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Comprehensive Framework for Optimizing Demand Forecasting Implementation: A Bibliometric Analysis

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ABSTRACT

Objective: *Geopolitical uncertainty, supply chain disruptions, and dynamic market conditions underscore the critical role of demand forecasting in modern business strategy. The results of accurate demand forecasting enable organizations to anticipate customer demand, perform optimal inventory management, improve supply chain efficiency, and make strategic decisions based on data. Forecasting models have currently experienced quite rapid development along with the integration of technologies such as machine learning and deep learning, which are able to overcome the limitations of traditional forecasting models in processing complex and nonlinear data. Integration of technology into demand forecasting models has been proven to improve the accuracy and adaptability of forecasting models, but there are still challenges in its implementation related to data quality, selection of appropriate forecasting models, and availability of computing resources. The purpose of this study is to identify research trends, literature gaps, and global collaborations in demand forecasting model development and to formulate a comprehensive framework to optimize demand forecasting implementation.* ***Method:*** *This study uses a mixed method by conducting bibliometric analysis on 502 documents and content analysis on 144 relevant documents from the Scopus database.* ***Results:*** *The results of this study indicate an increasing trend in the use of hybrid forecasting models that combine traditional forecasting models with machine learning or deep learning.* ***Novelty:*** *This study also proposes a comprehensive framework that can be used to optimize the implementation of demand forecasting with the aim of improving forecast accuracy and strengthening the organization's ability to anticipate a dynamic and uncertain global market environment.*

INTRODUCTION

The current global economic uncertainty is influenced by various interrelated factors. Geopolitical conflicts are among the main factors disrupting international trade and market stability. The global supply chain, which has remained unstable since the pandemic, has impacted the availability and prices of goods. This situation is exacerbated by fluctuations in energy prices that affect production and transportation costs. Additionally, inflation occurring in various countries results in a decrease in people's purchasing power. In facing economic instability, forecasting becomes a very important tool for predicting demand and managing resources effectively [1]. Additionally, forecasting can also be used as a tool to mitigate the impact of fluctuating market demand through a data-driven approach [2]. This situation makes forecasting increasingly recognized as one of the important components in business strategy planning to support better decision-making in facing risks and opportunities.

Forecasting is a systematic process to project or predict future events, values, or trends based on historical data and information related to the subject being forecasted using structured analytical techniques. The application of forecasting aims to reduce the risk of uncertainty caused by internal and external factors and provide guidance for decision-making in formulating strategic plans. Armstrong (2001) defines forecasting as a process that integrates quantitative approaches through statistical analysis with qualitative approaches such as expert judgment to produce accurate and reliable predictions [3]. Meanwhile, Hyndman and Athanasopoulos (2018) define forecasting as an analytical method used to identify patterns and their relationships within data to predict future conditions or outcomes [4].

The use of traditional forecasting models dominated in the early stages of their development. Traditional models focus on analyzing past data to recognize data patterns as a basis for predicting future trends or conditions. Traditional forecasting models such as linear regression, time series analysis, exponential smoothing, and ARIMA (Autoregressive Integrated Moving Average) have become the most popular and frequently used models. Traditional forecasting models are designed for data that exhibit stable patterns and linear structures. An example is the ARIMA model, which combines three main elements in forecasting: autoregression, data integration, and moving averages, making it a powerful tool for projecting seasonal and non-seasonal trends in various applications across different industrial sectors [5]. The advantage of traditional forecasting models is their high interpretability. Forecasting models with high interpretability facilitate a basic understanding of the generated predictions, thereby increasing confidence in the forecasting results. Additionally, high interpretability allows for the identification of anomalies or errors in the forecasting model through the explanation of different components. The simple structure of traditional forecasting models also makes them more transparent [4]. However, with the increasing complexity of data, traditional models have begun to show various limitations, especially in processing data with nonlinear patterns and high levels of uncertainty. Traditional models often struggle to analyze or identify modern data that has dynamic and unstructured characteristics. [6]. Although traditional forecasting models serve as the initial foundation, the demand for more flexible and sophisticated forecasting models has driven the development of new forecasting models that are more adaptive to process increasingly complex data characteristics.

In line with the rapid development of information technology and the increasing availability of big data, machine learning has become an important component in the development of forecasting. The use of machine learning techniques such as Neural Networks, Random Forest, and Support Vector Machines (SVM) in forecasting allows for a more in-depth and precise data analysis process while providing the capability to process data with complex characteristics and non-linear patterns, which are difficult to identify by traditional forecasting models [7]. Machine learning offers greater flexibility in capturing dynamic data patterns and generating predictions with higher accuracy compared to traditional models, especially in scenarios involving multivariate data or data with high noise levels [8]. In recent years, there has been significant development with the emergence of hybrid models in forecasting. The development of hybrid models in forecasting aims to improve the accuracy and reliability of forecasts through the combination of various forecasting models and to overcome the limitations of single methods, thereby capturing more complex and diverse data patterns [9]. Hybrid models integrate several forecasting models to leverage the strengths and address the weaknesses of each individual forecasting model. This combination allows for more accurate results because each model provides unique advantages that other models do not possess [10]. Hybrid models in forecasting enhance robustness by reducing the risk of overfitting on the data and improving generalization to new data, as well as providing flexibility that allows for adjustments to various types of data and domains. However, the complexity level of hybrid models requires greater computational resources and makes the forecasting results more difficult to interpret. In choosing the right hybrid forecasting model, a deep understanding of data characteristics is required, as well as accurate calibration techniques to maintain the consistency of forecasting results [11]. Nevertheless, hybrid models remain the primary choice in producing more consistent and accurate predictions across various sectors.

The implementation of forecasting plays an important role in various industrial sectors, providing data-driven insights that can support strategic decision-making. However, there are several challenges that must be faced to achieve optimal forecasting results. Data is the core element of every forecasting model, where the availability of adequate, high-quality, and representative data is crucial for producing reliable predictions. The challenge often faced in the forecasting process is the presence of incomplete or missing data. Conditions like this are caused by technical constraints during the data collection process or privacy policies that limit access to certain information. Complex computational techniques are required to process missing data, thereby increasing the potential uncertainty in the forecasting results. The differences in characteristics and complexity of data originating from various sources with varying formats and non-uniform scales pose unique challenges in the process of data integration and normalization [12]. Forecast accuracy is one of the most critical aspects in the implementation of forecasting models. This accuracy heavily depends on the quality of the data, the approach, and the model's ability to capture complex data patterns. The data used is often incomplete and contains noise or bias. This can cause the forecasting model to produce suboptimal results. Poor data quality and inadequate representation can be major obstacles in the implementation of forecasting [13]. Additionally, the challenges of overfitting and underfitting also frequently occur. Overfitting happens when the forecasting model is very accurate during the model training process but fails to generalize to new data, while underfitting occurs when the forecasting model is not complex enough to identify patterns in the data. Finding the right balance in model and parameter selection is a challenge that requires special attention [14]. On the other hand, many forecasting models rely on the assumption that past patterns will continue into the future, which is not always the case, especially in dynamic environments such as the stock market or the technology industry. Dependence on historical patterns can limit the accuracy of forecasts in unstable conditions [8].

In line with the development of forecasting models, research in this field has shown significant progress. Although many studies have been conducted to examine the implementation of forecasting from various perspectives, most of the research has focused on specific cases, such as the implementation of certain forecasting models in specific sectors or the measurement of forecasting model performance. Previous research also tends to have a limited scope of study and has yet to propose a comprehensive framework for optimizing demand forecasting implementation. Furthermore, the limited use of bibliometric analysis to map research trends, global collaboration patterns, and gaps in the literature has resulted in a less comprehensive understanding of the direction of development in this field. A summary of previous research related to forecasting models is presented in Table 1.

