The Applications of Dynamic Pricing in E-Commerce

[1] Dr. Richa Kalpesh Saxena, [2] Prapti Agarwal, [3] Radhika Pednekar, [4] Prachet Gupta, [5] Pranshu Khemka, [6] Parth Mehra

[1]Assistant Professor, Marketing & Operations, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India
[2,3,4,5,6]BBA, NMIMS, Anil Surendra Modi School of Commerce, Mumbai Campus, India

ABSTRACT: Dynamic pricing, the practice of continually adjusting prices according to demand, competitors' prices, inventory and customer behaviour, has become far more common with e-commerce. The present study applies a bibliometric approach along with a thematic literature review to map research on dynamic pricing in e-commerce from an Operations Research perspective. A Scopus search for "Pricing AND Analytics" was run on 11 September 2026, and the results were filtered in the PRISMA process to a final set of 533 papers published between 2015 and 2026. Biblioshiny, VOSviewer and Mendeley were used for the analysis. The findings show that annual output rose from 8 papers in 2015 to 104 in 2026 to date, with the United States, China and India leading the country counts. The keyword structure links machine learning, predictive analytics and pricing with supply chain, risk and sustainability themes. The study also identifies the gaps left by the existing reviews and sets out directions for future research.

KEYWORDS: Dynamic Pricing; E-Commerce; Operations Research; Machine Learning; Bibliometric Analysis

1. INTRODUCTION

Every time a shopper refreshes a product page, the price on screen may have been set by an algorithm only minutes earlier. Dynamic pricing, the practice of continually adjusting prices according to demand, competitors' prices, inventory and customer behaviour, originated in the airline, hotel and utility sectors (Elmaghraby & Keskinocak, 2003). E-commerce has made it far more common for two reasons: online retailers hold large volumes of transactional data (Bradlow et al., 2017), and prices can be adjusted immediately at very low cost. The research describing this practice has grown in step. Annual publications in the final dataset rose from 8 in 2015 to 76 in 2024 and 104 in 2026 to date, and 270 of the 533 papers (51%) appeared between 2024 and 2026 (Scopus search, 2026). India ranks third by country with 149 papers, behind the United States (287) and China (203) (Scopus search, 2026).

The topic sits at the centre of Operations Research because a price cannot be set in isolation from the system that delivers the product. The literature draws on three academic areas: operations research builds the models of price determination and inventory management (Harsha et al., 2019), marketing examines consumer behaviour (Duan et al., 2022), and computer science supplies the machine learning techniques (Nowak & Pawłowska-Nowak, 2024). The operations research contribution is particularly direct. Elmaghraby and Keskinocak (2003) treat dynamic pricing as an area of revenue management in which inventory considerations must be taken into account. Lei et al. (2018) study the joint problem of dynamic pricing and order fulfilment for e-commerce retailers, and Harsha et al. (2019) show that omnichannel retailers must set online and store prices together because both channels draw on the same inventory. Ulmer (2020) links pricing with routing for same-day delivery. In each case, a pricing decision changes order volume, inventory pressure and delivery requirements at the same time.

The motivation for this study is that the field has changed quickly and is spread across disciplines. Kopalle et al. (2023) describe dynamic pricing as a broad managerial problem rather than a single modelling problem. Fruchter and Tapiero (2005) analysed online and offline channel pricing through game theory, and Cross (2016) links the diversification of revenue management in the following decade to the price transparency that the internet created. From 2024 onwards the methods have shifted towards artificial intelligence: Guo and Zhang (2025) use neural networks, Loukili et al. (2025) use Deep Q-Networks, and Liu et al. (2026) apply deep reinforcement learning. Three questions recur across this work: what demand will be, what price maximises revenue or profit, and how prices affect customer satisfaction and trust. Few studies answer the last of these alongside the others (Guo & Zhang, 2025). Donthu et al. (2021) explain that bibliometric analysis reveals the development and structure of a field through performance analysis and science mapping, which makes it the appropriate method for seeing how these strands fit together.

The existing reviews show both a surplus and a lack of coverage. Of the Scopus records examined for the literature review, 33 are reviews, but most concern neighbouring areas such as energy markets and finance, and none addresses dynamic pricing in online retailing. Where reviews touch on the topic, it is usually as one application among many. Nishamali et al. (2024) review machine learning applications for online retailers, with dynamic pricing as only one of them, and Rajumesh (2024) includes dynamic pricing among the applications of artificial intelligence in marketing. Lemire and Gamache (2025) survey pricing models in manufacturing small and medium-sized enterprises. The closest review, de Lucas López et al. (2026), is a bibliometric mapping of 38 articles from 2019 to 2025 on AI ethics in pricing. Of the same records, 11 include "bibliometric" in their title or keywords, and none maps dynamic pricing in e-commerce. Three gaps therefore remain: no review considers the technology, business and consumer aspects together, the reviews are out of date given that 270 of the 533 papers appeared after 2023, and price fairness is rarely treated as a design consideration.

To address these gaps, this study applies a bibliometric approach to the literature. A Scopus search for "Pricing AND Analytics" was run on 11 September 2026, and the results were filtered in the PRISMA process (Page et al., 2021). The filters were applied in sequence. Publication year (2015–2026) reduced 1,491 records to 1,392, document type (articles and reviews) reduced these to 544, source type (journals) to 543, and language (English) to a final set of 533 papers. Biblioshiny was used for the performance indicators and the PRISMA flow diagram, VOSviewer for keyword co-occurrence mapping, and Mendeley for managing the records. Such methods are established for mapping research fields (Zupic & Čater, 2015). Preliminary results show that the 533 papers come from 364 sources, 1,574 authors and 2,036 author keywords, with an exponential growth trend ($R^2 = 0.906$). The keyword structure links machine learning, predictive analytics and pricing with supply chain, risk and sustainability themes.

2. LITERATURE REVIEW

General comments on the relevant literature

Dynamic pricing refers to the practice of continually adjusting the price of a product according to demand, competitors' pricing, inventories, and customer behavior. Dynamic pricing originated in the airline industry, hotel industry, and utility services sector (Elmaghraby & Keskinocak, 2003). However, E-commerce has facilitated dynamic pricing due to the two following reasons: firstly, because e-tailers possess large amounts of transactional data (Bradlow et al., 2017); and secondly, because the price can be adjusted immediately at very low costs. Three questions reappear consistently in all the papers reviewed here. The first one pertains to predicting demand, an issue covered by Ferreira et al. (2016) for the online retailer Rue La La. The second one is what price will produce the greatest revenue or profit and tested by Liu et al. (2026) through reinforcement learning. The third one concerns the impact of such prices on the customer's satisfaction and trust: Guo and Zhang (2025) assess profit and satisfaction simultaneously, while de Lucas López et al. (2026) stress the negative perception of algorithm-based prices. Three academic areas provide insights. The models of price determination and inventories management are developed within operations research (Harsha et al., 2019), marketing is responsible for consumer behavior (Duan et al., 2022), while computer science provides machine learning techniques (Nowak & Pawłowska-Nowak, 2024). The central database consists of 534 Scopus articles from 2015 to 2026, collected via the search query 'Pricing AND Analytics' with the help of the PRISMA approach. Out of them, 35 papers contain 'dynamic pricing' either in the title or author keywords. The smaller Mendeley database of 24 articles concerning dynamic pricing in e-commerce was used for the construction of the keyword map and for close reading of papers. The top 3 Scopus sources include Journal of Revenue and Pricing Management (13 articles), Management Science (9), and Manufacturing & Service Operations Management (9). 1,577 authors are included into the set of 534 Scopus papers, none of them having more than six documents, hence nobody can dominate the research field.

Previous research: a historical perspective

The connection between dynamic pricing and e-commerce was made in the early 2000s when Elmaghraby and Keskinocak (2003) discussed the application of pricing techniques used by airlines and hotels to inventory holding firms. In 2005, the game-theoretic analysis of pricing in online and brick-and-mortar settings was performed by Fruchter and Tapiero (2005). In the following ten years, revenue management became more diversified and Cross (2016) explained this diversification by the price transparency on the internet that encouraged companies to use data-driven pricing. Two most cited articles in the Scopus database belong to this period. Bradlow et al. (2017), who described the use of big data and predictive analytics in retail, had 455 citations. Ferreira et al. (2016) who applied machine learning in conjunction with price optimisation in the case of Rue La La had 415 citations. Harsha et al. (2019) developed the theory for omnichannel retailing which requires setting prices for online and brick-and-mortar stores simultaneously because both channels have access to the same inventory. Since 2024, the research methodology changed to the one based on artificial intelligence. Twelve out of thirty-five papers on dynamic pricing were published

in 2025 and 2026. Guo and Zhang (2025) rely on neural networks while Yoshi et al. (2025) introduce customer sentiment into the pricing algorithm. Loukili et al. (2025) use Deep Q-Network to set price levels. Liu et al. (2026) adopt deep reinforcement learning where a computer program sets prices through trial-and-error method. Kantaria et al. (2026) reported a profit improvement of about 13-18% compared to baseline pricing algorithms in simulations. The number of publications is consistent with the findings regarding methods used. The annual production in Scopus database increased from 8 articles in 2015 to 76 in 2024 and 104 in 2026 while 270 out of 534 articles (51%) appeared in 2024-2026.

