journals. The most frequent outlet is IEEE Access (13 documents), followed by the European Journal of Operational Research (10) and Expert Systems with Applications (9), which reflects the fact that forecasting is seen as an OR problem but many recent contributions come from outside the OR community. Citation impact is very skewed, with a median of 7 against a mean of about 27. The most cited items are De Caigny, Coussement and De Bock (2018) on churn prediction (490 citations), Ferreira, Lee and Simchi-Levi (2016) on demand forecasting and price optimisation (415), and the retail and supply chain reviews by Fildes, Ma and Kolassa (2022) and Boone et al. (2019). The most frequent author keywords are machine learning (69 records), predictive analytics (57), sales forecasting (31) and demand forecasting (25). The export also contains some fringe applications, such as customer churn, electricity load or cryptocurrency forecasting, so not every record is on sales forecasting.

Two VOSviewer maps, created from the Mendeley file and the bibliometric Excel data, identify a small technical core with application areas extending outward. A figure, drawn with a stricter threshold, identifies 13 keywords in three clusters: predictive analytics (the largest node) with sales forecasting and neural networks; sales, machine learning, deep learning and consumer behavior; and forecasting, artificial intelligence, electronic commerce and industry 4.0. Another figure , drawn with a looser threshold, shows about 26 keywords in four clusters. A red cluster pairs forecasting and demand forecasting with linear regression and neural networks; a green cluster combines sales, machine learning, sales management and decision support systems; a yellow cluster arranges predictive analytics, deep learning, CNN, time series analysis and sales forecasting; and a blue cluster gathers customer churn prediction, sentiment analysis, support vector machines and big data. The blue strand overlaps with sales forecasting through shared methods (Lau, Zhang and Xu, 2018; Abdul-Rahman et al., 2024). Three themes follow. First, method vocabulary dominates, with machine learning, deep learning and predictive analytics as the most central nodes. Second, classical techniques and neural approaches sit in separate clusters, mirroring the shift described by Ahaggach, Abrouk and Lebon (2024). Third, OR vocabulary such as inventory or optimisation does not appear in either map, although inventory management and supply chain management each occur in the author keywords of ten records, and decision support systems appears only at the edge of Figure 3. Variant spellings such as machine learning and machine-learning appear as separate nodes, so a thesaurus could sharpen the clusters.

Evidence on which method forecasts sales best is inconsistent. Causal models remain the reference point: Fildes, Ma and Kolassa (2022) concluded that they outperform simple benchmarks but that evidence on ML had not yet accumulated, and Huang, Fildes and Soopramanien (2014) and Ma, Fildes and Huang (2016) showed the value of competitors' prices and high-dimensional promotional variables at SKU level. Within ML, Pavlyshenko (2019) showed that stacked regression ensembles can generalise when little history exists. Results are mixed. Hobor et al. (2026) found that localised tree-based models, with

XGBoost reaching an RMSE of 4.833, outperformed deep architectures on intermittent retail demand, and Khani et al. (2026) reported LightGBM as most accurate on 844,275 transactions but with an R^2 of only 0.536. By contrast, Manoj, Baby and Devaraj (2025) reported an R^2 of 0.999895 for random forest on restaurant sales, a value whose validation deserves scrutiny. Deep and hybrid models are widely favoured for sequential demand: Punia, Singh and Madaan (2020) used LSTM networks in a cross-temporal hierarchy and found bottom-up forecasts more accurate than top-down ones, and Lingkon, Hossain and Chakrabortty (2026) reported that a hybrid of polylinear regression and a transformer-encoder LSTM beat a standard LSTM across products and locations. External data form a further strand. Lau, Zhang and Xu (2018) used sentiment analysis of online comments, and Koren, Perlman and Shnaiderman (2026) found that social-network activity improved prediction beyond sales data for fashion items, yet Wu, Xu and Bach (2023) found that Google Trends improved forecasts for conventional but not organic avocados, so gains are context-dependent. Finally, Bohanec, Kljajić Borštnar and Robnik-Šikonja (2017) argued that decision makers need explanations of ML predictions before adopting them.

Operations research is applied when a forecast feeds an optimisation or control model. Wang and Chen (2022) draw the dividing line: demand planning is commonly seen as the optimisation of internal resources by means of mathematical programming and game-theoretic modelling, whereas sales forecasting incorporates the effects of the external market through regression, time series and ML. Inventory control is the most common downstream decision. Papanagnou and Matthews-Amune (2018) showed that combining structured sales data with online customer information can improve inventory management through more accurate forecasting, and Hajek and Abedin (2020) replaced the stochastic approximation conventional in backorder prediction with an ML model whose decision threshold maximises expected profit. Wahid et al. (2026) generated dynamic reorder points from ML demand predictions and found fewer stockouts but higher stock, which reveals a trade-off between reliability and cost, and noted that lead time and abnormal demand strongly affect performance. Karami et al. (2026) went furthest in integration, embedding an LSTM demand forecast in a continuous-time Markov chain to optimise reorder points and order quantities under uncertain demand and delivery times, while Bo and Xu (2024) paired transformer forecasting with particle swarm optimisation to tune inventory parameters. In pricing, Ferreira, Lee and Simchi-Levi (2016) used ML to predict demand for products never sold before and fed the predictions into daily price optimisation, Branda, Marozzo and Talia (2020) reported that purchase-prediction rules used to design dynamic pricing raised tickets sold by 6% and revenue by 9%, and Cosguner and Seetharaman (2022) extended the Bass model to derive optimal dynamic prices for new products. Chen, Fan and Sun (2023) linked demand forecasting under cross-selling and substitution to assortment optimisation, and Zizi, Chafi and El Hammoumi (2026) joined deep learning forecasts to a multi-objective Pareto optimisation that balances cost and service.