Table 1. Previous Research.

Authors	Research Objective	Research Results
Sina, L.B.; Secco, C.A.; Blazevic, M.; Nazemi, K. [15]	Reviewing hybrid forecasting models that combine traditional models and neural networks on time-series data, with a focus on improving prediction accuracy compared with single forecasting models.	Hybrid forecasting models show a higher level of accuracy when assessed using the RMSE and MAPE indicators and have significant potential to be applied in visual analytics systems to support the decision-making process. Various cross-disciplinary studies, ranging from economics to the environment and health, consistently reveal the advantages of this approach, thereby further emphasizing its relevance in the development of data-driven systems.
Jaimin Shah; Darsh Vaidya; Manan Shah [16]	Reviewing hybrid forecasting models in the context of stock market prediction that emphasize the integration of various approaches, such as ARIMA, LSTM, CNN, and other hybrid model combinations, to improve the level of accuracy and efficiency in forecasting stock price movements.	Hybrid forecasting models show higher accuracy in stock price forecasting compared with single models, with CNN-LSTM being one of the most effective models for predicting short-term and long-term stock trends. The analysis also reveals the potential of this model in trading applications and data-driven decision-making.
Aamer, A.; Eka Yani, L.; Alan Priyatna, I. [17]	Reviewing the application of Machine Learning forecasting models to predict supply chain demand. The focus of this research includes the algorithms	The findings in this study show that Neural Networks (27%), ANN (22%), SVR (18%), and SVM (10%) are the most widely used forecasting models, and

	used in forecasting, current forecasting trends, and the existing gaps in research in the forecasting field.	most studies are conducted in the industrial sector (65%). This study also shows significant potential to improve forecasting accuracy by using machine learning to support supply chain efficiency.
Palomero, L.; García, V.; Sánchez, J.S. [18]	Reviewing fuzzy-based forecasting models on time-series data, with a focus on their development and application during the 2017–2021 period, as well as evaluating their contributions, trends, and potential applications in various fields.	The results of the bibliometric analysis show that fuzzy models are superior in handling data uncertainty. Hybrid forecasting models combining fuzzy models with other approaches have been proven to improve prediction accuracy. This study also maps global publications related to fuzzy models that can be used as a basis for developing more innovative forecasting models.
Jaramillo, M.; Pavón, W.; Jaramillo, L. [19]	This study evaluates the contributions and limitations of various currently available forecasting models, including Deep Learning models such as LSTM. The evaluation process was conducted using a bibliometric approach in research on electrical energy consumption to support the development of sustainable energy systems.	Modeling energy consumption dynamics has significant potential for forecasting models such as LSTM and Deep Learning. However, these techniques require substantial computing power and high-quality data. This study calls for collaboration to advance energy forecasting techniques while highlighting important barriers such as data limitations and technical complexity.
Hong N. Dao; Wang Chuan Yuan; Aoshi Suzuki; Hitomi Sudo; Li Ye; Debopriyo Roy [20]	Conducting a bibliometric analysis of the application of AI in stock market forecasting, with a focus on Deep Learning models that include both hybrid forecasting models and single forecasting models. This study also assesses the advantages and contributions of these forecasting models in improving stock market forecasting accuracy.	Deep Learning-based forecasting models, such as RNN, LSTM, CNN, and Transformer, have higher levels of accuracy than traditional forecasting models for stock market prediction. Hybrid models that combine textual data with numerical data have also been proven to improve forecasting accuracy. This study also projects further research development related to AI integration for stock market forecasting.

Based on the description of the background and previous research, it can be concluded that bibliometric analysis is still rarely used to evaluate research trends, identify literature gaps, and map global collaboration in the development of demand forecasting models. Although there have been many studies examining the implementation of forecasting models, including hybrid models, machine learning, and deep learning, their application across various sectors has not yet been integrated and remains fragmented. Until now, a comprehensive framework that can serve as a guide for the systematic implementation of forecasting across various sectors is still not available. The challenges in implementing forecasting include the diverse characteristics of data and the complexity of forecasting models that have not been well-mapped, making it difficult for practitioners to effectively address these challenges. The objective of this research is to identify and map the main challenges in the implementation of forecasting and to offer strategic solutions to improve the efficiency and accuracy of forecasting. These efforts are realized through the development of a comprehensive framework for demand forecasting implementation. Through this research, it is expected to provide practical guidelines for the implementation of demand forecasting so that the forecasting results can be optimal and applicable in various sectors.

RESEARCH METHOD

This research uses a mixed-methods approach with bibliometric analysis and content analysis. Bibliometric analysis is a quantitative method used to study the structure of knowledge and the development of research fields based on the analysis of related publications [21]. Bibliometric analysis is used to identify research trends, research gaps, and global collaborations in the development of demand forecasting models. On the other hand, content analysis is a qualitative method used to conduct in-depth analysis of the content of written or printed information [22]. Content analysis is used to formulate a comprehensive framework to optimize the implementation of demand forecasting. The stages that the researchers will undertake in conducting bibliometric analysis and content analysis in this study can be outlined as follows:

1. Collecting data from the Scopus database and defining search terms.
2. Conducting data cleaning and harmonization processes, then processing the data using biblioMagika®, biblioMagika@split, and Open Refine.
3. Creating data visualizations using bibliomagika®, VOSviewer, iimaps, and Biblioshiny.
4. Interpreting the results obtained from the data visualizations.
5. Conducting content analysis on documents that meet the research criteria.

In this study, data were obtained from the Scopus database. The Scopus database was chosen because it has a wide coverage, including journal publications, conference proceedings, and books from various disciplines, making it one of the largest academic databases in the world. Additionally, the Scopus database is known for its high credibility as it only includes publications that have undergone a rigorous selection process, ensuring the quality and reliability of the data used in this research [23]. Scopus is also equipped with various comprehensive bibliometric indicators, such as citation counts, h-index, and collaboration analysis. These indicators are very useful for supporting the implementation of in-depth bibliometric analysis. In addition, Scopus's compatibility with analytical software such as VOSviewer facilitates the data processing, while its advanced search features allow for filtering publications based on keywords, publication years, or document types. [24]. With these advantages, Scopus becomes an appropriate data source for comprehensively and reliably projecting research trends.

The combination of keywords used is: TITLE ("Demand Forecasting" OR "Demand Prediction") AND TITLE ("Machine Learning" OR "Deep Learning" OR "Traditional forecasting" OR "Traditional Prediction" OR "Hybrid Ensemble" OR "Hybrid forecasting" OR "Hybrid") to identify all target publications. The researchers collected publications within the time frame from 2015 to 2024. This search resulted in a total of 502 documents. The data obtained from the Scopus database is then downloaded and stored in the Scopus dataset (scopus export refine value.csv, scopus.csv). The dataset will subsequently go through the stages of data cleaning, data harmonization, and further data processing using Bibliomagika, BiblioMagika@split, and Open Refine [25], [26]. After data cleaning, harmonization, and processing are completed, the next step is to visualize the data using Bibliomagika, VOSviewer, iimaps, and Biblioshiny. The next step is to interpret the visualization results to gain a deeper understanding.

The content analysis process is conducted systematically to ensure that every piece of information processed is valid and supports the achievement of the research objectives. Content analysis is carried out in-depth on data that meets the criteria of relevance and data quality to identify key patterns, indicators, and factors that influence the application of the demand forecasting model. This aims to develop a comprehensive framework that can serve as a guideline for optimizing demand forecasting implementation. The data used is meticulously selected with attention to its relevance to the research context, thereby providing a strong foundation for the development of a comprehensive, accurate, and applicable framework.