Previous research: areas investigated

The research areas have been found using keyword co-occurrence analysis done in VOSviewer using the Mendeley collection containing 90 author keywords. Thresholds of 2, 3, 4, and 5 have been used. However, the map with a minimum of 2 occurrences was used since higher thresholds did not provide enough keywords. The three most frequent keywords are dynamic pricing (10 occurrences), e-commerce (8) and machine learning (6). Six clusters were formed. Since the 24 paper collection is a small one, the clusters were further verified manually into five research areas.

Table 1 shows the ten most frequent author keywords in the 534 Scopus documents.

Rank	Author keyword	Occurrences
1	machine learning	57
2	pricing	37
3	predictive analytics	34
4	data analytics	33
5	artificial intelligence	30
6	dynamic pricing	28
7	big data	23
8	revenue management	18
9	deep learning	15
10	analytics	14

Table 1. Ten most frequent author keywords in the 534 Scopus documents

The first area is pricing theories and competition. The works by Fruchter and Tapiero (2005) and Chen and Xiao (2026) utilize game theory, which along with revenue management (Cross, 2016) appears to be the most explicit theory in the literature on the subject. The second area is personalization. Nowak and Pawłowska-Nowak (2024) developed an approach which modifies the prices based on customers' behavior and competitors' prices, whereas Chukwunweike et al. (2024) discuss privacy issues and biases. The third area is profit and customer satisfaction. One of the few articles measuring those two aspects simultaneously is that by Guo and Zhang (2025). The fourth area is review text as a data source. It is the newest topic among those considered in this review. Le et al. (2024) employed review sentiment and prices for predicting customer satisfaction, and Ren et al. (2026) used large language models to forecast sales of Amazon products. The fifth area is the effects of customer reviews on pricing. He and Chen (2018) discovered that high-quality electronics sellers might keep initial prices low so that good reviews would accrue faster. Duan et al. (2022) observed that negative reviews have less impact on sales if the product is expensive.

Previous research: methodological approaches taken

Most of the studies that have been reviewed here are based on quantitative research methods and four methodologies. The first is the application of game theory and analysis to find an optimal price from the model of behaviour of businesses and consumers (Fruchter & Tapiero, 2005; Chen & Xiao, 2026). The second is the optimisation approach to finding an optimal price under uncertain conditions of demand (He & Chen, 2018; Zhang & Tian, 2024). The third is machine learning algorithms that learn pricing patterns from big datasets (Nowak & Pawłowska-Nowak, 2024; Guo & Zhang, 2025). The fourth is empirical tests for price effects on sales through real-world sales and review data (Duan et al., 2022; Le et al., 2024).

Most of the older articles employed analytical models that provide reasons for the effectiveness of a certain pricing model but are based on unrealistic assumptions. Machine learning is the dominant research method among the newer articles. According to Liu et al. (2026), the reinforcement learning approach increased cumulative profit margins by more than 16.7% on the basis of simulations derived from Amazon products' data. However, machine learning approaches are "black-box models" that can generate an optimal price but fail to explain the reasons behind it. The

review papers also differ in the methodological approach to the research. Elmaghraby and Keskinocak (2003) and Cross (2016) employ the narrative review approach. Lemire and Gamache (2025) survey the models of pricing in manufacturing SMEs, and Nishamali et al. (2024) conduct a review using a systematic process. Only de Lucas López et al. (2026) conduct a bibliometric mapping review but for the area of AI pricing ethics.

Summarising the review: previous reviews, gaps and this study's niche

Dynamic pricing has been studied since 2003, but the reviews are limited to certain aspects of it. Elmaghraby and Keskinocak (2003) looked at firms holding inventories, while Cross (2016) explored the history of revenue management. Chukwunweike et al. (2024) and Nishamali et al. (2024) performed reviews of machine learning applications for online retailers, dynamic pricing being just one of them. Lemire and Gamache (2025) focused on another environment: manufacturing small and medium-sized enterprises. Out of 534 documents, Scopus labels 33 as reviews. Most of them are related to neighboring areas such as energy markets and finance; no review is found for dynamic pricing within online retailing. The literature does not contain many bibliometric studies either. Out of 534, 11 have "bibliometric" in their title or author keywords; none of them provides mapping of dynamic pricing in e-commerce. The closest paper is by Rajumesh (2024), who included dynamic pricing among applications of AI in marketing. The most relevant review is de Lucas López et al. (2026); they analyzed 38 articles published from 2019 to 2025 on AI and ethics.

These reviews leave three gaps. First, there has been no literature that considers the technology, business and consumer aspects of dynamic pricing together. Second, the reviews are not up-to-date because 270 out of the total 534 documents have been published during 2024 and 2026. Third, pricing strategies seldom consider price fairness as a design consideration. Price fairness is an author keyword in only one of the 534 documents, and most of the technical studies evaluate their pricing strategies based on profitability or accuracy alone.

This review bridges the first two gaps mentioned above. The analysis uses both bibliometric analysis of the 534 Scopus documents and thematic literature review of the papers. Moreover, it spans 2015 to 2026, which is a wider time span compared to the time period of 2019 to 2025 covered by de Lucas López et al. (2026).

3. RESEARCH METHODOLOGY

Systematic Literature Review

The current research on Dynamic Pricing in E-commerce adopts the approach of systematic literature review to identify and organize the existing research conducted on the chosen topic. Systematic literature review enables the author to consolidate the available researches on a specific topic in a systematic way. This way of literature search will help the author to understand the existing knowledge and observe the progress of research in this area(Asim et al., 2024).

The authors decided to adopt systematic approach for conducting literature review because the chosen topic of dynamic pricing in e-commerce is a wide topic, related to various areas like pricing strategies, analytics, technology and decision making. Rather than adopting a random approach to select research articles, a systematic process was adopted to conduct a search on the chosen topic using a recognized academic database. (Jawabreh et al., 2026)

The process of selecting literature in this paper has been done using the PRISMA method. PRISMA is a structured process that is used in the identification and selection of literature for conducting a review. In this study, the PRISMA method was employed to demonstrate the reduction of the total number of records into the final selected number of records through various filters. The use of the PRISMA method also makes the selection process easy to follow, while at the same time providing clarity on the number of records that have been selected and not selected at various stages.

Article selection, inclusion, exclusion criteria

A literature search was performed using the database Scopus on 11 September 2026. Scopus was chosen as the primary database for gathering research literature due to its availability of an extensive collection of academic papers and bibliographic data. The literature search was performed based on the keywords “Pricing AND Analytics”. These keywords were used with the aim of selecting the literature that links pricing and analytics, thereby forming the basis of the study of literature related to dynamic pricing within the e-commerce environment.

This search gave a total of 1,491 papers. This marked the beginning of the process of literature selection. Then, further filtering of the results was done in order to obtain a smaller dataset. Filtering was needed since the initial search provided papers in different years, document types, sources, and languages.

The first filter implemented was publication year. All articles published between 2015 and 2026 have been included in the research. On applying the said filter, the number of articles used has been cut down to 1,392 articles by excluding 99 articles which do not meet the time frame criteria set.

The following stage involved applying filters related to the document type. Articles and review papers were selected as the documents at this stage. Following application of the filter, the number of records was reduced to 544 records with exclusion of 848 records. At this stage, the study managed to concentrate on those publications which would be most appropriate for the reviewing of existing academic literature.

Finally, another filter of the document/source type was implemented in order to select only journal publications. Following implementation of the filter, 543 records were left with one more record being excluded.

The final filter of the PRISMA model involved the language filter in which only those papers written in the English language were selected. Through this process, 10 papers out of 543 were removed as they were written in other languages, bringing the total number of papers from 543 to 533.

Thus, with the completion of different filtering steps, 533 articles were left as the final output. The entire selection process, along with the number of records selected and excluded, is given through PRISMA flow chart prepared by the use of Biblioshiny tool (Figure 1).