The literature demonstrates a wealth of research into forecast models but provides limited evidence on the benefits of improved forecasts for decision making. Most studies evaluate error measures such as RMSE or R^2 but rarely proceed to actual implementation, and those that do (Ferreira, Lee and Simchi-Levi, 2016; Chen, Fan and Sun, 2023; Karami et al., 2026; Zizi, Chafi and El Hammoumi, 2026) have only marginal prominence in the keyword analysis. Kuhlmann and Pauly (2023) address the issue by proposing a dynamic systems model that incorporates the costs of overstocking and shortages, giving a more realistic perspective than error measures alone. Comparability is another concern, as accuracy varies greatly between studies using the same approach, ranging from $R^2 = 0.536$ (Khani et al., 2026) to $R^2 = 0.999895$ (Manoj, Baby and Devaraj, 2025) depending on the dataset and validation methodology. This makes most articles difficult to compare and makes the warning of Fildes, Ma and Kolassa (2022) about premature conclusions on ML applicability particularly relevant. Literature on external data is equally mixed, with Koren, Perlman and Shnaiderman (2026) reporting benefits while Wu, Xu and Bach (2023) find no improvement for organic avocados, and none of the papers provides objective criteria for when to use such data. Notably, the review file contains one retracted article (Shukla et al., 2023), which was excluded from consideration. In conclusion, the literature suggests several avenues of improvement, including evaluating forecasts by inventory, service and profit-related metrics, implementing predict-and-optimise frameworks, establishing common benchmarks, and further investigating sparse, new-product and disrupted-demand categories. While the field of sales forecasting has seen an explosion of research and ML applications, its intersection with operations research remains underexplored, and the opportunities for improvement suggest that the connection is worth pursuing.

3. RESEARCH OBJECTIVES

The fundamental aim of this study is to determine the extent to which sales forecasting research has been linked to OR decision making, and to identify the areas in which that linkage is weak. This is achieved through four smaller objectives:

1. To map the field bibliometrically in terms of publication trends, journals, authors, countries and keywords.
2. To synthesise the forecasting methods used in the literature.
3. To investigate how forecasts feed into OR decision models such as inventory, pricing and assortment planning.
4. To outline the missing areas and a research agenda for future work.

4. RESEARCH METHODOLOGY

A popular research method used in many fields is the Systematic Literature Review (SLR). An SLR is a structured and methodical approach used to identify, evaluate and synthesise existing research on a specific topic. Its benefit is that it helps plan research that expands current knowledge and identifies research gaps while avoiding duplicated work (Paul and Criado, 2020). The current study uses an SLR to identify trends in sales forecasting in relation to operations research, which matters today because of rapid technological advancement and a fast-paced, unpredictable business environment. The authors used the SLR to relate relevant studies and to understand how the area has been explored in existing literature. This helps identify the key concepts that link the two topics and the areas that deserve future research. The SLR also provided a reliable basis for working with a large body of data. For this review, a systematic search was conducted using the PRISMA framework (Moher et al., 2010), in which a large number of existing articles are narrowed down, using their titles and abstracts, to a smaller and more focused dataset by setting relevant criteria and excluding records that do not meet them.

4.1 Article selection, inclusion and exclusion criteria

For data collection, a Scopus database search was conducted on 11 September 2026. It returned 1,147 records dating from 2009,

and articles from all available years, without any time restriction, were taken as the initial dataset. The search covered important areas of study such as business, management, engineering and mathematics, reflecting the wide range of applications of the topic. The data was then filtered by document type so that only articles and reviews were kept, which reduced the records from 1,147 to 323. Next, only English-language documents were retained, reducing the records from 323 to 317, which means 6 were non-English. Finally, a source-type filter excluded everything except journal publications, which removed 1 record and left a final dataset of 316 studies for bibliometric analysis. The screening steps are shown as a PRISMA flow diagram in Figure 1.

The 316 screened studies were then analysed at different stages. The Bibliometrix export used for the literature review and keyword mapping contains 315 documents. The data analysis in Section 5 covers 255 documents for 2012–2025, because the 60 documents from 2026 were excluded: 2026 is a partial year, and including it could distort the historical trend.

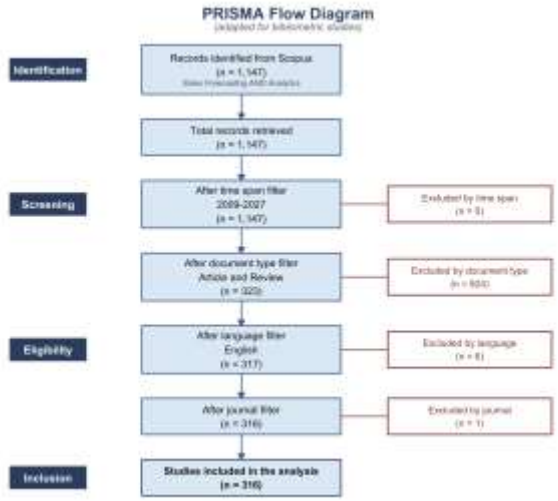


Figure 1. PRISMA flow diagram for data filtering

4.2 Bibliometric review and visualization

The data included a large number of articles and an extensive amount of reading, so the researchers carried out a bibliometric analysis. Bibliometric analysis helps researchers identify correlations and trends in large amounts of data and gain an overall understanding of the topic being researched (Donthu et al., 2021). After export from Scopus, the dataset was saved in the Mendeley reference manager, a free desktop tool that helps store, organise and cite research papers. It also helped screen and merge duplicates and acted as secure storage for the data used. To examine systematically how sales forecasting has changed and what it looks like now in operations research, the dataset was saved as a BibTeX file and uploaded to Biblioshiny. Biblioshiny is a tool that lets researchers carry out full science mapping without advanced coding. It works with the bibliometrix package in R and offers a point-and-click dashboard through which users can import bibliographic data from databases such as Scopus or Web of Science. The program then turns that data into visual analytics, including keyword co-occurrence maps, co-citation networks and thematic maps. This makes it very useful for exploring a research field: it reveals trending topics and keywords, the number of papers published over the years, the structure of core and related literature, and the collaboration links among authors and institutions. Furthermore, the application VOS Viewer was used to create visual networks and maps such as the keyword co-occurrence (thematic clustering) based on the data, which highlights the various relations in the articles.