The data criteria used in this research include documents with an open access status that allow for unrestricted and flexible access. The type of documents selected is limited to research articles, to ensure a focus on research-based scientific works. Furthermore, only documents written in English are included in the analysis to facilitate generalization and cross-country communication. The source of the documents is limited to journals, which are recognized to have higher credibility and quality compared to other sources. Only documents that have reached the final publication stage are included to ensure that the data used is fully mature and has undergone the editing and peer review process. Additionally, this research integrates data from various fields and domains to support cross-domain analysis, enabling the identification of relevant patterns and insights across different sectors. With this multidisciplinary scope, this research provides a strong foundation for optimizing demand forecasting implementation in various industrial and academic contexts. The data that meet the criteria in this study amount to 144 documents.

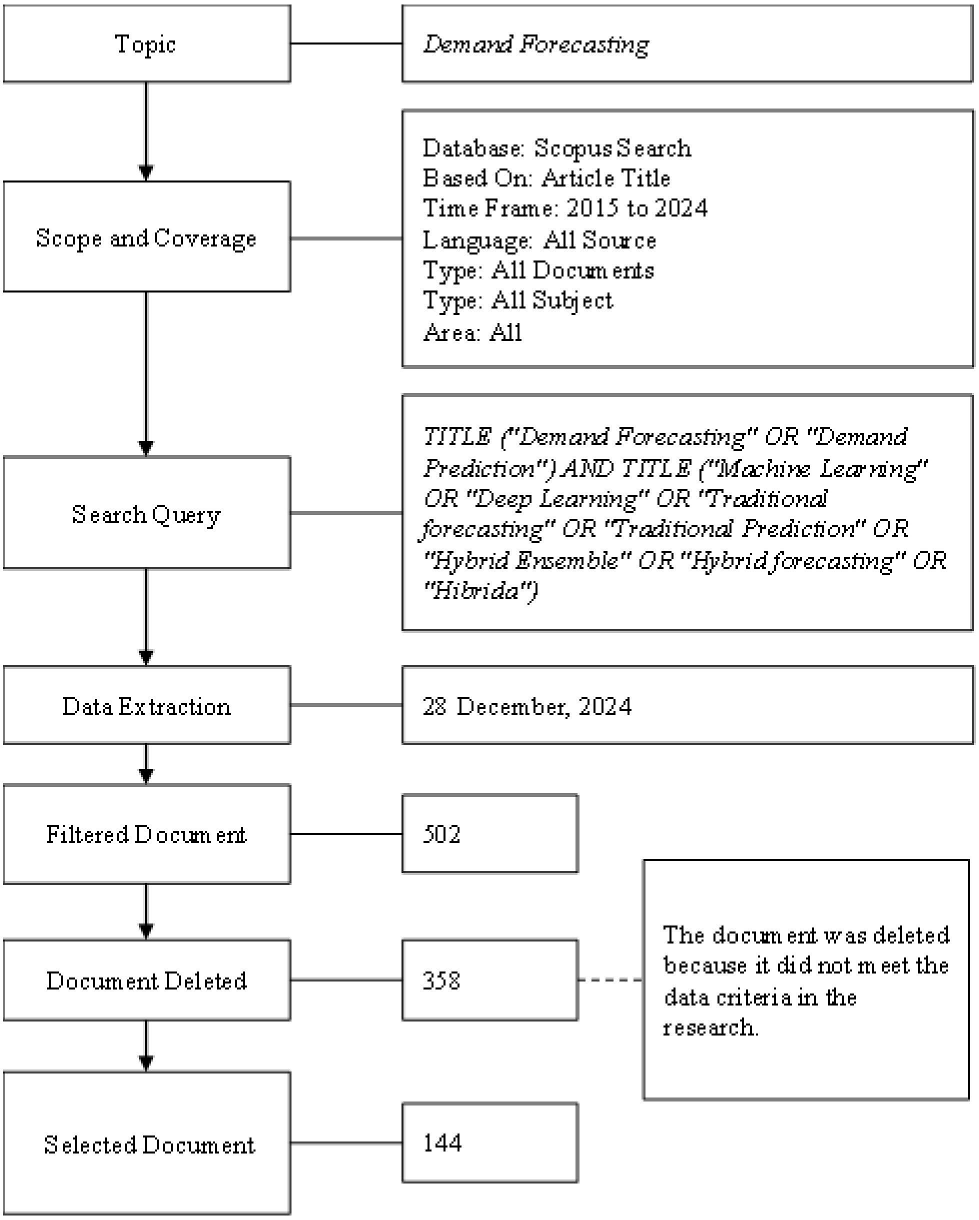

Figure 1. Data Filtering and Screening Process.

RESULTS AND DISCUSSION

To obtain an overview as well as deeper insights into research in the field of demand forecasting, several general statistics from data that meet the search criteria will be evaluated, reviewed, and analyzed based on the following aspects:

1. Document profiles, including citation metrics and research fields,
2. Research productivity over time, to identify trends in research development,
3. Publications by researchers to identify the most contributing researchers and the interconnections among researchers,
4. Publications by country to identify the global distribution of research results,
5. Keywords to identify emerging research topics.

Document Profile

Table 2 presents a summary of citation metrics for documents collected up to December 28, 2024, from the Scopus database. These citation metrics were obtained through data processing using biblioMagika® by importing CSV files, which were then displayed in raw citation format.

Table 2. Citation Metrics.

Main Information	Data
Publication Years	2015 - 2024
Total Publications	502
Citation Years	11
Number of Contributing Authors	1887
Number of Cited Documents	375
Total Citations	8.060
Average Citations per Document	16,06
Average Citations per Cited Document	21,49
Average Citations per Year	895,56
Average Citations per Author	4,27
Average Authors per Document	3,76
Total Citations in the h-Core	6.678
h-Index	49
g-Index	75
m-Index	4,455

Source: Processed using biblioMagika®

This study includes publications on demand forecasting over a 10-year period from 2015 to 2024, with a total of 502 documents published. Of the total number of documents, 375 have received citations. The total citations recorded amount to 8,060, with an average of 16.06 citations per document and 21.49 citations for each cited document. The average number of citations per year recorded is 895.56. This figure indicates a relatively consistent annual impact rate. Research in the field of demand forecasting involves a total of 1,887 authors with an average of 4.27 citations per author and 3.76 authors per document. In addition, the citations concentrated in the h-core reached a total of 6,678, contributing to an h-index value of 49. This indicates that 49 documents have each received at least 49 citations. The g-index is recorded at 75, indicating the collective influence of highly cited documents, while the m-index value of 4.455 reflects a high growth rate of impact in this research field. Overall, these findings reflect a high level of productivity and extensive collaborative participation among researchers, as well as a strong scientific impact in the field being studied.

Table 3. Research Fields.

Research Field	Total Publications	Percentage
Engineering	273	54,38%
Computer Science	266	52,99%
Mathematics	126	25,10%
Energy	103	20,52%
Environmental Science	72	14,34%
Decision Sciences	63	12,55%

Social Sciences	60	11,95%
Business, Management, and Accounting	53	10,56%
Physics and Astronomy	44	8,76%
Materials Science	29	5,78%

Source: Processed using biblioMagika®

Next, the publications in this research are categorized based on research fields as presented in Table 3. The fields of Engineering (54.38%) and Computer Science (52.99%) dominate the number of publications in the field of demand forecasting research. Followed by the fields of Mathematics (25.10%), Energy (20.52%), and Environmental Science (14.34%). Other fields, such as Decision Science (12.55%), Social Science (11.95%), and Business, Management, and Accounting (10.56%), also make significant contributions. These findings indicate that the main focus of publications is on the fields of engineering and applied sciences, while other fields play a supporting role with a lower proportion of publications.