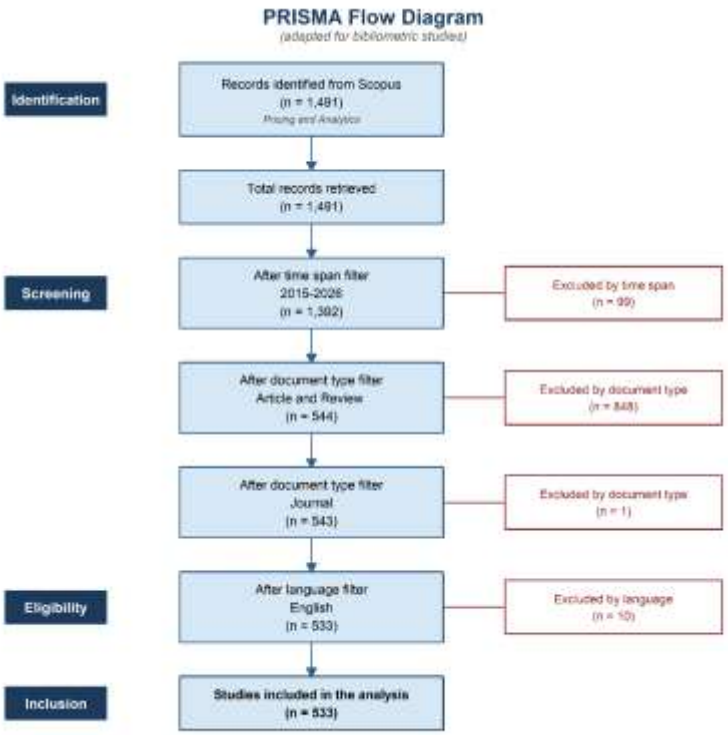


Figure 1. PRISMA Flow Diagram for Article Selection

The final 533 publications were considered suitable for the next stage of the study. The filtering process helped reduce the initial broad search results to a more focused collection of literature relevant to the research objectives.

Bibliometric Review and Analysis

As there were 533 studies included in the final dataset, reading each one in detail would be a tedious task and it would be hard for us to notice any trends among all the literature available. Thus, in order to study the chosen research, bibliometric analysis will be performed by the authors.

Bibliometric analysis enables us to analyse a large body of academic publications based on bibliographic data such as years of publication, authors, sources, keywords and other publication information that is available (Singh et al., 2024). This method can be useful in identifying trends in research area and showing what kind of topics and relations have been emphasized.

In the present study, bibliometric analysis was applied to understand the research field associated with dynamic pricing in e-commerce. Bibliometric analysis can enable the authors to learn about the evolution of research, research areas and relations between various concepts discussed in literature(Rajumesh, 2024).

Various softwares were used at various stages of the research process. Mendeley was used in organizing and management of the literature records gathered during the research process. It helped in organization of the literature database and removal of duplicates where needed. Tableau and VOSviewer were used for visualisation of the research data in order to present the findings in a clear and understandable manner. It helped in representing the data through visual formats, making it easier to observe patterns, compare different aspects of the dataset and understand the trends emerging from the collected literature. Biblioshiny was also used in the process of bibliometric analysis and drawing of the PRISMA flow chart showing the selection of the articles. Microsoft Excel was used for managing and sorting the collected research papers and their associated data. It helped in arranging the records in a structured manner, making the dataset easier to organize, review and use for further analysis.

Such a set of software helped the authors to move from a literature search stage to an organized and analysable research database. Therefore, the methodology used in the research process included systematic search in Scopus, using defined filters, and documentation of the process of selection using PRISMA and bibliometric analysis of the final 533 publications.

4. DATA ANALYSIS

Introduction and Main Information



Figure 2. Main Information of The Bibliometric Analysis

The bibliometric analysis examines research on Dynamic Pricing in E-Commerce during the period 2015 to 2026, with the primary objective of understanding the changes that have taken place in research in this area and of assessing the contributions made by various authors, countries and research topics.(Zupic & Čater, 2015) Dynamic pricing in online markets has also been studied in relation to consumer behavior and buying decisions.(Kannan & Kopalle, 2001)

Figure 2 gives us the main information about the research. The dataset includes 533 documents from 364 sources and thus provides sufficient information for an examination of the development of the research area. The annual growth rate shown by the Main Information is 26.26 per cent; the dataset includes 1,574 authors, 59 of whom have been involved in single-authored documents. The average number of co-authors per document is 3.27, indicating that it is typical for researchers to work together. The rate of international co-authorship is 36.21 per cent, which also demonstrates that collaboration in research occurs between authors from different countries.

A further noticeable point relates to the number of keywords in the dataset: there are 2,036 author keywords, which indicates that the research encompasses a rather broad range of topics. These keywords are helpful for gaining an understanding of the main themes in the literature and are also employed in the co-occurrence analysis that takes place later in the report. Since the average document age is 3.41 years, many of the publications are fairly recent. The average

number of citations per document is 18.05; this figure should be taken into account together with the age of the documents because publications that are more recent have had less time to accumulate citations.

The results also show something about the degree of collaboration in the field. Many authors have contributed to the literature, and a large amount of the research involves collaboration between countries. Together, the number of publications, the number of authors, the keywords and the collaborations provide a useful starting point for understanding the research area.

Annual Scientific Production

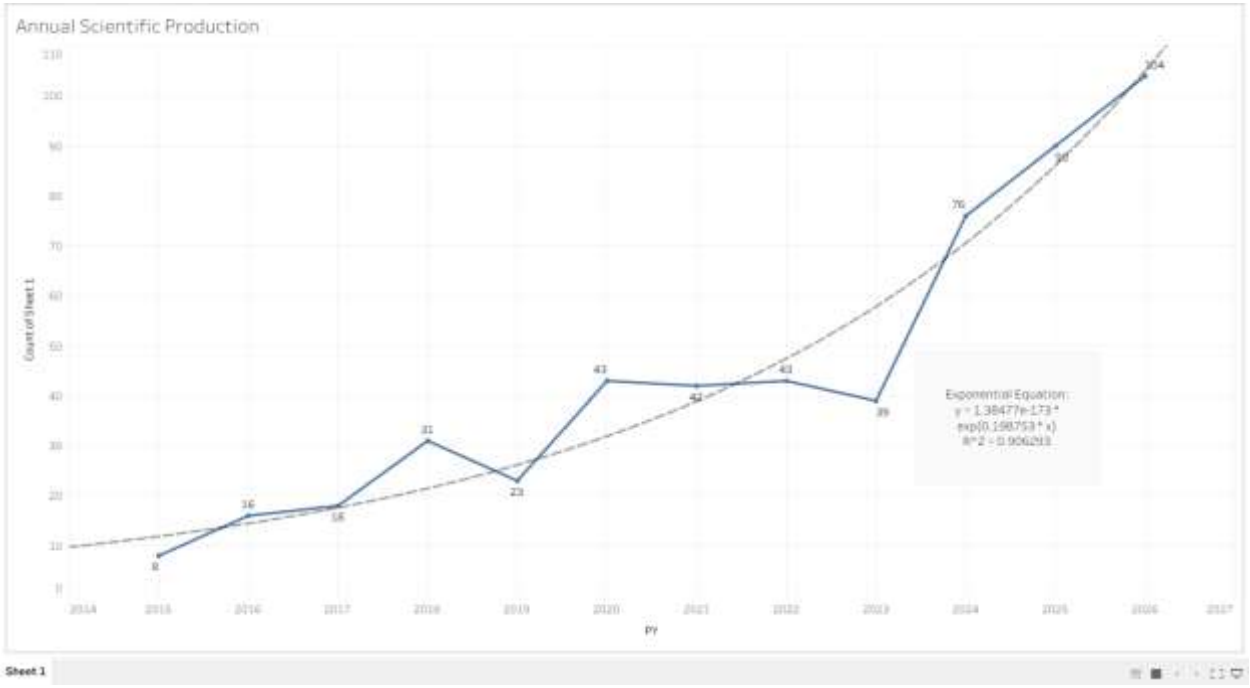


Figure 3. Annual Scientific Production

Figure 3 gives the number of publications produced each year from 2015 through to 2026. The general trend is one of growth, even though the amount rising each year is not constant. In 2015 there were 8 publications, this rising to 16 in 2016 and 18 in 2017. The figure then reached 31 publications in 2018. This indicates a steady increase in research output in the early years.

In 2019 the pattern altered a bit since the number of publications fell from 31 to 23. The next year there was a much greater increase, with 43 publications in 2020. For the following two years the figure remained fairly steady, there being 42 publications in 2021 and 43 in 2022. There was then a further small decrease in 2023, the number dropping to 39 publications.

The most significant change in the graph is evident from 2024. The number of publications rose from 39 in 2023 to 76 in 2024 and then increased further to 90 in 2025; the dataset also includes 104 records for 2026. Unlike in the earlier years, there has been a much quicker rise in the number of publications.

The exponential trendline also aligns with the general upward trend; it has an R^2 value of 0.906293 and a p-value less than 0.0001. The fact that the R^2 value is so high indicates that the exponential trend matches the publication data very well.

It is clear that there is a difference between the earlier and the later sections of the graph. For most of the earlier years the number of publications stayed under 50 documents, but from 2024 it rose well above that figure. The graph as a whole indicates a clear rise in scientific output, the most noticeable increase occurring in the last years of the period.