In short, Biblioshiny turns raw citation data into easy-to-understand insights. The SLR helped the researchers determine which studies were relevant, and the bibliometric analysis and visualization helped them understand the patterns, trends, relationships and development of research on sales forecasting and operations research.

5. DATA ANALYSIS AND RESULTS

Using data from published research, this section looks at how sales forecasting and predictive analytics have been studied over time (Aria and Cuccurullo, 2017; Chen, 2017). The dataset covers academic articles published between 2012 and 2025. 2026 was intentionally left out because the calendar year is not over, and including partial data could distort the overall historical trend. In total, 255 unique documents published across 179 journals and other sources were analysed.

5.1 Main information

What stands out in this dataset is the amount of collaboration. Of 816 authors, only 25 documents were single-authored. The rate of international co-authorship is 25.88%, which shows large-scale global collaboration, and an average of 3.4 authors worked on every paper. The field is growing rapidly, at approximately 35.91% a year (Zupic and Čater, 2015). The average document age is only 4.64 years and the average citations per document are 33.17. This means the topic is very modern and relevant, and that scholars and companies are depending on this recent research to understand the future of retail, marketing and supply chain operations. Data analytics is no longer a "nice-to-have" IT capability; businesses are now integrating it into their core.



Figure 4. Main information, 2012–2026 (315 documents)



Figure 5. Main information, 2012–2025 (255 documents)

5.2 Scientific production

Between 2012 and 2017 there were barely any articles on this niche, starting at a single paper in 2012 and reaching only 9 in 2017. Growth then accelerated. A large jump occurred in 2020, from 10 publications the year before to 37. This is consistent with the macroeconomic environment: the COVID-19 pandemic disrupted global retail and supply chains. Popescu et al. (2025) noted that the pandemic permanently changed

consumer behaviour and turned e-commerce from a convenient option into a necessity. Because market dynamics became volatile and unpredictable, companies needed data-driven forecasting to keep operations running. Popescu et al. (2025) also highlighted a "hybrid consumption model", in which people buy essential goods online but prefer physical stores for luxury items, making forecasting more complicated. Publications dropped slightly to 33 in 2021 and 26 in 2022, but recovered to a record peak of 54 articles in 2025. This reading of the 2020 jump is plausible, but bibliometric analysis cannot prove it.

Insert Figure 6 here: Annual scientific production, 2012–2025, with exponential trend line



Figure 6. Annual scientific production and exponential trend line

5.3 Trend line

The amount of research published in this area is growing exponentially. When the annual number of publications is plotted, the exponential trend line gives the equation y = 1.8071e^(0.2473x), with an R^2 (coefficient of determination) of 0.7324. This means that about 73% of the variation in publication counts is explained by the upward trend, showing that the volume of studies is snowballing as companies realise they need better data to compete.

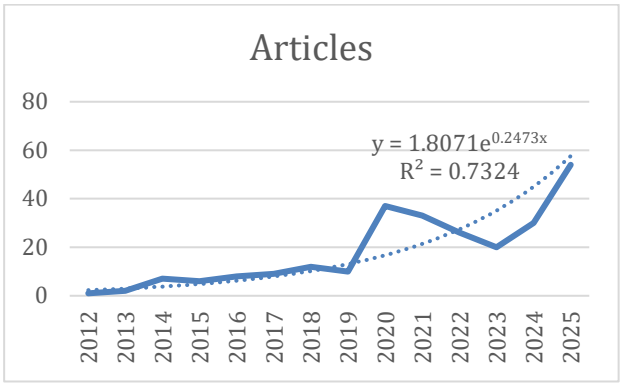


Figure 7. Trend Line

5.4 Three-field analysis

To understand the main ideas driving the field, a three-field plot (Aria and Cuccurullo, 2026) was used to map the connections between countries, authors and keywords. The top publishing countries are the United Kingdom, Belgium, the USA and China. The plot suggests a broad consensus across regions: researchers and companies everywhere are applying advanced algorithms to the same commercial problems. The most common keywords tying the countries together are "forecasting", "sales", "predictive analytics" and "machine learning".