Publication Trends

The results of this study show a significant upward trend in the number of publications year by year, as presented in Table 4. In 2015 and 2016, the number of publications was still relatively small, with only 8 documents each year, accounting for approximately 1.59% of the total publications. The number of publications increased in 2017 to 20 documents (3.98%). The growth trend in publications continued and peaked in 2024 with 114 documents, equivalent to 22.71% of the total publications. During the period from 2015 to 2024, a total of 1,887 authors contributed to publications in the field of demand forecasting. As the number of publications increased, the contribution of authors also saw a rise. A total of 431 authors were involved in research in 2024, the highest number compared to previous years. Overall, this increase reflects a rapid growth in research, with the largest contributions occurring in recent years. This indicates an increasing focus on the topic being studied throughout the analysis period.

Table 4. Publications by Year.

Year	TP	%	Cumulative TP	Cumulative %	NCA	NCP	TC	C/P	C/CP
2015	8	1,59%	8	1,59%	27	6	332	41,50	55,33
2016	8	1,59%	16	3,19%	29	8	153	19,13	19,13
2017	20	3,98%	36	7,17%	64	17	546	27,30	32,12
2018	18	3,59%	54	10,76%	66	17	965	53,61	56,76
2019	35	6,97%	89	17,73%	134	32	1252	35,77	39,13
2020	45	8,96%	134	26,69%	178	43	1586	35,24	36,88

2021	63	12,55%	197	39,24%	240	60	1395	22,14	23,25
2022	92	18,33%	289	57,57%	344	84	1165	12,66	13,87
2023	99	19,72%	388	77,29%	374	65	499	5,04	7,68
2024	114	22,71%	502	100,00%	431	43	167	1,46	3,88
Overall Total	502	100,00%			1887	375	8060	16,06	21,49

Note: TP=Total number of publications; NCA=Number of contributing authors; NCP=Number of cited publications; TC=Total Citations; C/P=average citations per publication; C/CP=average citations per cited publication.
Source: Processed using biblioMagika®

Figure 2 shows the graph of the distribution of the number of documents published and the number of citations per year over the period from 2015 to 2024. This graph displays a significant upward trend in the number of publications, with relatively stable growth until it reached a peak of 114 publications in 2024. In contrast, the annual citation trend shows a different pattern, with the number of citations peaking in 2020 at 1,586 citations, despite the number of publications that year being lower than in subsequent years. The graph also shows that published documents still require time to gain recognition and impact other research, as reflected in the number of citations received.

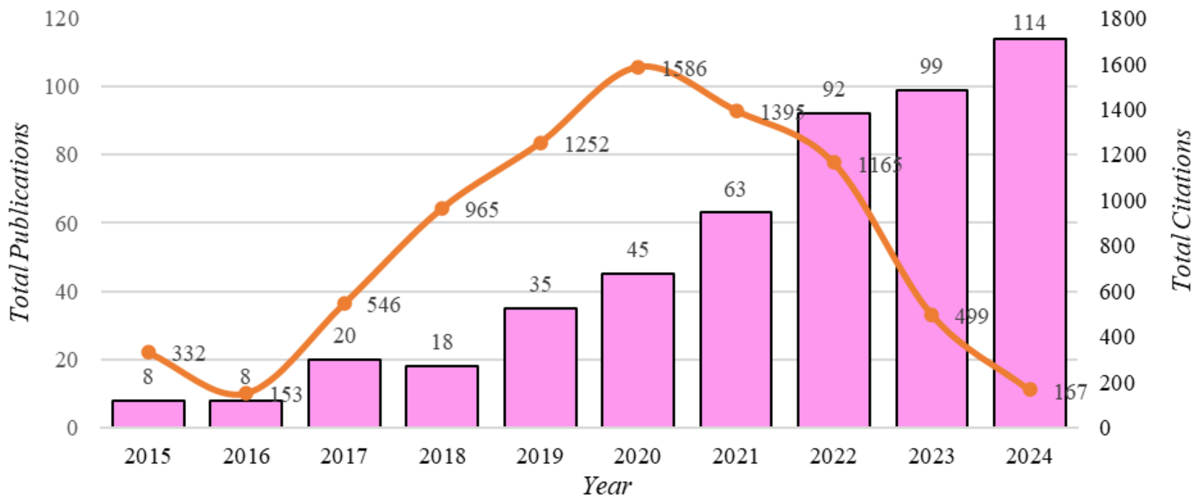

Figure 2. Total Publications and Citations by Year.
Source: Processed using biblioMagika®

Publication Based on Researchers

This research further analyzes the collaboration among authors by conducting a co-authorship analysis using the VOSviewer application. This analysis focuses on influential authors with more than 4 citations, calculated using the fractional counting method. Elements such as color, circle size, text size, and line thickness are used to indicate the strength of relationships between authors. Connected authors, marked with the same color, are usually in the same group. As shown in Figure 4, Ravinesh C. Deo (in red) is one of the central authors and shows close relationships with several authors, such as S. Ali Pourmousavi and Sujan Ghimire. The group in red stands out due to its significant contribution to the collaboration network. Figure 4 also shows that Jan F. Adamowski (in purple) has direct connections with Mukesh K. Tiwari and other authors, but appears as a smaller group.

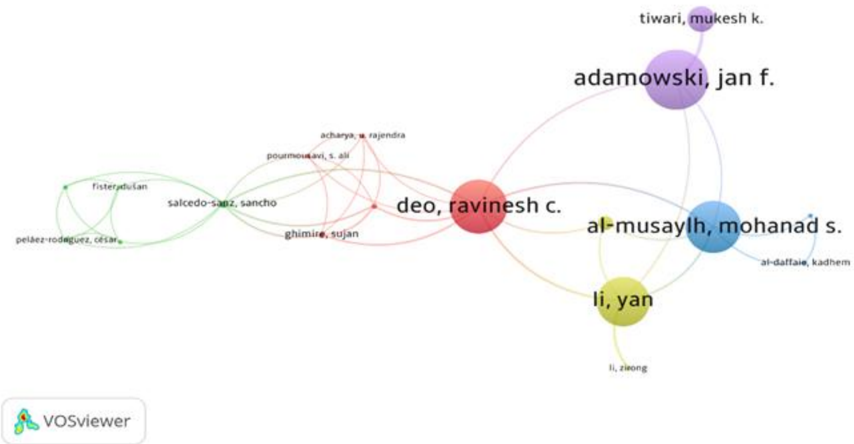

Figure 3. Visualization map of the co-authorship network based on authors with at least four citations (using the fractional counting method).
Source: Processed using VOSviewer.

Publications by Country

Table 5. Top 10 Countries Contributing to Publications.

Country	TP	NCA	NCP	TC	C/P	C/CP	h	g	m
China	141	206	101	2957	20,97	29,28	26	54	2,364
India	72	112	46	929	12,90	20,20	15	30	1,364
United States	29	47	23	653	22,52	28,39	13	25	1,625
Türkiye	22	30	14	309	14,05	22,07	9	17	1,000
Iran	20	25	17	363	18,15	21,35	10	19	1,250
South Korea	20	32	18	367	18,35	20,39	9	19	0,900
Spain	19	23	16	360	18,95	22,50	8	18	0,727
United Kingdom	19	27	14	433	22,79	30,93	10	19	1,111
Canada	17	22	17	508	29,88	29,88	12	17	1,091
Australia	16	19	14	703	43,94	50,21	9	16	1,125

Note: TP=Total number of publications; NCA=Number of contributing authors; NCP=Number of cited publications; TC=Total Citations; C/P=average citations per publication; C/CP=average citations per cited publication; h=h-index; g=g-index.
Source: Processed using biblioMagika®

Table 5 displays the top ten countries contributing to publications related to demand forecasting. China ranks first in the world with the highest number of publications, totaling 141 publications and 2,957 citations. This data shows that China has a significant influence on publications related to demand forecasting. India, with a total of 72 publications, and the United States, with a total of 29 publications, occupy the second and third positions. Australia is the country with the greatest impact based on the average citations per publication, with a score of 43.94, despite having only 16 publications related to demand forecasting. These findings indicate that developed countries have played a significant role in research in the field of demand forecasting compared to developing countries.