Three-Field Plot

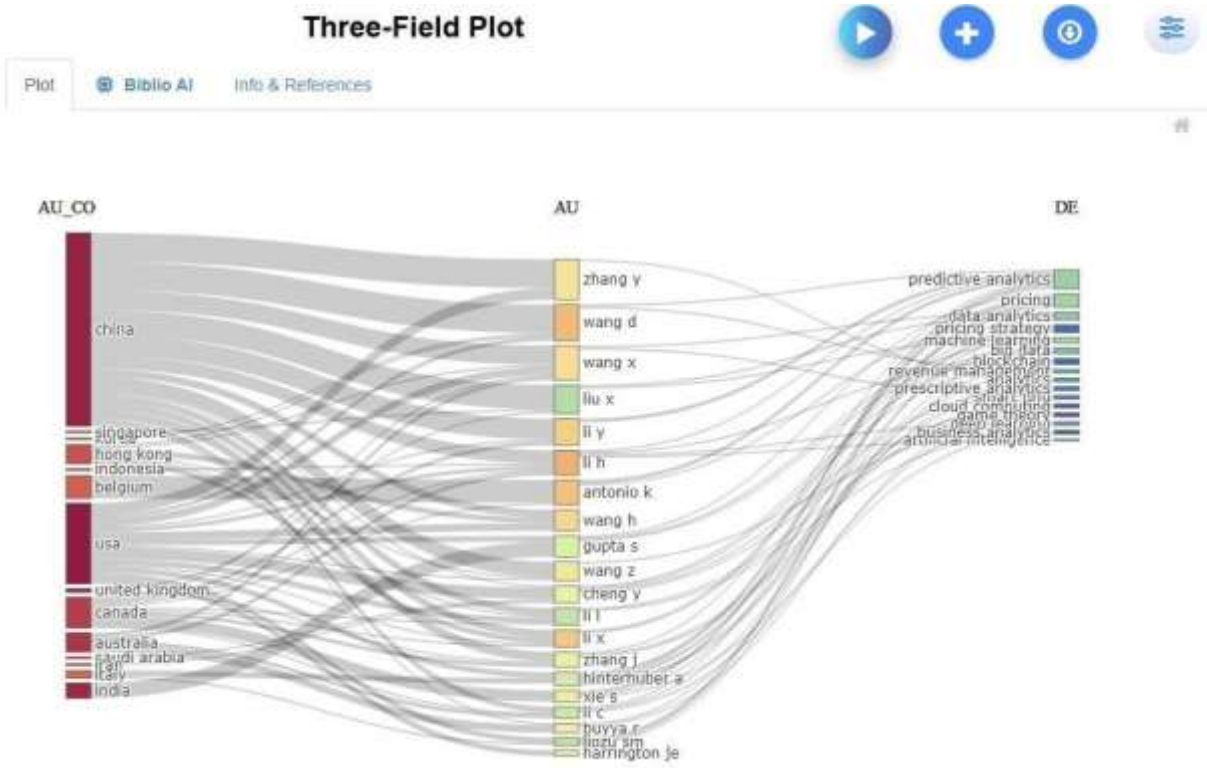


Figure 4. Three Field Plot

As shown in Figure 4 there is the relationship between the Author Countries (AU_CO), the Authors (AU) and the Author Keywords (DE). When these three fields are considered together, it becomes possible to see which research topics are associated with authors from different countries and also provides a clearer view of how the research themes are distributed among the authors in the dataset.(Aria & Cuccurullo, 2017)

China, the United States and India are clearly present in the diagram, together with a number of links to the authors located in the middle. Other countries such as the United Kingdom, Australia, Canada, Germany, Spain, Italy and Saudi Arabia are also included. The fact that these different countries are involved indicates that the research has inputs from a rather wide variety of nations.

There are among the authors and the keywords a number of links with subjects including analytics, machine learning, predictive analytics, pricing and artificial intelligence.(El Youbi et al., 2023) In these links appear the authors Zhang Y, Wang D, Wang X, Liu X and Li Y. In the diagram you can also find other keywords such as big data, deep learning, dynamic pricing, revenue management, sustainability, blockchain and business analytics.

The thickness of the flows is also a significant element of the plot; thicker flows indicate stronger or more frequent relationships, whereas thinner flows show weaker ones. Hence, the diagram gives more information than just indicating which countries, authors and keywords are included, since it also suggests how strongly they are connected.

The plot is useful since it brings the countries, the authors and the keywords together in a single location.(Chen, 2017) While a country map can indicate where research is being carried out, it cannot show which researchers or topics are associated with those countries. The Three-Field Plot offers this extra information and thus links the country-level results with the research themes.

The figure as a whole indicates that various countries and researchers are linked to a wide variety of topics, with themes including analytics, artificial intelligence, machine learning and pricing being especially apparent, while other areas such as sustainability, blockchain and big data are also included in the research.

Countries' Scientific Production

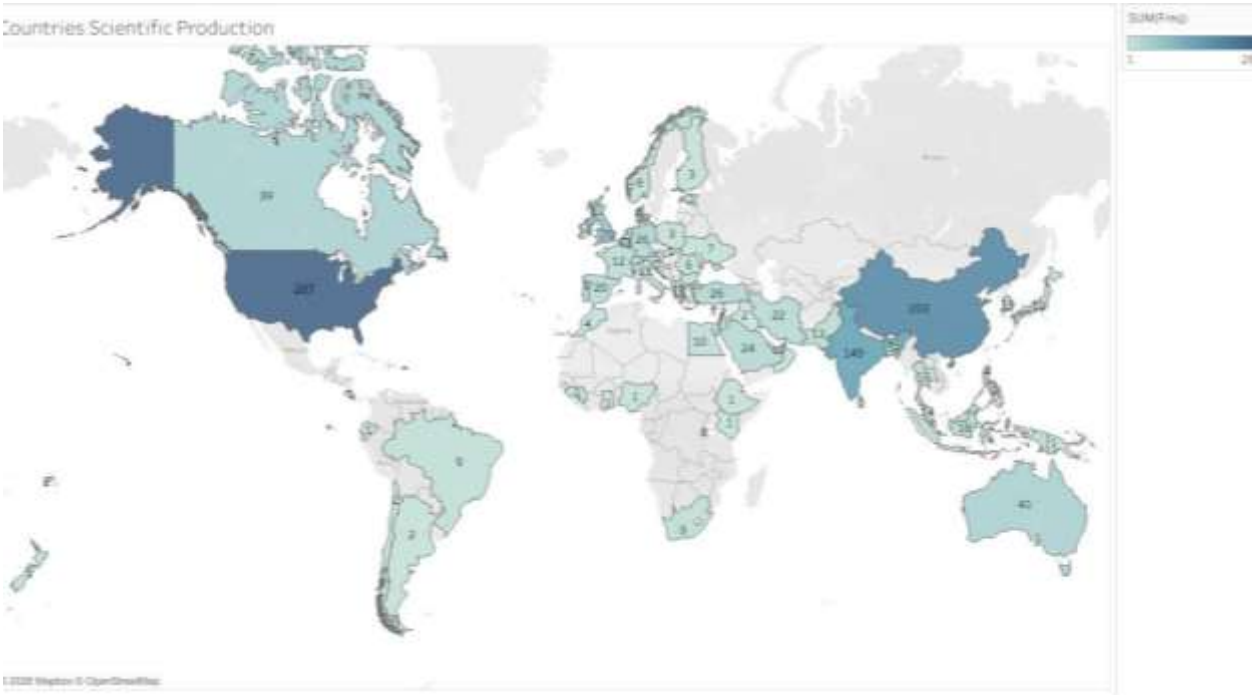


Figure 5. Countries Scientific Production

Figure 5 presents the scientific output of the countries that are included in the dataset; the map enables one to see where research is being carried out and the way in which the number of publications varies from country to country.

The United States leads in the number of publications, having 287, then comes China with 203 and India with 149; the United Kingdom has 70 publications as well. Canada, Australia, Germany, Spain, Italy and Saudi Arabia are also involved in the research, even though their numbers of publications are lower.

The map illustrates the level of research activity in North America, Asia, Europe and Australia and therefore indicates that the research area does not cover just one geographical region. Meanwhile, the difference in publication output between the countries at the top of the list and all the other countries is very clear.

The country's results can likewise be compared with the system of the Three-Field Plot; several of the countries shown on the map are also included in the author-country relationships in Figure 4, thus establishing a connection between the number of publications from a country and its involvement with various authors and research topics.

One thing that is evident from the map is that the various countries participate to different extents. Some have a much more extensive publication presence, whereas others are represented less often. Nevertheless, the inclusion of countries from a number of regions indicates that the research has progressed through the involvement of a group of researchers from around the world.

The map indicates that scientific production is distributed among various parts of the world, with the United States, China and India having the highest number of publications in the dataset, alongside a number of other countries making contributions to the literature.