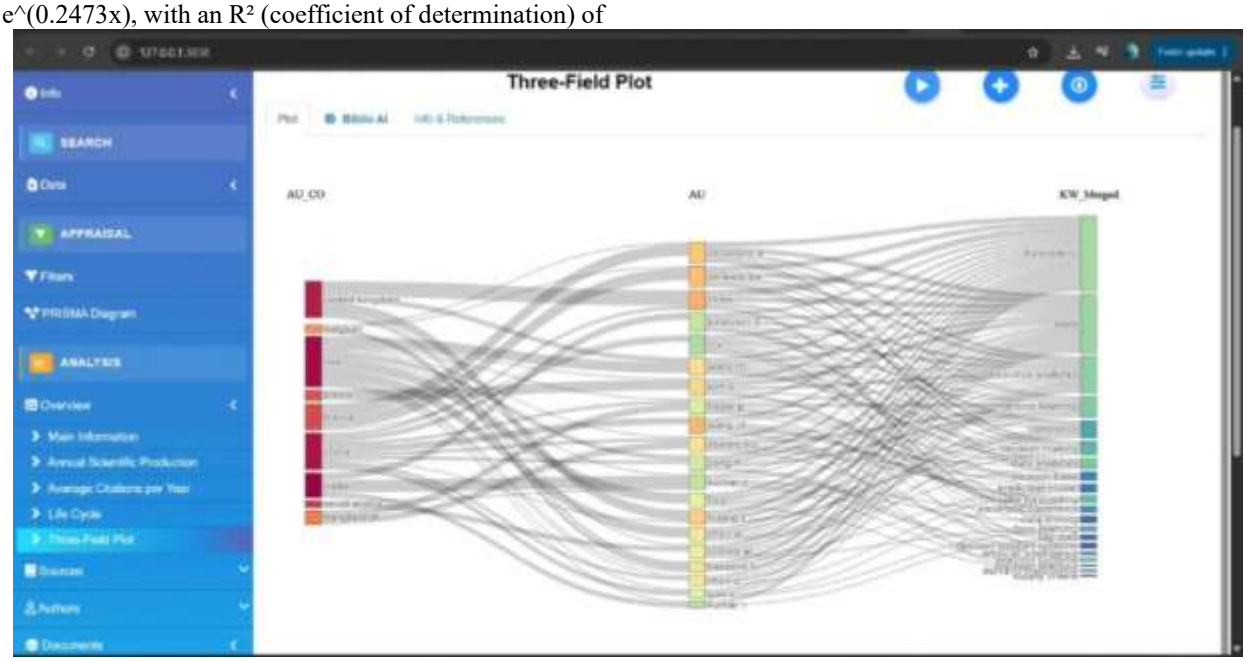


Figure 8. Three-field plot

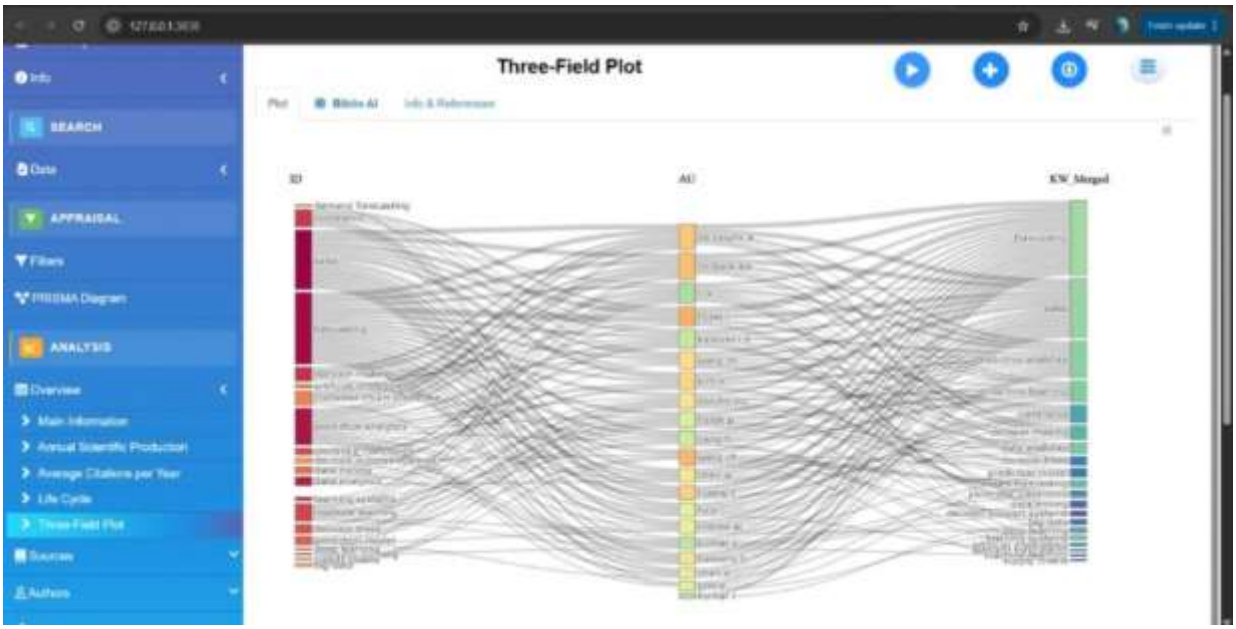


Figure 9. Three-field plot (alternate view)

5.5 Thematic clustering

By mapping how often keywords appear together (Callon et al., 1983; Callon et al., 1991; Van Eck and Waltman, 2010), the literature can be split into six main clusters (Aria et al., 2025; Cobo et al., 2011; Cobo et al., 2012). These represent the most important themes in sales forecasting and operations today.