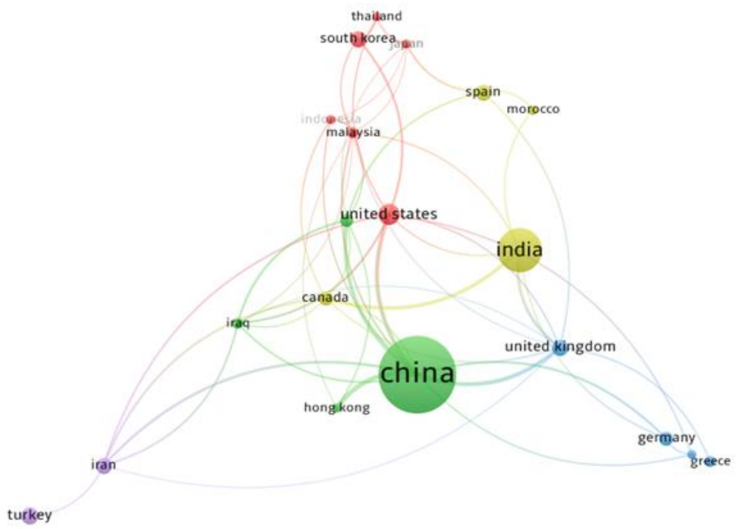

Figure 4. Visualization map of the co-authorship network based on countries with at least ten publications (using the fractional counting method).
Source: Processed using VOSviewer.

Figure 4 displays a visualization of the co-authorship analysis results to map collaboration between countries using the VOSviewer application. This analysis focuses on countries with a minimum of 10 or more publications, with calculations performed using the fractional counting method. The largest circle is held by China, reflecting its significant contribution and influence in the field of demand forecasting research. Other countries like India and the United States play significant roles, evident from their strategic positions with numerous connections to other countries. In the Southeast Asian region, countries like Indonesia, Malaysia, and Thailand form a smaller network, which indicates significant regional collaboration, especially with other Asian countries. These findings illustrate a global collaboration pattern dominated by developed countries, with a supporting role from developing nations. Figure 5 presents the distribution of publications in the field of demand forecasting research worldwide, indexed by the Scopus database, providing an overview of the global geographical distribution.

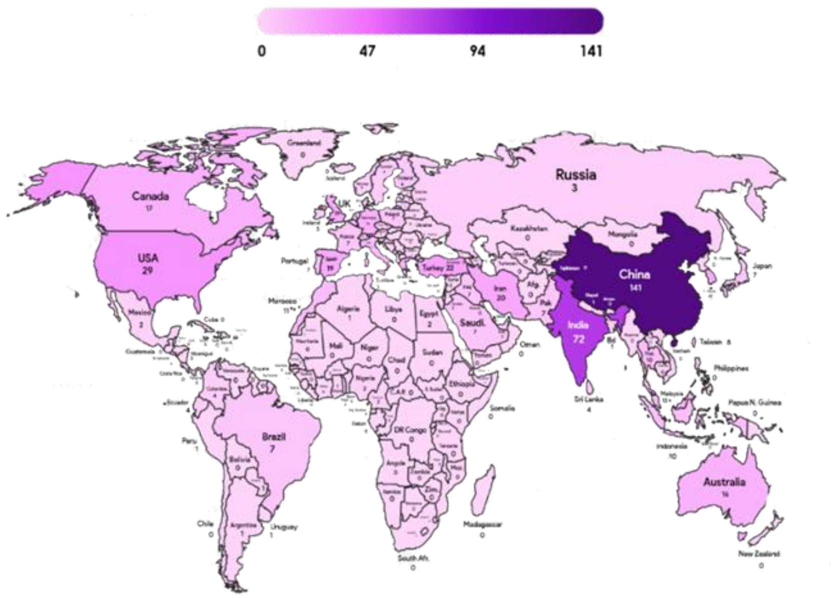

Figure 5. Distribution of Worldwide Demand Forecasting Research Publications Indexed by Scopus.
Source: Processed using iipmaps.com

Keyword Analysis

In this study, the keywords used by the authors are also mapped using the VOSviewer application, as visualized in Figure 6. This visualization uses color, circle size, font size, and line thickness to depict the relationships and strength of the connections between the keywords used by the authors. The results of the keyword analysis used by the authors indicate the presence of four clusters in the research related to demand forecasting. The first cluster is red, the second cluster is green, the third cluster is blue, and the fourth cluster is yellow.

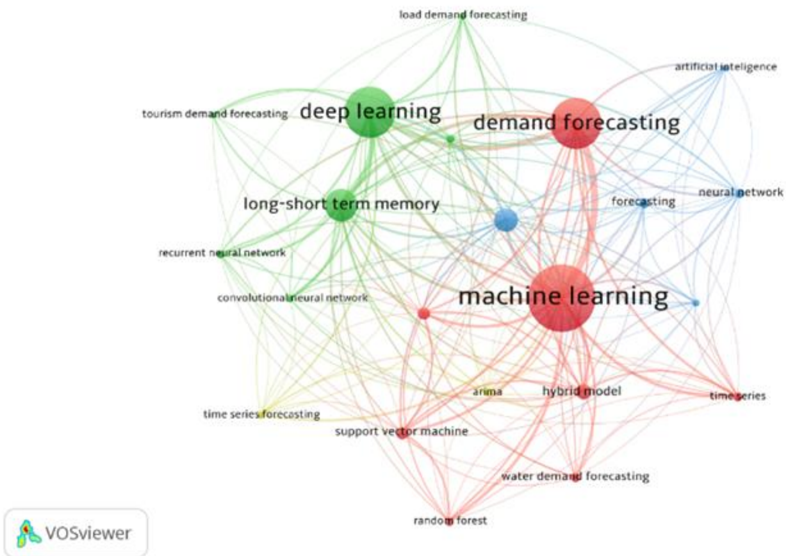

Figure 6. Visualization Map of Author Keyword Network.
Source: Processed using VOSviewer.

The keywords Machine Learning and Deep Learning, which are included in the first cluster colored red, appear to be the main focus of this research, marked by a large circle and numerous connections to other keywords. There are keywords such as Demand Forecasting and Long-Short Term Memory (LSTM) in the second cluster, which is green, indicating a strong connection. This indicates that the keywords in the green cluster are often used in research in the field of demand forecasting. The third cluster, colored in light blue, includes keywords such as Artificial Intelligence. Overall, this visualization shows that the research focus related to demand forecasting lies in the integration of machine learning and deep learning models to improve prediction accuracy across various sectors, with strong connections between subtopics reflecting trends in collaboration and integration. in research.