Keyword Co-occurrence Analysis

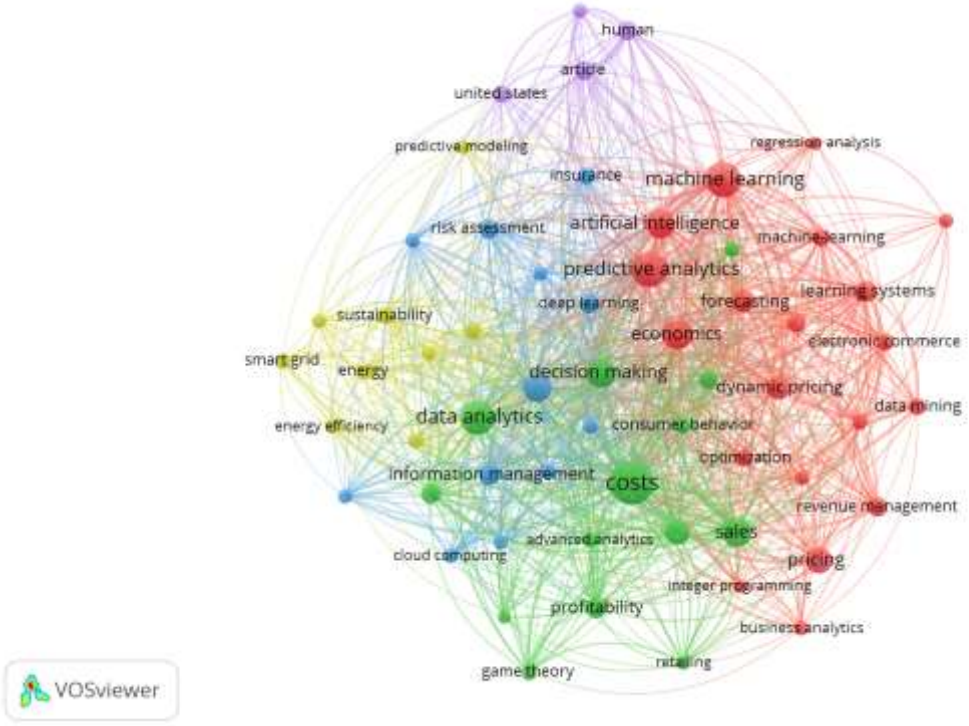


Figure 6. Keyword Co-occurrence Network

The keyword co-occurrence network is illustrated in Figure 6 and includes 59 keywords grouped into five clusters, each consisting of terms that occur at least 10 times. There are 979 links between the keywords, indicating that a number of the terms tend to occur together and thus define related research areas. By examining the keywords in each cluster it is possible to grasp the main themes and see how the various concepts are connected.(Callon et al., 1983)

Cluster 1 (Red) is the biggest one and has the largest number of keywords, mainly includes artificial intelligence, machine learning, predictive analytics, data mining, forecasting and regression analysis; these techniques are closely linked with pricing, dynamic pricing and revenue management, which suggests that analytical and predictive techniques are being used in price related research. (Suresh Kumar et al., 2023)Whereas optimization and decision support systems link the analytical methods to business decision-making.

Cluster 2 (Green) places a greater emphasis on business applications. Data analytics and advanced analytics are associated with decision making, costs, profitability, sales and investments. Moreover, consumer behavior, marketing and retailing are linked to competition and game theory, revealing a connection between customer behavior and strategic decisions. Supply chain management is given an operational dimension within the cluster.

Cluster 3 (Blue) relates digital technologies to topics related to risk. Big data, cloud computing, digital storage and information management are connected with technologies including deep learning, reinforcement learning and the Internet of Things. The connections go on to insurance, risk assessment and risk management, thus showing the application of technology in addressing uncertainty.

Cluster 4 (Yellow) is primarily concerned with energy and sustainability; energy management, energy efficiency and smart grids are linked to sustainability, whereas predictive and stochastic models are associated with dealing with uncertainty. Blockchain is also included in this group, linking emerging technology with energy management and sustainability.

The theme of Cluster 5 (Purple) is less specific since it includes general terms such as article, human and United States.

Overall, the relationships within the clusters show that the research links analytical methods and emerging technologies to practical areas such as pricing, decision making, risk and sustainability.

5. FUTURE RESEARCH AGENDA

The bibliometric evidence portrays dynamic pricing research as a rapidly expanding, international and methodologically varied field. Its growth, however, appears to have outpaced its conceptual and empirical foundations. Constructs are defined inconsistently, performance claims rest mostly on simulation, consumer-facing outcomes are rarely measured directly, and competitive, regulatory and managerial conditions are weakly integrated with the dominant optimisation literature. The central question for future research is therefore whether the performance gains reported in simulation survive contact with real markets, consumers, competitors and institutions.

This section sets out six directions for addressing that question, summarised in Table 2. The first five respond to substantive evidence gaps: realised performance, consumer fairness and welfare, competition and regulation, managerial adoption, and contextual generalisability. The sixth supplies the conceptual and methodological infrastructure on which the other five depend.

Direction	Observation from the corpus	Core research question	Methodological approach	Expected contribution
1. From simulation to realised market performance	Reported gains of approx. 13–18% and above 16.7% are simulation-based	Do simulated gains persist under operational, competitive and consumer conditions?	Meta-analysis; multi-arm field experiment	Comparable, causal estimates of realised performance
2. Consumer fairness, trust and welfare	Fairness is an author keyword in 1 of 533 records	Is fairness neglected or merely under-labelled, and what drives consumer acceptance?	Full-text synthesis; theory-driven experiments	Validated account of consumer responses
3. Competition, regulation, accountability and AI agents	Most frequent keywords are technical (machine learning, 57; pricing, 37; predictive analytics, 34)	How do interacting algorithms and legal regimes shape prices and welfare?	Multi-agent simulation; market audits; natural experiments; LLM-agent benchmarks	Evidence on efficient and proportionate governance
4. Explainability and managerial adoption	Black-box concerns are raised, but performance is the dominant evaluation criterion	When do managers understand, trust, override and responsibly use recommendations?	Decision experiments; field and case studies	Design principles for adoptable pricing systems
5. Context, equity and generalisability	The United States, China and India have the highest publication counts	Which findings generalise across markets, consumers and institutions?	Harmonised cross-national replication	Clarified boundary conditions
6. Conceptual coherence and evidence infrastructure	“Dynamic pricing” appears in the title or keywords of only 35 of 533 records	What counts as dynamic pricing, and is the field’s growth substantive?	Shared taxonomy; living evidence synthesis	A cumulative, reproducible evidence base

Table 2. Summary of future research directions

From Simulation to Realised Market Performance

Machine learning is the most frequent keyword in the corpus (57 occurrences), and the reviewed studies report simulated profit improvements of approximately 13–18% (Kantaria et al., 2026) and above 16.7% (Liu & Li, 2026). These figures rest on different demand models, baselines, cost structures and evaluation horizons, and so cannot be compared directly. Earlier work links pricing with inventory, fulfilment and routing (Harsha et al., 2019; Lei et al., 2018; Ulmer, 2020), which suggests that operational constraints and competitor responses may substantially erode headline gains. Until simulated gains are tested against realised outcomes, managerial claims about algorithmic pricing remain externally unvalidated. Future work should therefore establish how large realised profit, conversion and inventory effects are relative to transparent baselines, and under which product, demand and competitive conditions simulated gains decline or reverse.

Two complementary designs would address this. First, a meta-analysis should classify reported effects by evaluation design (simulation-only, offline policy evaluation, observational evaluation or field experiment) and extract effect sizes only where baselines, profit definitions and horizons are comparable. Robust variance estimation or multilevel models (Hedges et al., 2010) can handle multiple effects per study, and small-study effects can be examined with PET-PEESE (Stanley & Doucouliagos, 2014) recognising its limitations. Second, a multi-arm field experiment with an online retailer should compare the incumbent policy, a learning-based policy, and a learning-based policy with explicit consumer-protection constraints. Randomisation at the product-market or product-time level, using a switchback design where appropriate (Bojinov et al., 2023), would permit causal comparison, with spillovers from substitution and shared inventory addressed in the design. A single primary outcome, such as incremental gross profit per product-week, should be specified in advance, with secondary outcomes covering inventory, fulfilment, repeat purchase, perceived fairness and trust. Together, these designs would replace simulation-based claims with causal, operationally realistic estimates of when algorithmic pricing creates value, and for whom.

Consumer Fairness, Trust and Welfare

Price fairness appears as an author keyword in only one of the 533 records, yet related consumer concerns are discussed under other labels, including satisfaction (Guo & Zhang, 2025), negative perceptions of algorithmic prices (de Lucas López et al., 2026), and privacy and bias. The gap may therefore reflect labelling rather than genuine neglect, and keyword counts alone cannot distinguish the two. More fundamentally, the field lacks an integrated behavioural account of when consumers accept, resist or are harmed by dynamic prices.