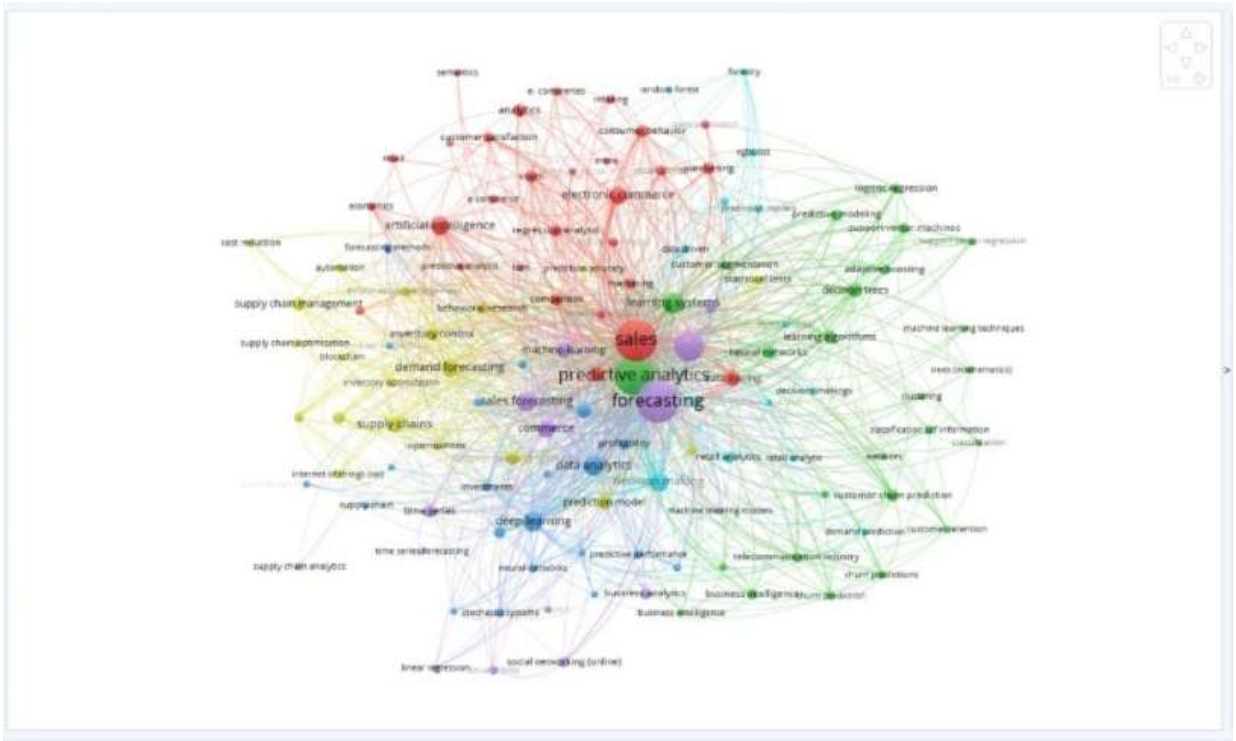


Figure 10. Keyword co-occurrence network (1)

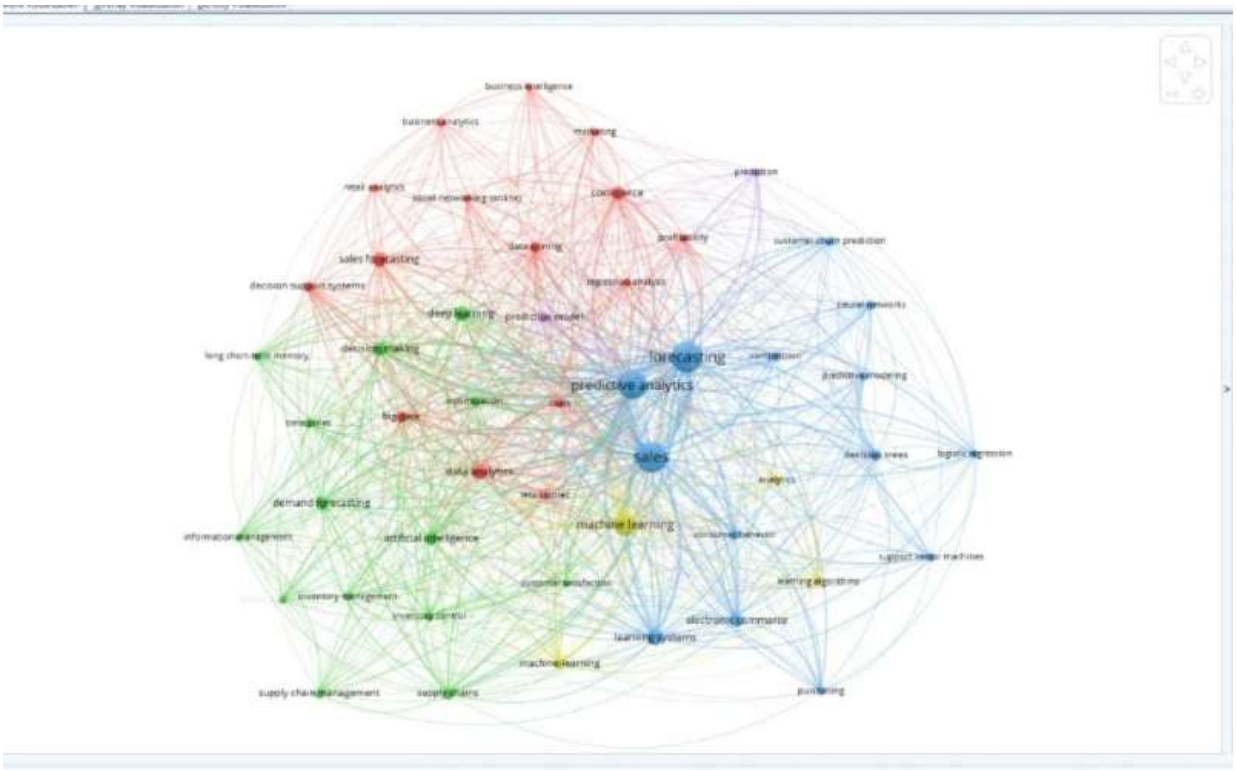


Figure 11. Keyword co-occurrence network (2)