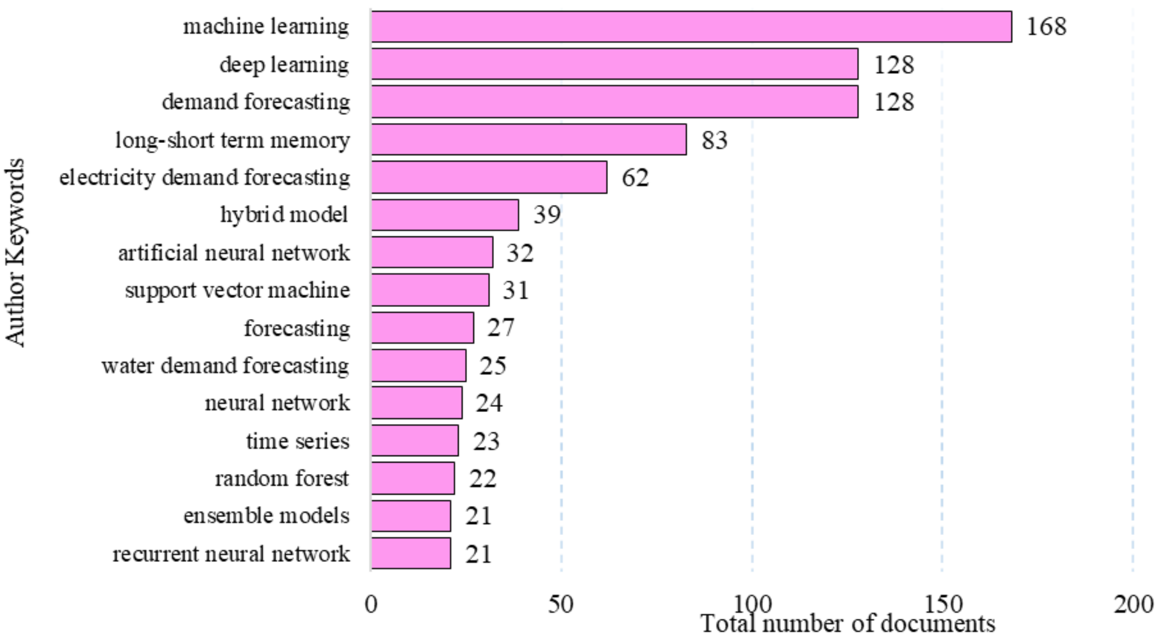

Figure 7. Most Popular Keywords.
Source: Processed using biblioMagika®

Figure 7 presents the most frequently used author keywords in research related to demand forecasting. Machine Learning has become the most dominant keyword with the highest occurrence, namely 168 times, followed by Deep Learning and Demand Forecasting, each appearing 128 times. Other keywords, such as Long-Short Term Memory (LSTM), Artificial Neural Network, and Support Vector Machine, indicate a research focus on the integration of Machine Learning and Deep Learning to improve forecasting accuracy in various domains.

In this study, a thematic map is presented in Figure 8. The thematic map is a visualization tool for analyzing research themes based on two main parameters: development level (density) and relevance (centrality). The goal is to identify established themes, emerging themes, and themes that are declining or becoming less relevant. This map is divided into four quadrants: Motor Themes (core themes that are relevant and developing), Basic Themes (important but less developed core themes), Niche Themes (specific themes with high development but less relevance), and Emerging or Declining Themes (themes that are less developed or starting to be abandoned) [27]. The themes of forecasting, demand forecasting, and machine learning, which are located in the center of the map, serve as central themes that act as a bridge between specific themes and basic themes in research in the field of demand forecasting. Basic Themes, such as electric power utilization, neural networks, and mean square error, which are located in the lower right quadrant, are fundamental themes with high relevance but relatively low development levels. Meanwhile, the themes of forecasting method, water demand, and prediction are positioned as Niche Themes in the upper left quadrant, which depicts specific themes with high development levels but still limited relevance. The lower left quadrant on Emerging or Declining Themes does not display any themes, indicating that there are no clearly emerging or declining themes. Overall, this map provides an overview of the conceptual structure and research focus that are currently being developed related to demand forecasting.

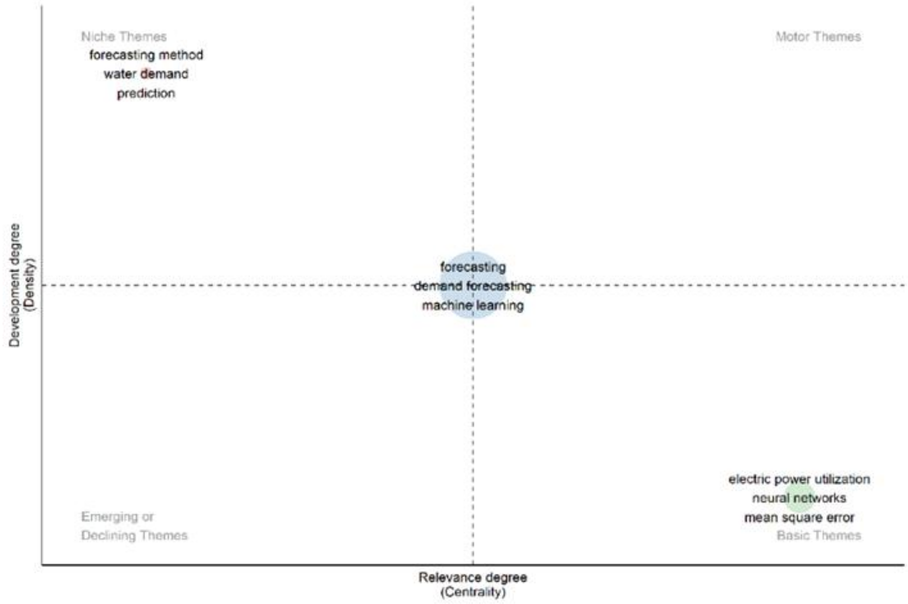

Figure 8. Thematic Map.
Source: Processed using Biblioshiny.

Demand Forecasting Development In the last decade, demand forecasting models have undergone significant development. The need for higher accuracy and efficiency in forecasting models has driven the shift from traditional forecasting models to hybrid forecasting models. Traditional forecasting models play an important role in this development because they are used as a basis for predicting future demand thru the analysis of historical data and relevant factors [28]. However, traditional forecasting models are overly dependent on the quality of historical data, which is often inadequate or incomplete, especially for new products with limited sales history [29]. Moreover, traditional forecasting models have limitations in capturing complex and nonlinear data patterns, which can reduce prediction accuracy in dynamic environments [30]. With the advancement of technology, machine learning offers better capabilities in processing large-scale data and complex patterns compared to traditional forecasting models, as well as providing more adaptive and robust forecasting abilities [31]. Furthermore, the emergence of deep learning further enhances the performance of forecasting models with its ability to capture nonlinear and intricate relationships present in the data [32]. Testing forecasting models on empirical data shows that hybrid models can provide more accurate results compared to traditional forecasting models or single machine learning or deep learning models [33]. Hybrid models are forecasting models that generally integrate traditional models with machine learning and/or deep learning, allowing for the simultaneous identification of short-term and long-term demand trend fluctuations. In the energy sector, the LSTM-CNN hybrid model has proven to improve the accuracy of electricity demand forecasting by combining contextual information such as temperature and humidity [34]. Another hybrid model, the CNN-GRU, used to predict urban water demand, has high forecasting accuracy with a MAPE of 1.65% over a 24-hour period [35]. In the tourism sector, the hybrid CNN-LSTM model successfully predicted post-COVID-19 tourism demand in Vietnam. CNN played a role in identifying spatial patterns in tourism data, while LSTM was used to analyze demand change patterns over time, making this model relevant for supporting decision-making in dynamic demand conditions [36]. The Stacked Autoencoder hybrid model has also proven to improve the accuracy of tourism demand forecasting by utilizing real-time consumer interest and behavior data [37]. The hybrid model not only improves forecasting accuracy but also accommodates various data sources, thereby enhancing its adaptability to tourism trends and supporting strategic decision-making.

Demand forecasting in the retail sector has made significant progress with the advent of hybrid forecasting models. The LSTM-Random Forest hybrid model has proven to enhance demand forecasting accuracy in multichannel retail. This model enables companies to better understand demand patterns and complex, nonlinear data relationships to support more effective operational planning and decision-making [38]. The SVM-LSTM hybrid model emphasizes the flexibility of the hybrid approach in the food retail sector, demonstrating higher forecasting accuracy compared to the traditional ARIMA forecasting model [39]. These findings indicate that the hybrid model provides a more comprehensive approach to understanding consumer behavior, optimizing inventory management, and supporting managerial decision-making in retail demand forecasting.