Several established theories provide a foundation for such an account. Dual entitlement theory holds that consumers accept price increases linked to cost changes but reject those that appear to extract surplus opportunistically. Research on algorithm aversion and algorithm appreciation suggests that reactions differ when a price is attributed to an algorithm rather than a person (Logg et al., 2019). Personalisation raises a privacy trade-off, in which relevance gains may be offset by lost trust when data use is perceived as excessive (Dinev & Hart, 2006). Identical pricing rules can also impose unequal burdens across income, digital literacy and urgency, which introduces a distributional dimension. Against this background, two questions merit attention: whether fairness is genuinely absent from the literature or discussed under alternative labels, and which pricing features (volatility, personalisation, algorithmic attribution, data use and explanation) most affect perceived fairness and trust, and for which consumer groups.

A full-text synthesis should first distinguish firm-level outcomes (profit, sales, predictive accuracy) from consumer-facing outcomes (perceived fairness, trust, transparency, welfare, discrimination), coding whether each is measured empirically, modelled or discussed only conceptually, and recording the geographical origin of the evidence. Experiments should then manipulate pricing rationale, algorithmic versus human attribution, price-change frequency, data-use disclosure and opt-out availability, and link perceptions to behavioural outcomes such as purchase, switching and churn. This would establish whether claims about responsible pricing are supported by measured consumer outcomes and identify design features that improve both trust and welfare.

Competition, Regulation, Accountability and AI Agents

The most frequent keywords in the corpus are technical (machine learning, pricing, predictive analytics), consistent with an optimisation literature that typically models a single firm facing exogenous demand. In practice, pricing algorithms interact. Learning algorithms can converge on supra-competitive prices without explicit communication (Calvano et al., 2020), and empirical evidence from retail markets suggests that algorithmic adoption can affect margins and competition (Assad et al., 2024). Regulation is also moving faster than the evidence base: EU law now requires traders to disclose when a price has been personalised through automated decision-making (Ren et al., 2026), and broader rules on automated systems are emerging, but the effects of such measures on trust, firm conduct and pricing performance remain largely untested. How interacting algorithms and legal regimes jointly shape prices and welfare is therefore an open question, which multi-agent simulations, audits of live markets and natural experiments around regulatory changes are well placed to address.

A further question is whether these findings carry over to pricing agents built on large language models (LLMs), where prices are set from prompts rather than from a trained reward function. The corpus contains little on this work. LLM terms do not appear among the 59 keywords that occur at least ten times, and the one LLM study in the close-reading set (Ren et al., 2026) uses LLMs for sales forecasting rather than for setting prices. Early experimental evidence nevertheless raises concern: LLM agents placed in simulated markets can reach supra-competitive prices, and outcomes shift with the wording of the prompt. Because the corpus is limited to English-language journal articles and was built with the search string “Pricing AND Analytics”, it probably under-represents this work, which tends to appear first in conference papers and preprints. A targeted scan of Scopus, Web of Science and preprint servers should therefore count and classify LLM-related pricing studies. Benchmarks comparing LLM, reinforcement-learning and rule-based agents, together with audits of chatbot price quotes, should then test whether the collusion findings of

(Calvano et al., 2020) carry over to prompt-based systems. Taken together, this work would connect pricing analytics with industrial organisation, competition economics and consumer-protection scholarship, give regulators evidence on which interventions protect consumers while preserving legitimate pricing innovation, and provide early evidence on whether newer AI-based pricing agents raise the same risks as earlier algorithms.

Explainability and Managerial Adoption

Concerns about black-box models recur in the reviewed literature, alongside evidence of consumer wariness towards algorithmic prices (de Lucas López et al., 2026), yet studies mostly evaluate predictive or financial performance rather than whether managers understand, trust and act on recommendations. Research on algorithm aversion in augmented decision-making shows that people often discount algorithmic advice even when it is accurate (Burton et al., 2020), while over-reliance on automation is an equally documented risk (Parasuraman & Manzey, 2010). A model that performs well in simulation creates little value if it is overridden, misused or abandoned in practice. Future research should therefore ask which forms of explanation increase appropriate reliance rather than blind acceptance or indiscriminate rejection, and when human oversight improves pricing decisions rather than introducing automation bias or inconsistent intervention.

Field studies, case studies and decision experiments with pricing, revenue-management and operations managers should manipulate explanation type, override rights and accountability mechanisms, with outcomes including decision quality, override frequency, calibration of trust and profitability. Organisational factors such as incentives, data quality and coordination between pricing, inventory and fulfilment teams deserve particular attention. Such work would link model design to organisational reality and identify the governance conditions under which algorithmic pricing creates realised value.

Context, Equity and Generalisability

The United States, China and India have the highest numbers of publications, and the keyword co-occurrence map shows clusters relating to energy and smart grids as well as to insurance and risk, which points to application areas beyond e-commerce. Geographic and sectoral concentration, however, does not mean that findings can be applied generally. Consumer expectations, retail structures, payment systems, regulatory frameworks and digital maturity vary greatly across environments, especially in emerging markets where informal retail practices and bargaining customs persist. It remains unclear which dynamic-pricing effects are consistent across markets and which depend on the institutional framework, and whether the advantages and disadvantages of personalisation differ by income level, age group, digital literacy and vulnerability.

Cross-national replications using the same designs, measures and analysis plans would show which findings are transferable. These could be supplemented by mixed-method studies in emerging markets, in platform economies and in regulated industries such as energy, transport and insurance, where expectations regarding fairness and legal constraints differ. This would establish boundary conditions and ensure that results obtained in one market or sector are not assumed to apply everywhere.

Conceptual Coherence and Evidence Infrastructure

Of the 533 records, only 35 contain “dynamic pricing” in the title or author keywords, and the term ranks sixth in frequency (28 occurrences), after more general ones. The field is covered under a number of overlapping labels, such as pricing analytics, revenue management, personalised pricing and algorithmic pricing, and it also relates to other adjacent applications. This fragmentation impedes search, comparison and replication. It also complicates the interpretation of growth: annual output rose from eight papers in 2015 to approximately 42 per year in 2020–2023, then to 76 in 2024, 90 in 2025 and 104 in 2026 (a partial year), but it is unclear whether this reflects substantive expansion, terminological change or growth in the wider analytics literature. Two questions follow: what conditions are necessary for classifying research as dynamic, personalised or algorithmic pricing, and how much of the apparent growth is specific to dynamic pricing.

A shared taxonomy with explicit inclusion rules should be validated through multi-database searches, independent double coding and testing against seed papers such as (Harsha et al., 2019), (Kopalle et al., 2023), (Ulmer, 2020) and (Lei et al., 2018). Growth should be assessed with segmented negative-binomial models (Muggeo, 2003), Bayesian changepoint models or interrupted time-series models, comparing core dynamic-pricing research with adjacent analytics fields. A living evidence synthesis with a registered protocol, periodic updates and a public replication package would keep the evidence base current, and where commercial data cannot be shared, standardised synthetic benchmarks could support replication. These measures would improve construct validity, comparability and reproducibility, and provide the foundation for cumulative evidence in the five preceding directions.

Directions for Future Bibliometric Work

The corpus underpinning this study also points to limits that future bibliometric work can address. It comprises English-language journal articles retrieved with the search string "Pricing AND Analytics", and so probably under-represents research published under neighbouring labels, in other languages, or in conference papers and preprints. Rebuilding the corpus with an expanded and validated search strategy across Scopus, Web of Science and preprint servers would test the robustness of the keyword, country and growth patterns reported here. Analyses that go beyond author-keyword co-occurrence, such as co-citation and bibliographic coupling, would clarify the intellectual structure of the field, while full-text mining would show whether themes such as fairness and trust are neglected or merely under-labelled. Finally, tracking keyword evolution over time and benchmarking against adjacent analytics fields would reveal whether terms such as LLM and fairness are emerging, and how much of the observed growth is specific to dynamic pricing.

Conclusion

These directions converge on a single practical question: under what conditions can algorithmic and dynamic pricing generate lasting value without shifting costs onto consumers, competitors or society? Conceptual coherence and a robust evidence infrastructure form the foundation. Realised performance and measured consumer outcomes then determine whether value has in fact been created, while competition, regulation, managerial adoption and context determine whether that value is sustainable and fairly distributed, especially as AI-based pricing agents become more widespread. In this way, the rapid growth of the field can be transformed into a cumulative research programme that provides reliable evidence for managers, regulators and consumers.

6. CONCLUSION

This study set out to map research on dynamic pricing in e-commerce from an Operations Research perspective. The literature review traced the subject from its origins in airline and hotel pricing to recent machine learning methods, and identified five research areas: pricing theories and competition, personalisation, profit and customer satisfaction, review text as a data source, and the effect of customer reviews on pricing. It also identified the gaps described in the introduction. The methodology screened 1,491 Scopus records down to 533 papers through the PRISMA process. The data analysis then examined those papers by annual output, countries, sources, authors and keyword co-occurrence, so the study moves from a scattered body of research to a documented evidence base.