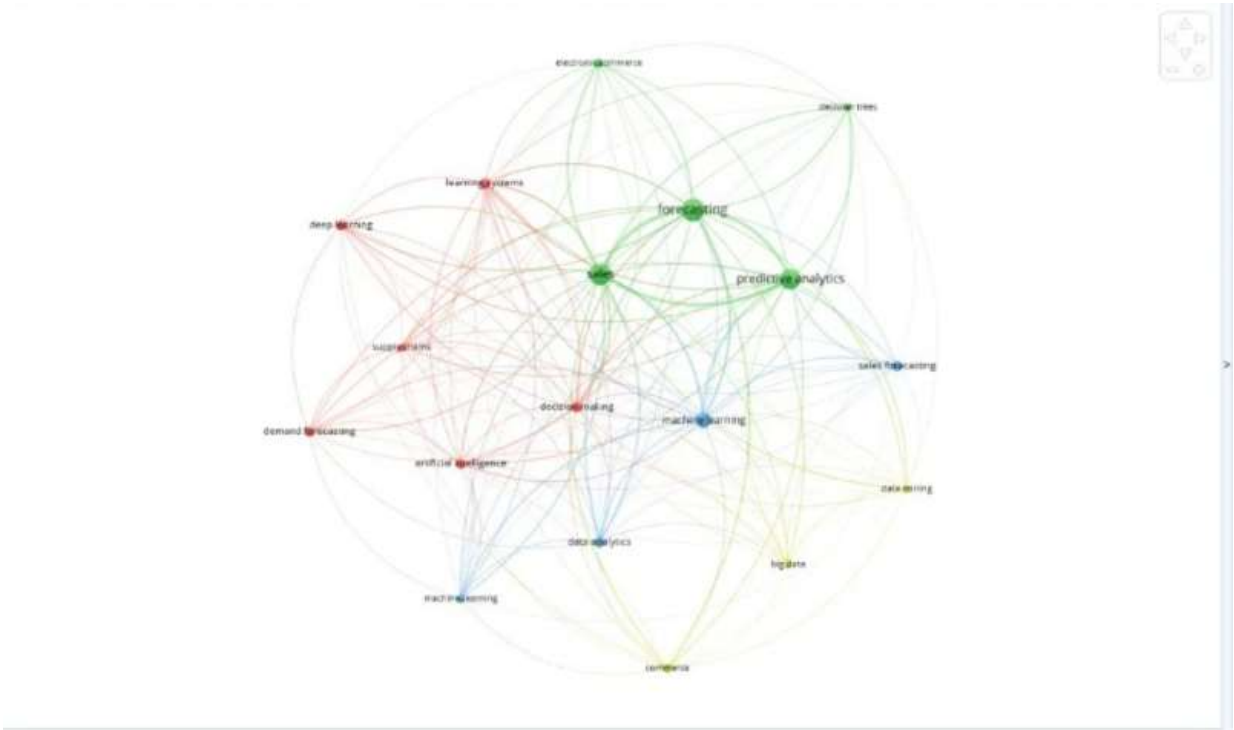


Figure 12. Keyword co-occurrence network (3)

Cluster 1: Commercial and marketing applications. This group focuses on how predictive analytics is used in marketing and e-commerce. It includes terms such as "sales", "electronic commerce", "regression analysis", "retail" and "consumer behavior". Many of these studies look at how customers interact with digital storefronts. Wu, Xu and Bach (2023) showed how companies can use Google Trends search data to predict Hass avocado sales across regions of the US. In the fashion industry, Koren, Perlman and Shnaiderman (2026) found that Facebook likes, comments and shares predict demand for substitute products such as sneakers better than past sales alone. Going further into consumer behaviour, Albuquerque et al. (2026) explored "neuroforecasting", using fMRI brain-scan data to predict whether store managers and consumers would adopt new packaged goods. This shows how modern marketers use alternative behavioural data to anticipate what consumers will buy.

Cluster 2: Advanced algorithmic methodologies. This cluster covers the technical side, connecting "machine learning" with algorithms such as "decision trees", "support vector machines", "random forest" and "adaptive boosting". It reflects a shift from basic statistics to advanced ML for better prediction accuracy. Khani et al. (2026) used LightGBM to analyse over 840,000 sales transactions from an FMCG (fast-moving consumer goods) retail chain in Iran, and found that discount percentage, price and store location were the biggest drivers of demand. In the global video game industry, Abdolazimi et al. (2026) used hybrid models such as XGBoost to forecast sales from critic

evaluations, user ratings and online search intensity. These tools are changing how companies plan product launches.

Cluster 3: Strategic data utilisation and big data. This group examines keywords such as "predictive analytics", "decision making", "big data" and "business analytics". It links commercial strategy with raw data and bridges the gap between them. According to this research, firms can use big data to optimise profits and manage inventory without overspending. In supply chain management, Pathak, Yadav and Singh (2026) designed a big-data framework using Apache Hadoop and Tableau to give supply chains real-time "procurement visibility". By combining past sales with live stock feeds, the system triggers reorders when stock gets low, which reduces empty shelves and raises customer satisfaction. Baumann et al. (2018) showed how firms can use anonymous website clickstreams to estimate the likelihood that an online user will make a purchase.

Cluster 4: Logistics and supply chain operations. The fourth cluster is rooted in operations management, focusing on "supply chains", "inventory control", "demand forecasting" and "supply chain management". It deals with the physical side of business, making sure sales predictions match the actual flow of inventory in warehouses. Arvind et al. (2025) studied "intelligent warehousing" and showed that combining ML with IoT (Internet of Things) devices such as smart shelves and RFID sensors can cut order fulfilment times by over 70% and reduce carrying costs. Liu et al. (2025) addressed stockouts by analysing over 1.6 million SKUs (stock keeping units) for a retailer, finding that combining current inventory levels with short-term demand forecasts is the best way to prevent empty shelves. Xia et al. (2026) examined how ML can manage end-to-end supply chain uncertainty and help companies avoid backorders even when global disruptions occur.