The manufacturing industry is increasingly adopting hybrid forecasting models to improve prediction accuracy and operational efficiency. The GA–LSTM hybrid model has proven to improve forecasting accuracy in concrete block production, achieving a MAPE value of 2.8%, which is significantly better than traditional models with MAPE values between 4% and 6% [40]. The LSTM–Random Forest hybrid model used for supply chain demand forecasting shows superior performance with a Mean Squared Error (MSE) value of 0.25, compared to 0.45 in single forecasting models [41]. Demand forecasting in the financial, economic, and healthcare sectors also benefits from hybrid models. The LSTM–ARIMA hybrid model has proven effective in predicting economic demand during the pre-pandemic and pandemic periods, showing higher accuracy and resilience compared to traditional forecasting models [42]. The AR-HOW hybrid model, which integrates ARIMA and Holt–Winters for pharmaceutical demand forecasting, has significantly reduced forecasting errors and outperformed traditional forecasting models such as Exponential Smoothing State Space [43].

The agricultural sector also experienced significant improvements in demand forecasting thru the application of hybrid models. The Holt–Winters–SVM hybrid model proved capable of reducing the Mean Absolute Percentage Error (MAPE) to 6.2% in forecasting red onion seed demand, compared to 9.5% in the single Holt–Winters model [44]. The IWRAM hybrid model used for forecasting irrigation water needs achieved a Mean Absolute Percentage Error (MAPE) of 5.1%, lower than the traditional model with a MAPE of 7.3% [45]. These findings affirm the effectiveness of hybrid models in optimizing resource allocation and enhancing the quality of decision-making for stakeholders in the agricultural sector.

Demand Forecasting Category

Demand forecasting plays an important role in both strategic and operational planning across various industrial sectors. Demand forecasting enables organizations to estimate the level of demand for products and services in the future. Based on the time frame, demand forecasting can be categorized into short-term, medium-term, and long-term forecasts, as outlined in Table 6. Each category of forecasting has specific objectives and methodological approaches, tailored to the needs of business decision-making and policy formulation.

Table 6. Demand Forecasting Categories Based on Time Frame.

Forecasting Category	Time Horizon	Purpose
Short-Term	Minutes to Weeks	1. Operational planning 2. Resource allocation
Medium-Term	Weeks to Months	1. Inventory management 2. Production planning
Long-Term	Months to Years	1. Strategic planning 2. Infrastructure development 3. Investment decision-making

Short-term demand forecasting covers a time frame from a few minutes to a few weeks and plays a crucial role in direct operational decision-making. This type of forecasting focuses on high-frequency data and short-term fluctuations to optimize inventory management, production scheduling, and resource allocation. Various methods, such as time series analysis, machine learning models, and hybrid approaches, are used to improve forecasting accuracy. Several studies show that hybrid models combining machine learning techniques, such as Long Short-Term Memory (LSTM), with traditional statistical methods are effective in predicting demand in volatile sectors, such as electricity and water [46], [47]. Additionally, the application of advanced models that integrate error correction techniques has proven capable of improving prediction accuracy in real-time decision-making systems [35], [48].

Medium-term demand forecasting covers periods of several weeks to several months and plays a crucial role in tactical planning. This type of forecasting generally integrates seasonal patterns and cyclical trends, making it highly relevant for industries whose demand is influenced by weather factors, economic conditions, and consumer behavior. The application of a combination of seasonal decomposition techniques with machine learning algorithms has proven to improve the accuracy of medium-term forecasting, particularly in sectors such as retail and transportation [49], [50]. Additionally, hybrid models that integrate time series analysis with deep learning techniques demonstrate higher predictive performance, thereby supporting organizations in aligning production schedules, managing supply chains, and optimizing inventory levels more effectively [17], [51].

Long-term demand forecasting covers periods of several months to several years and plays a crucial role in strategic decision-making and resource allocation. Unlike short-term and medium-term forecasting, long-term forecasting heavily relies on macroeconomic indicators, demographic trends, and historical data to project future demand trends. Various methods, such as regression analysis, econometric models, and deep learning-based forecasting techniques, have been widely used to improve the accuracy of long-term predictions [52]. Recent studies show that Long Short-Term Memory (LSTM)-based deep learning models can capture long-term dependencies in data, making them effective for application in the tourism, transportation, and energy infrastructure planning sectors. This approach supports organizations in investment decision-making, capacity expansion planning, and risk mitigation due to long-term demand fluctuations [53].

Factors Affecting Demand Forecasting

External factors significantly influence data collection and model selection in demand forecasting, thereby directly impacting the accuracy and reliability of the prediction results. Economic conditions, such as inflation, unemployment rates, and economic growth, shape consumption behavior, where an economic slowdown reduces the demand for non-essential goods, while economic expansion increases it [42], [53]. The integration of economic indicators into forecasting models can enhance accuracy by capturing changes in consumer behavior [48]. Additionally, seasonal and temporal factors, including seasons, holidays, and weather conditions, cause demand fluctuations in sectors such as retail and energy, so models that consider these factors are able to predict cyclical demand patterns more accurately [54]. Technological advancements, particularly in big data and machine learning, have revolutionized demand forecasting by enhancing accuracy through artificial intelligence capable of identifying complex historical patterns, supported by real-time IoT-based data collection that increases the granularity and responsiveness of the model [50], [55], [56]. Additionally, social and behavioral factors, such as changes in consumer preferences, demographics, lifestyles, and the growth of e-commerce, have altered traditional purchasing patterns, necessitating adjustments to forecasting models, including thru social media sentiment analysis to capture dynamic consumer trends [57], [58], [59]. Environmental factors, such as climate change and extreme weather, also affect demand in the agriculture, energy, and water resource sectors, making the integration of environmental data important to enhance readiness and prediction accuracy. In addition, demand patterns are shaped by government policies and regulations as well as competitive dynamics, including pricing strategies, marketing, and product innovation. This condition encourages organizations to adjust their forecasting models to better cope with market changes. [60], [61].

The data collection process and the selection of forecasting models are significantly influenced by internal factors, making their role very important in demand forecasting. The quality and availability of data, methodological approaches, internal competencies, and operational processes are factors that directly determine the accuracy and effectiveness of forecasting models. Low-quality data, incomplete data, or data with low granularity can result in incorrect predictions, while high-quality data with adequate volume and granularity has been proven to improve forecasting model performance [62], [63]. The selection of the right model is also crucial because each method has advantages and limitations that depend on the context of its application, where hybrid models and machine learning-based ensemble approaches have proven capable of improving prediction accuracy [64], [65]. Additionally, the expertise of human resources and the availability of adequate technological infrastructure support the optimal selection, implementation, and interpretation of models, including the application of deep learning techniques [52], [66]. Internal operational processes, such as effective data management and the implementation of feedback mechanisms through error compensation, also contribute to the continuous improvement of forecasting accuracy [67], [68].

Demand Forecasting Workflow

The implementation of demand forecasting is a multidimensional process consisting of several sequential stages to ensure accuracy and reliability across various industrial sectors, such as manufacturing, retail, agriculture, finance, and healthcare. This process can be classified into single model approaches and hybrid model strategies, each with different methodologies in data management, model selection, training, and evaluation. Figure 9 illustrates the workflow in the implementation of demand forecasting.