The findings show a field that has expanded rapidly. Annual output rose from 8 papers in 2015 to 76 in 2024, 90 in 2025 and 104 in 2026 to date, and an exponential trend fits the series closely ($R^2 = 0.906$, $p < 0.0001$). Before 2024 output stayed mostly under 50 papers a year; from 2024 it rose well above that. The research base is collaborative and international. Papers average 3.27 co-authors, and 36.21% involve international co-authorship. The United States (287 papers), China (203), India (149) and the United Kingdom (70) lead the country counts, and the three-field plot links these countries to authors and keywords. The 533 papers are spread across 364 sources, which reflects the range of disciplines involved.

The keyword analysis shows that the field has two balanced components. The first is the operations research core: optimisation, revenue management, dynamic programming, game theory and decision support. The second is a technology component built around machine learning, predictive analytics, artificial intelligence, deep learning and reinforcement learning. Of the 2,036 author keywords, 59 terms appear at least ten times and form five clusters with 979 links. Cluster 1 combines artificial intelligence, machine learning and predictive analytics with pricing and revenue management. Cluster 2 links data analytics with profitability, consumer behaviour, competition and supply chain management. Cluster 3 joins big data and deep learning with insurance and risk management. Cluster 4 connects energy management, smart grids and blockchain with sustainability. The most cited papers, Bradlow et al. (2017) with 455 citations and Ferreira et al. (2016) with 415, both date from the mid-2010s. Because recent papers have had less time to be cited, the average of 18.05 citations per document should be read with that in mind.

The findings have implications for academics, businesses, society and policy, as set out below.

Academic implications. This study adds a structured bibliometric map of dynamic pricing in e-commerce, a gap that the existing reviews leave open. By bringing together operations research, marketing, information systems and computer science, it gives future researchers a common reference point. Three research directions follow from the gaps. The first is the joint treatment of profit and customer satisfaction (Guo & Zhang, 2025). The second is pricing combined with inventory, fulfilment and forecasting decisions (Lei et al., 2018; Ren et al., 2026). The third is learning-based pricing for markets in which demand changes over time (Misra et al., 2019).

Business implications. Businesses can treat pricing as part of a wider decision system. Prices should be planned alongside inventory, fulfilment and delivery decisions (Harsha et al., 2019; Lei et al., 2018; Ulmer, 2020). Customer reviews also matter: He and Chen (2018) find that high-quality electronics sellers may keep initial prices low so that good reviews accumulate faster, and Duan et al. (2022) find that negative reviews have less effect on sales for expensive products. Learning-based tools are promising. Kantaria et al. (2026) report profit improvements of about 13–18% over baseline pricing algorithms, and Liu et al. (2026) report cumulative profit margin gains above 16.7%. Both results come from simulations, so firms should test them on live sales before relying on them, and should weigh profit gains against customer satisfaction (Guo & Zhang, 2025).

Social implications. Because dynamic pricing shapes what consumers pay, its consequences extend beyond the firm. The literature stresses the negative perception of algorithm-based prices (de Lucas López et al., 2026), and this study finds that price fairness appears as an author keyword in only one of the reviewed records. Treating fairness and transparency as design criteria, alongside profitability and accuracy, would help make online pricing more acceptable to consumers.

Policy and regulatory implications. The papers can inform rule-making, but they cannot justify specific regulations on their own. A bibliometric map shows the shape of the literature, not the effect of any pricing practice. The literature does give some grounds for policy attention. Machine learning pricing models are often criticised as black boxes that can produce an optimal price without explaining why, and consumers are wary of algorithmic prices (de Lucas López et al., 2026). Regulators and platforms could therefore consider requirements for transparency about how prices are set, and for evaluating pricing algorithms on fairness as well as profit. Any such rule would need to be tested against empirical evidence from the individual studies.

Limitations. This study has several limitations. First, it relies on a single database, Scopus, so relevant work indexed elsewhere, such as in Web of Science or Google Scholar, may be missing. Second, the search string “Pricing AND Analytics” requires both terms, and only 35 of the 534 Scopus records contain “dynamic pricing” in their title or author keywords. The corpus therefore covers pricing analytics more broadly than dynamic pricing in e-commerce specifically. Third, the restriction to English-language journal articles and reviews excludes conference proceedings, which can under-represent fast-moving computer science work such as Nishamali et al. (2024). Fourth, the 2026 figures reflect a search run in September 2026 and cover only part of the year. Fifth, the keyword map in the literature review was built from a small collection of 24 papers, with a minimum of two occurrences, and its clusters were verified manually. Sixth, keyword analysis depends on how authors label their work, and citation counts favour older papers while publication counts measure output rather than quality. Finally, the co-citation, co-authorship and author-level performance analyses are not included in this version, so the study does not claim that any author, institution or country is the most influential. These results should be added once they are complete.

Despite these limitations, the 533-paper dataset provides a useful base for understanding the scope of research on dynamic pricing in e-commerce. Rapid growth, an international research base, and a keyword structure that spans optimisation, learning, consumer and operational themes show that the subject is approached from both established and newer perspectives. The next stage is to map the relationships between these themes in detail and to examine how the field has evolved.

REFERENCES

1. Aria, M., & Cuccurullo, C. (2017). bibliometrix: An R-tool for comprehensive science mapping analysis. *Journal of Informetrics*, *11*(4), 959–975. https://doi.org/10.1016/j.joi.2017.08.007

2. Asim, M. M., Din, F. U., Karim, A., & Shafiabady, N. (2024). A systematic review of data analytics approaches in smart electricity markets. *International Journal of Energy and Environmental Engineering*, *15*(4). https://doi.org/10.57647/ijeee.2024.1504.16

3. Assad, S., Clark, R., Ershov, D., & Xu, L. (2024). Algorithmic pricing and competition: Empirical evidence from the German retail gasoline market. *Journal of Political Economy*, *132*(3), 723–771.

4. Bojinov, I., Simchi-Levi, D., & Zhao, J. (2023). Design and analysis of switchback experiments. *Management Science*, *69*(7), 3759–3777.

5. Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The role of big data and predictive analytics in retailing. *Journal of Retailing*, *93*(1), 79–95. https://doi.org/10.1016/j.jretai.2016.12.004

6. Burton, J. W., Stein, M.-K., & Jensen, T. B. (2020). A systematic review of algorithm aversion in augmented decision making. *Journal of Behavioral Decision Making*, *33*(2), 220–239.

7. Callon, M., Courtial, J.-P., Turner, W. A., & Bauin, S. (1983). From translations to problematic networks: An introduction to co-word analysis. *Social Science Information*, *22*(2), 191–235. https://doi.org/10.1177/053901883022002003

8. Calvano, E., Calzolari, G., Denicolò, V., & Pastorello, S. (2020). Artificial intelligence, algorithmic pricing, and collusion. *American Economic Review*, *110*(10), 3267–3297.

9. Chen, C. (2017). Science mapping: A systematic review of the literature. *Journal of Data and Information Science*, *2*(2), 1–40. https://doi.org/10.1515/jdis-2017-0006

10. Chen, Z., & Xiao, T. (2026). Returnable-after-deep-trial policies in e-commerce supply chains with opportunistic consumers. *Transportation Research Part E: Logistics and Transportation Review*, *209*, Article 104728. https://doi.org/10.1016/j.tre.2026.104728

11. Chukwunweike, J. N., Abiodun, D., Bright, O., & Taiwo, R. (2024). Enhancing productiveness in e-commerce through machine learning: Challenges, future perspectives, and a MATLAB-based approach. *World Journal of Advanced Research and Reviews*, *23*(2), 2120–2132. https://doi.org/10.30574/wjarr.2024.23.2.2585

12. Cross, D. (2016). A history of revenue management and the advent of next-generation RM. *Journal of Revenue and Pricing Management*, *15*, 293–298. https://doi.org/10.1057/rpm.2016.5

13. de Lucas López, A. P., Gorneanu, A. E., Aránega, A. Y., & Gallego Martín, L. (2026). Ethics, transparency, and consumer trust in AI-enabled pricing: Implications for sustainable technology entrepreneurship and economic policy. *Sustainable Technology and Entrepreneurship*, *5*(2), Article 100131. https://doi.org/10.1016/j.stae.2026.100131

14. Dinev, T., & Hart, P. (2006). An extended privacy calculus model for e-commerce transactions. *Information Systems Research*, *17*(1), 61–80.

15. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, *133*, 285–296. https://doi.org/10.1016/j.jbusres.2021.04.070

16. Duan, Y., Liu, T., & Mao, Z. (2022). How online reviews and coupons affect sales and pricing: An empirical study based on e-commerce platform. *Journal of Retailing and Consumer Services*, *65*, Article 102846. https://doi.org/10.1016/j.jretconser.2021.102846

17. El Youbi, R., Messaoudi, F., & Loukili, M. (2023). Machine learning-driven dynamic pricing strategies in e-commerce. In *2023 14th International Conference on Information and Communication Systems (ICICS 2023)*. https://doi.org/10.1109/ICICS60529.2023.10330541

18. Elmaghraby, W., & Keskinocak, P. (2003). Dynamic pricing in the presence of inventory considerations: Research overview, current practices, and future directions. *Management Science*, *49*(10), 1287–1309. https://doi.org/10.1287/mnsc.49.10.1287.17315

19. Ferreira, K. J., Lee, B. H. A., & Simchi-Levi, D. (2016). Analytics for an online retailer: Demand forecasting and price optimization. *Manufacturing & Service Operations Management*, *18*(1), 69–88. https://doi.org/10.1287/msom.2015.0561

20. Fruchter, G. E., & Tapiero, C. S. (2005). Dynamic online and offline channel pricing for heterogeneous customers in virtual acceptance. *International Game Theory Review*, *7*(2), 137–150. https://doi.org/10.1142/S0219198905000454

21. Guo, X., & Zhang, L. (2025). Dynamic pricing models in e-commerce: Exploring machine learning techniques to balance profitability and customer satisfaction. *IEEE Access*, *13*, 72994–73002. https://doi.org/10.1109/ACCESS.2025.3563371

22. Harsha, P., Subramanian, S., & Ettl, M. (2019). A practical price optimization approach for omnichannel retailing. *INFORMS Journal on Optimization*. https://doi.org/10.1287/ijoo.2019.0018

23. Harsha, P., Subramanian, S., & Uichanco, J. (2019). Dynamic pricing of omnichannel inventories. *Manufacturing & Service Operations Management*, *21*(1), 47–65. https://doi.org/10.1287/msom.2018.0737

24. He, Q. C., & Chen, Y. J. (2018). Dynamic pricing of electronic products with consumer reviews. *Omega*, *80*, 123–134. https://doi.org/10.1016/j.omega.2017.08.014

25. Hedges, L. V., Tipton, E., & Johnson, M. C. (2010). Robust variance estimation in meta-regression with dependent effect size estimates. *Research Synthesis Methods*, *1*(1), 39–65.

26. Jawabreh, O., Alshatnawi, E. A. R., & Mahmoud, R. (2026). Applications of machine intelligence and decision analytics in hospitality: A systematic review. *IAES International Journal of Artificial Intelligence*, *15*(3), 2024–2040. https://doi.org/10.11591/ijai.v15.i3.pp2024-2040

27. Kannan, P. K., & Kopalle, P. K. (2001). Dynamic pricing on the Internet: Importance and implications for consumer behavior. *International Journal of Electronic Commerce*, *5*(3), 63–83. https://doi.org/10.1080/10864415.2001.11044211

28. Kantaria, M. H., Sharma, M., Lakshmi, B. S., Krishnakumari, S., Sangeetha, M., & Rao, P. V. (2026). Machine learning framework for dynamic pricing: Integrating LSTM forecasting and reinforcement learning optimization. *Journal of Theoretical and Applied Information Technology*, *104*(2), 390–402.

29. Kopalle, P. K., Pauwels, K., Akella, L. Y., & Gangwar, M. (2023). Dynamic pricing: Definition, implications for managers, and future research directions. *Journal of Retailing*, *99*(4), 580–593. https://doi.org/10.1016/j.jretai.2023.11.003

30. Le, H. S., Do, T. V. H., Nguyen, M. H., Tran, H. A., Pham, T. T. T., Nguyen, N. T., & Nguyen, V. H. (2024). Predictive model for customer satisfaction analytics in e-commerce sector using machine learning and deep learning. *International Journal of Information Management Data Insights*, *4*(2), Article 100295. https://doi.org/10.1016/j.jjimei.2024.100295

31. Lei, Y., Jasin, S., & Sinha, A. (2018). Joint dynamic pricing and order fulfillment for e-commerce retailers. *Manufacturing & Service Operations Management*, *20*(2), 269–284. https://doi.org/10.1287/msom.2017.0641

32. Lemire, G., & Gamache, S. (2025). Dynamic pricing in manufacturing SMEs: A literature review. *IFAC-PapersOnLine*, *59*(10), 202–207. https://doi.org/10.1016/j.ifacol.2025.09.036

33. Liu, K., & Li, W. (2026). Behavior-based pricing of low-carbon products via data-driven pricing under cap-and-trade and subsidies. *International Journal of Production Economics*, *302*. https://doi.org/10.1016/j.ijpe.2026.110179

34. Liu, Y., Cui, T., Li, G., Payne, T. R., Yue, Y., & Man, K. L. (2026). A multimodal deep reinforcement learning framework for dynamic pricing optimisation in e-commerce. *IEEE Access*, *14*, 57358–57386. https://doi.org/10.1109/ACCESS.2026.3680140

35. Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*, 90–103.

36. Loukili, M., Messaoudi, F., El Aalouche, O., El Youbi, R., & Loukili, R. (2025). Adaptive pricing strategies in digital marketing: A machine learning approach with Deep Q-Networks. *Statistics, Optimization & Information Computing*, *14*(3), 1244–1251. https://doi.org/10.19139/soic-2310-5070-2200

37. Misra, K., Schwartz, E. M., & Abernethy, J. (2019). Dynamic online pricing with incomplete information using multiarmed bandit experiments. *Marketing Science*, *38*(2), 226–252. https://doi.org/10.1287/mksc.2018.1129

38. Muggeo, V. M. R. (2003). Estimating regression models with unknown break-points. *Statistics in Medicine*, *22*(19), 3055–3071.

39. Nishamali, M. K. C. P., Pathirage, G. S., Herath, S., Herath, P., & Wickramarathne, J. (2024). A systematic study of machine learning applications in e-commerce UX personalization. In *2024 4th IEEE International Conference on Mobile Networks and Wireless Communications (ICMNWC)* (pp. 1–6). IEEE. https://doi.org/10.1109/ICMNWC63764.2024.10872138

40. Nowak, M., & Pawłowska-Nowak, M. (2024). Dynamic pricing method in the e-commerce industry using machine learning. *Applied Sciences*, *14*(24), Article 11668. https://doi.org/10.3390/app142411668

41. Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., et al. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ*, *372*, Article n71. https://doi.org/10.1136/bmj.n71

42. Parasuraman, R., & Manzey, D. H. (2010). Complacency and bias in human use of automation: An attentional integration. *Human Factors*, *52*(3), 381–410.

43. Rajumesh, S. (2024). Nexus between artificial intelligence and marketing: A systematic review and bibliometric analysis. *International Journal of Electronic Marketing and Retailing*, *15*(6), 709–732. https://doi.org/10.1504/IJEMR.2024.141799

44. Ren, X., Li, M., Li, W., & Qu, T. (2026). LLM sentiment analysis-integrated sales forecasting for e-commerce: A case study on Amazon. *Digital Engineering*, Article 100134. https://doi.org/10.1016/j.dte.2026.100134

45. Singh, N., Lai, K.-H., & Zhang, J. Z. (2024). Intellectual core in supply chain analytics: Bibliometric analysis and research agenda. *International Journal of Information Technology & Decision Making*, *23*(2), 539. https://doi.org/10.1142/S0219622023300021

46. Stanley, T. D., & Doucouliagos, H. (2014). Meta-regression approximations to reduce publication selection bias. *Research Synthesis Methods*, *5*(1), 60–78.

47. Suresh Kumar, S., Margala, M., Siva Shankar, S., & Chakrabarti, P. (2023). A novel weight-optimized LSTM for dynamic pricing solutions in e-commerce platforms based on customer buying behaviour. *Soft Computing*. https://doi.org/10.1007/s00500-023-08729-1

48. Ulmer, M. W. (2020). Dynamic pricing and routing for same-day delivery. *Transportation Science*, *54*(4), 1016–1033. https://doi.org/10.1287/trsc.2019.0958

49. Yoshi, A. M., Rohan, A., Mitu, S. A., Rabbi, M. M. K., Akther, S., & Ahmed, K. R. (2025). Real-time dynamic pricing using machine learning: Integrating customer sentiment and predictive models for e-commerce. *International Journal of Advanced Computer Science and Applications*, *16*(9), 22–30. https://doi.org/10.14569/IJACSA.2025.0160904

50. Zhang, C., & Tian, Y. X. (2024). Joint optimization of dynamic pricing, quality, and production quantity in the presence of online reviews: A distributionally robust optimization approach. *Computers & Operations Research*, *169*, Article 106720. https://doi.org/10.1016/j.cor.2024.106720

51. Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational Research Methods*, *18*(3), 429–472. https://doi.org/10.1177/1094428114562629