Cluster 5: Deep learning and sequential forecasting. This cluster, which uses deep learning and neural networks for time-series forecasting, is the most advanced frontier of forecasting. It includes neural networks used for sequential data that standard statistical models cannot handle. For example, an LSTM (long short-term memory) model has successfully predicted insurance sales (Wang, 2020). Manoj, Baby and Devaraj (2025) applied deep recurrent neural networks (RNN) and LSTM models to predict twelve months of future sales for a restaurant chain in the Middle East. The uses are not limited to retail: Alatawneh and Torok (2024) applied predictive modelling to forecast the adoption of battery-electric and autonomous vehicles in Europe. Such models help businesses automate processes to reduce food waste from expiry, mispricing of assets and stockouts of popular items.

Cluster 6: Customer classification and churn prediction. The final cluster focuses on keeping the customers a business already has. It highlights keywords such as "customer churn prediction", "classification" and "clustering". Keeping an existing customer is usually cheaper than finding a new one. Studies here combine archival data with unstructured interactions to predict whether a customer is about to leave. Almuqren, Alrayes and Cristea (2021) used Arabic Twitter mining to predict customer churn in Saudi Arabian telecom companies in real time. Alboukaey, Joukhadar and Ghneim (2020) showed that a customer's daily dynamic behaviour predicts churn more accurately than monthly behaviour, allowing mobile operators to intervene before the customer leaves. Celsi et al. (2021) used ML to predict when customers would reopen technical support tickets on 5G fibre-optic networks, so providers could fix issues proactively. By clustering customers on behaviour, businesses can make personalised, data-driven operational decisions that save money.

6. RESEARCH GAPS AND FUTURE RESEARCH AGENDA

1. Lack of integrated forecasting–marketing frameworks. Most work addresses sales or demand forecasting and marketing prediction separately. There is little work linking forecasting results to their influence on marketing decisions such as pricing, promotion, customer targeting, inventory management and budgeting. *Future research agenda:* create an integrated decision support framework that covers demand forecasting, customer behaviour prediction, marketing strategy and operational decision making.

2. Overemphasis on prediction accuracy. Many recent papers compare ML and deep learning methods using measures such as RMSE, MAE, MAPE and accuracy. High predictive power does not guarantee appropriate business decisions or profitability. *Future research agenda:* evaluate predictive models by business results such as profit, ROI, CLV, reduced inventory levels, campaign success and marketing effectiveness.

3. Limited explainability of AI models. Recent work is mostly based on deep learning, transformers, neural networks and ensembles, and most of these models are black boxes. *Future research agenda:* explore applications of explainable AI (XAI) in sales forecasting and predictive marketing.

4. Insufficient causal analysis. Current literature predicts future sales or customer behaviour from past data. Prediction, however, does not show whether a sales increase was caused by marketing actions such as discounts or promotion campaigns. *Future research agenda:* apply ML to causal inference and experimental design to understand the effects of marketing on sales and customer behaviour.

5. Limited research on real-time and dynamic forecasting. Few papers go beyond historical sales data, while modern markets are affected by fast-changing variables such as social media trends, online consumer feedback, competitors' decisions and economic fluctuations. *Future research agenda:* build adaptive forecasting models based on real-time streaming data from social media, Google Trends, e-commerce websites, reviews and other external sources.

6. Limited cross-industry generalisability. Most work considers a single industry, such as retail, e-commerce, pharmaceuticals, fashion, banking, agriculture or energy, so there is no evidence that a model built for one industry can be used effectively in another. *Future research agenda:* carry out comparative studies across industries and countries to see which forecasting and predictive marketing models generalise and which must be tailored.

7. Underrepresentation of SMEs and developing economies. Although some studies consider e-commerce and developing countries, most recent work presupposes large amounts of quality data and advanced technology. *Future research agenda:* develop low-cost, scalable AI models designed for SMEs and for companies in developing countries that may lack data.

8. Data quality and bias remain underexplored. Much attention goes to complex algorithms, but few authors consider missing data, imbalanced datasets, customer information bias, synthetic data and poor-quality marketing data. *Future research agenda:* study the effects of data quality on prediction accuracy and design effective mechanisms for data cleaning, bias detection, fairness and uncertainty estimation.

9. Ethical and privacy concerns need more empirical attention. As AI-enabled personalisation and consumer marketing grow, research on consumer concerns about privacy, discrimination, manipulation and the ethics of personal data remains modest compared with other topics. *Future research agenda:* study the impact of ethical AI, privacy, consumer trust and regulatory compliance on the efficacy and acceptability of predictive marketing systems.

10. Limited human–AI collaboration research. Most papers treat AI as a substitute for conventional forecasting methods or judgement, yet early forecasting literature notes the importance of combining statistical and judgemental methods. *Future research agenda:* study human-in-the-loop forecasting systems that combine AI with managerial judgement, and find out when human judgement adds or subtracts value.

7. DISCUSSION AND IMPLICATIONS

Findings

The clearest pattern is rapid expansion led by method. Of the 315 documents in the corpus, 260 (83%) were published since 2020, and the 255-document corpus has been growing by around 35.91% a year, with 54 articles published in 2025. The 2019–2020 increase (+27 publications) coincides with the disruption of retail and supply chains during the pandemic (Popescu et al., 2025), but this reading cannot be substantiated by bibliometric analysis. Collaboration has also increased, with 816 authors (3.4 authors per paper on average) and 25.88% of papers internationally co-authored. The six thematic clusters, from marketing and e-commerce to algorithmic methods, big data, logistics, deep learning for sequential data and customer churn, are united by a shared vocabulary of technique. Machine learning, predictive analytics and deep learning are the most salient terms, while inventory, optimisation and decision support are less salient: inventory management appears as an author keyword for ten records and decision support systems for four. Most of the field's development has focused on prediction, and far less on what is done with the prediction.