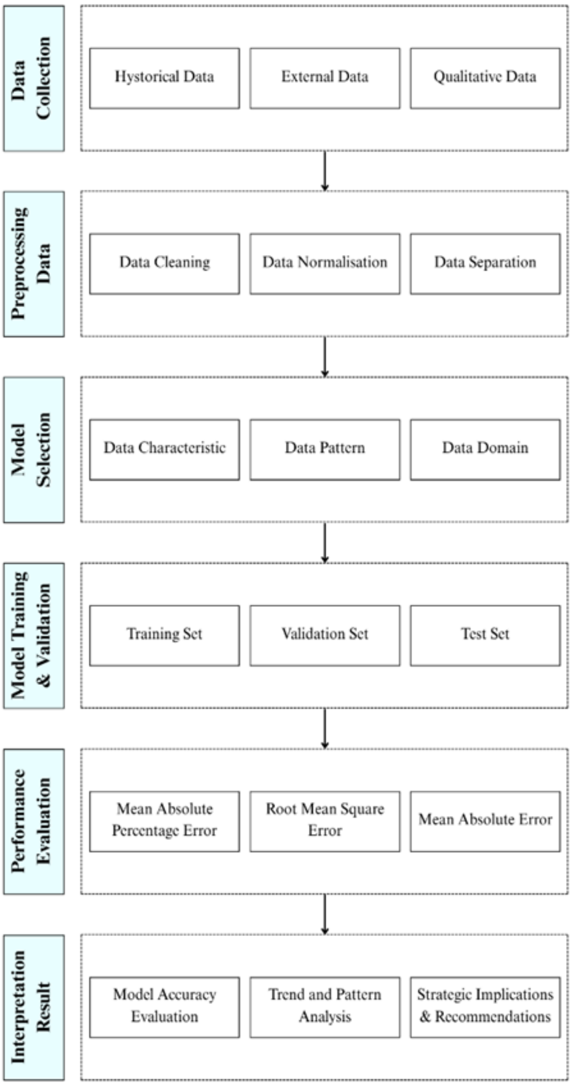

Figure 9. Demand Forecasting Workflow.

Figure 9 shows the proposed workflow for optimizing demand forecasting implementation. The workflow translates the forecasting concept into a structured process consisting of six stages: (1) data collection, (2) data preprocessing, (3) model selection, (4) model training and validation, (5) performance evaluation, and finally (6) result interpretation. These stages are carried out to improve forecasting accuracy, maintain the consistency of the forecasting model, and strengthen the organization's ability to face uncertainty. The first stage in demand forecasting is the collection of relevant data, which will serve as the primary basis for developing the forecasting model. In the manufacturing sector, data such as historical sales data, production schedules, and inventory levels are important components in demand forecasting [69]. In the retail sector, sales data, consumer behavior, and seasonal variations are used to improve forecasting accuracy [66]. The agricultural sector generally relies on climate condition data and crop yield data [70], while the financial sector utilizes macroeconomic indicators and historical demand patterns, and the healthcare sector depends on patient volume and seasonal disease patterns [16], [71].

The second stage is data preprocessing. This process is used to handle missing data, perform data normalization, and select relevant features. Missing data can introduce bias in forecasting, so organizations apply imputation techniques, such as using the mean, median, or more complex methods [70]. The data normalization process is carried out to ensure that each variable contributes equally in the analysis while minimizing bias during the modeling phase [47]. Meanwhile, the feature selection process is carried out to help reduce redundancy and improve model efficiency, using methods such as Recursive Feature Elimination and LASSO to ensure that only the most significant variables can influence the forecasting results [72]. The selection of forecasting models depends on the characteristics of the data and the specific needs of each industry. Single models, such as ARIMA, are traditionally used in conditions of relatively stable and predictable demand, for example in the manufacturing sector [73]. Meanwhile, Long Short-Term Memory (LSTM) as a deep learning technique excels in capturing long-term dependencies in time series data, making it suitable for dynamic environments such as retail and energy [53], [72]. The Random Forest model is effectively applied in sectors with complex nonlinear relationships and has resilience against outliers [38]. On the other hand, hybrid models combine the strengths of various models to improve prediction accuracy. For example, the LSTM–ARIMA hybrid model combines the advantages of LSTM in modeling temporal dynamics with the statistical analysis power of ARIMA [73]. The CNN–LSTM model has proven to be very effective in handling cases such as energy forecasting that involve data with multidimensional features [74]. The combination of other forecasting models, such as Random Forest combined with XGBoost, provides an effective ensemble approach to increase variance while reducing bias, resulting in more accurate forecasting outcomes [75].

The model training and validation stage is carried out by inputting the training data into the selected forecasting model. This process adjusts the parameters to achieve optimal performance. In addition, this process divides the data into training, validation, and testing sets to ensure the model's generalization capability. The k-fold cross-validation technique is often used to thoroughly evaluate the robustness of the model and has proven to produce reliable evaluations across various neural network architectures in electricity demand forecasting studies [76]. After the training process is completed, the forecasting model's performance will be evaluated using metrics such as Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to assess the overall accuracy of the forecasting results [69]. For example, the LSTM model shows a higher accuracy level compared to traditional models based on RMSE and MAPE values, particularly in capturing the nonlinear patterns present in the data [77]. Hybrid models are also able to significantly improve performance compared to single approaches, as indicated by lower MAPE values thru the application of ensemble or hybrid techniques [50]. The final stage is the interpretation of the results, which not only focuses on accuracy metrics but also on understanding the influence of various features on demand patterns, including the relationship of external factors such as economic indicators in demand forecasting in the financial sector [78].

CONCLUSION

Fundamental Finding: This research presents a comprehensive review of the developments in demand forecasting research, particularly in the context of increasing market volatility and technological advancements. Significant theoretical and methodological transformations in forecasting practices were identified thru a bibliometric analysis of 502 publications indexed in Scopus during the period 2015–2024, as well as a content analysis of 144 selected studies. The results of the bibliometric analysis in this study indicate a continuous development and growth in publications related to demand forecasting, especially after 2020. These findings indicate an increase in global attention toward data-driven demand forecasting in line with the uncertain economic conditions and numerous disruptions in the supply chain. The fields of engineering and computer science have become the main sources of research related to demand forecasting, with major countries like China and the United States as the primary contributors, supported by increasingly close international collaboration networks. The results of the keyword mapping indicate that the themes of machine learning, deep learning, and hybrid models have become the most dominant research topics during the study period, signifying a paradigm shift from traditional model approaches to adaptive models based on artificial intelligence. Further content analysis provides deep insights into the implementation of demand forecasting across various industrial sectors. The research findings indicate that forecasting performance is influenced by external factors, such as macroeconomic fluctuations, environmental changes, and social dynamics, as well as internal organizational factors, which include data quality, technological infrastructure, and analytical competence. In that context, hybrid models have consistently proven to exhibit superior performance compared to single forecasting models, whether traditional, machine learning, or deep learning. **Implication:** Based on these findings, this research proposes a framework for demand forecasting implementation that includes stages of data collection, preprocessing, model selection, training and validation, performance evaluation, and result interpretation. The proposed framework can serve as a guideline both conceptually and practically for organizations in their efforts to improve the accuracy of demand forecasting results, strengthen decision-making, and enhance organizational resilience in facing uncertain conditions. In addition, this framework can also serve as a bridge between theoretical research and managerial applications thru a replicable structure that can be adapted to various industrial contexts. **Limitation:** This research has limitations in the form of dependence on the Scopus database and publications in English, which could potentially limit global representativeness. The lack of empirical validation based on industry data also leaves many gaps for this research to be developed. The application of hybrid models requires significant computational resources and technical expertise, which are not always evenly available, especially for small and medium-sized organizations. **Future Research:** The development of cross-sector case studies in the application of probabilistic forecasting models that integrate explainable artificial intelligence (XAI) approaches to enhance transparency and inclusivity is recommended for future research. Ongoing research that combines the evolution of studies with industry validation, as well as the expansion of bibliometric coverage to non-English databases, is also considered important to strengthen the understanding of the real impact of methodological innovations in demand forecasting practices.

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