The methodological evidence supports no simple ranking of methods. Causal models remain the reference point in retail (Fildes, Ma and Kolassa, 2022). For intermittent demand, tree-based models performed better (Hobor et al., 2026), while deep and hybrid models were preferred for sequential demand (Punia, Singh and Madaan, 2020; Lingkon, Hossain and Chakrabortty, 2026). Reported R^2 values range from 0.536 (Khani et al., 2026) to 0.999895 (Manoj, Baby and Devaraj, 2025). These numbers must not be read as proof that one method is superior, as they depend on the datasets and validation methods used. External data sources show the same context dependence: social-network activity improved fashion demand prediction (Koren, Perlman and Shnaiderman, 2026), while Google Trends helped for conventional but not organic avocados (Wu, Xu and Bach, 2023).

The major studies show how the field has developed. Boone et al. (2019) and Fildes, Ma and Kolassa (2022) formalised forecasting as an input to supply chain and retail planning, and the latter warned against jumping to conclusions about machine learning. Ferreira, Lee and Simchi-Levi (2016), the second most cited work in the corpus with 415 citations, argued early that demand forecasts could be used to optimise prices. Ahaggach, Abrouk and Lebon (2024) documented the transition to ML and DL, and Bohanec, Kljajić Borštnar and Robnik-Šikonja (2017) stressed the need to explain model output to decision makers. More recent studies have broadened the data and settings (Khani et al., 2026; Koren, Perlman and Shnaiderman, 2026) and turned to the decision itself: Wahid et al. (2026) on reorder points, Karami et al. (2026) on inventory control and Zizi, Chafi and El Hammoumi (2026) on multi-objective optimisation. These integrated studies are a minority, and the keyword analysis places them at the periphery of the field.

The central point is that a good forecast is valuable not because of its accuracy but because a bad forecast cannot support a good decision or create business value. RMSE, MAE, MAPE and R^2 measure how close a forecast is to the outcome, but they do not capture the cost of error, and these costs are often asymmetric. An understocked product loses sales, while an overstocked product ties up capital and may also lose sales. Wahid et al. (2026) show the result: dynamic reorder points cut stockouts but increased inventories, which an error measure alone would not have revealed. Branda, Marozzo and Talia (2020) reported a 6% increase in tickets sold and a 9% increase in revenue from purchase-prediction rules and dynamic pricing. Kuhlmann and Pauly (2023) and Hajek and Abedin (2020) argue, respectively, that overstocking and shortage costs, or expected profit, are the appropriate benchmarks for forecasts. The distinction is between predictive accuracy and decision value, and far more literature quantifies the former than the latter. It is therefore more defensible to say that accuracy is required but not sufficient, and that forecasts should also be assessed on profitability, return on investment, inventory, stockouts, service and customer outcomes.

Implications

For managers, the value of a forecasting system should be judged by the decisions it enables. An assessment should consider not only error but also inventory, service and margin, since a model with slightly higher error may be preferable if it reduces stockouts at an acceptable inventory cost. Forecasts and other marketing predictions are best developed together with the decisions they support, rather than as stand-alone analytical outputs, because the gap analysis revealed little connection between forecasting and marketing prediction. Evidence on external data such as search trends or social media is mixed, so each product and market should be tested before adoption. Finally, the use of more sophisticated AI depends partly on whether planners understand and trust the models, which makes explainability a practical issue as well as a research one.

For researchers, the study shifts attention from sales forecasting as a statistical exercise to forecasting as a component of OR models, and from pure prediction to decision optimisation, a shift that is not evenly distributed across the field. It highlights the need for decision-oriented evaluation, common benchmarks and integrated frameworks, and identifies opportunities to work across forecasting, optimisation and marketing. There are also social implications, which should be expressed carefully. Individual studies in the corpus link better forecasting with fewer empty shelves, less waste and more efficient use of resources, but this is shown for specific applications and not by the corpus as a whole. The more directly supported concerns are privacy, fairness, consumer trust and the quality of the data used for personalised prediction, which the research agenda found to be thinly studied. These point to the need for policy and regulation, responsible AI practice, transparency in how predictions are generated, and careful handling of consumer data. This study does not provide grounds for any legal claims.

8. CONCLUSION AND LIMITATIONS

This study aimed to determine the extent to which sales forecasting research has been linked to OR decision making, and the areas in which that link has not been strong. Four tasks followed: mapping the field bibliometrically, synthesising the

forecasting methods used, investigating how forecasts feed into OR decision models, and outlining missing areas for future research. The evidence comes from a Scopus search with a 315-document English-language export, a literature mapping, and a bibliometric analysis of a further 255 documents published from 2012 to 2025. The first, second and fourth tasks were well accomplished: the two analyses described the growth, structure and methods of the field consistently, and the gaps are well supported. The link between forecasting and OR can be traced and a few integrated studies were found, but the literature review used abstracts and keywords rather than full texts. The evidence therefore shows areas where proof of decision value is low, and it does not measure the impact that better forecasts have on decisions.

The field has moved beyond the question of how accurate a sales forecast is. The next question is what impact forecasts have on decisions about inventory, pricing, assortment and resources, and what those decisions deliver in profitability, service and customer outcomes. Answering it requires the tools of OR, namely optimisation and decision models, together with managerial judgement and responsible use of the data on which forecasts rely. A forecast is only as good as the decisions it helps to improve.

Several limitations apply. The analysis is based on one database (Scopus), on English-language articles and reviews in journals, and on bibliographic metadata, so relevant studies outside these parameters are missing. Only titles, abstracts and keywords were examined in the literature review, and full texts were not checked. Keyword-based analysis is sensitive to thresholds and spellings, and some records in the corpus, such as electricity load forecasting, churn or cryptocurrency forecasting, are only loosely related to sales forecasting. The figures of 316, 315 and 255 documents come from different analytical stages, and the 2026 data cover a partial year. Bibliometric analysis can describe patterns but cannot establish causal relationships, and most studies focus on specific industries, so their findings may apply only partially elsewhere.

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