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Application of Operations Research in Customer Satisfaction in E-Commerce

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ABSTRACT

This study combines a systematic literature review with a bibliometric analysis to examine research on customer satisfaction and analytics from an Operations Research (OR) perspective in e-commerce. The authors aim to identify publication trends, dominant themes and the extent to which analytics support OR-based decisions. Data were retrieved from Elsevier's Scopus database and screened using the PRISMA framework, giving a final dataset of 518 articles and 30 review papers. The findings show that the field has grown rapidly since 2018, with machine learning, big data and sentiment analysis as its dominant themes, while core OR methods remain largely absent.

Keywords: *Customer Satisfaction, Operations Research, E-Commerce, Analytics, and Bibliometric Analysis.*

1. INTRODUCTION

In online retail, an unhappy customer does not walk out of a shop; they simply click away, and their review stays behind for every future buyer to read. The stakes of that click are global. In 2024, businesses in 46 developed and developing economies recorded nearly US$28 trillion in e-commerce sales, and these economies make up about three-quarters of world GDP (UNCTAD, 2026). The benefits of this growth are not shared equally, since access to digital services still differs widely between countries (UNCTAD, 2024). In such a large and competitive market, customer satisfaction decides which businesses keep their customers. Satisfied customers return, buy again and recommend the brand to others, which is why satisfaction is seen as a key measure of business success (Irshad et al., 2024). Online, satisfaction also depends on how well the business runs behind the screen, from accurate product information to on-time delivery and quick replies to complaints.

Operations Research (OR) is the use of mathematical models to make better decisions. It helps organisations get the most out of limited resources such as money, stock, staff and delivery capacity. Many of the problems that frustrate online shoppers can be addressed with OR tools. Inventory models help prevent stock-outs, vehicle routing shortens delivery times and queueing models reduce how long customers wait for support. Linear programming can decide how a fixed budget is split between these improvements, and simulation can test a new policy before it is used. Recent research argues that data is valuable only when it leads to better decisions, and shows how prediction models can be turned into decision models (Bertsimas & Kallus, 2020). The most accurate prediction, however, does not always produce the best decision (Elmachtoub & Grigas, 2022). In e-commerce, such decision-focused applications are only beginning to appear, for example in the use of genetic algorithms to optimise marketing strategies (Yang & Peng, 2026).

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The authors chose this topic because of a gap they noticed between data and decisions. E-commerce platforms now collect huge amounts of ratings, reviews and order data, and tools such as machine learning and sentiment analysis are widely used to study them. These tools can tell a manager that late deliveries are making customers unhappy. They cannot tell the manager whether to hire more couriers, keep stock closer to customers or promise longer delivery times. Each option has its own costs and limits, which makes the choice an OR problem. In the authors' view, predicting dissatisfaction is useful only if it helps a business decide what to fix first and how much to spend. This paper therefore examines how far customer satisfaction research has made this link to OR.

The literature reviewed in Section 2 shows how analytics is used to study satisfaction. Studies of online reviews identify what drives satisfaction and dissatisfaction (Gruss et al., 2024). Sentiment analysis turns large volumes of customer comments into information for forecasting sales (Lau et al., 2018). Predictive analytics, in turn, improves procurement and stock planning, which helps keep customers satisfied (Pathak et al., 2026). Only a few studies take the next step of using these insights to allocate resources, such as setting budgets for hotel apps from user reviews (Liu et al., 2027). Overall, the literature is strong at understanding customers but weaker at turning that understanding into decisions.

To study this field, the authors carried out a bibliometric analysis, a method that uses statistics to map a large body of research (Donthu et al., 2021). Publications were collected from the Scopus database on 10 September 2026 using the search phrase "Customer Satisfaction AND Analytics". The search covered the years 2002 to 2027 and included only English-language articles and reviews in business, management, engineering, computer science, decision sciences and mathematics. The records were screened using the PRISMA framework. They were then analysed with Biblioshiny, the web interface of the Bibliometrix package (Aria & Cuccurullo, 2017). Keyword maps were drawn in VOSviewer. Because the search phrase did not include OR terms, the study maps analytics research on customer satisfaction and then examines it through an OR lens.

The final dataset contains 548 documents from 375 sources. Research in this area has grown quickly, from 3 documents in 2002 to 115 in 2025, or about 17% a year. Almost nine in ten documents were published from 2018 onward. India, the United States, China and South Korea are the leading contributors. The most common keywords are customer satisfaction, machine learning, big data, sentiment analysis and artificial intelligence. The keyword maps group these topics into five connected themes, with customer satisfaction at the centre. Typical OR terms such as optimisation, linear programming and simulation do not appear among the main keywords. This suggests that the field focuses on measuring and predicting satisfaction rather than on deciding how to improve it.

In short, the paper describes how research on customer satisfaction and analytics has developed and asks what it offers for OR-based decisions in e-commerce. Its main contribution is to show that the field is focused on prediction rather than decision-making, and to propose six priorities for connecting customer analytics with OR. These priorities range from turning predictions into decisions to making sure that optimised systems treat customers fairly. The rest of the paper is organised as follows. Section 2 reviews the literature, Section 3 explains the methodology, Section 4 presents the results, Section 5 sets out the future research agenda and Section 6 concludes.

The main aim of the study is to understand how customer satisfaction research uses analytics and how it can be better connected with OR. To achieve this aim, the study sets four objectives, each linked to a research question:

1. **Publication trends:** To analyse how research in this area has grown and who leads it. (RQ1: How has the field grown since 2002, and which countries, sources and authors contribute most?)
2. **Research themes and the link with OR:** To identify the main topics in the field and assess how far they connect customer analytics with operational decisions. (RQ2: Which themes dominate the field, and to what extent are their insights turned into OR-based decisions?)
3. **Future research agenda:** To identify research gaps and propose directions for future work. (RQ3: What should future research focus on to connect customer analytics with OR in e-commerce?)
4. **Implications:** To draw out lessons for researchers, managers, society and policymakers. (RQ4: What do the findings mean for each of these groups?)

2. LITERATURE REVIEW

2.1 Definition of important terms

Table -1: Definition of important terms

Important Term	Definition and Relevance to the study
Customer satisfaction	Customer satisfaction refers to the extent to which a product or service meets or exceeds customer expectations. It plays an important role in building customer loyalty, encouraging repeat purchases, and maintaining a positive relationship between the business and its customers. A company's strategic efforts and customer loyalty are inextricably linked by customer satisfaction, which is usually considered a key measure of corporate success. Customer satisfaction increases a brand's chances of brand loyalty, repeat purchases, and favorable word-of-mouth referrals. (Irshad et al., 2024)

Important Term	Definition and Relevance to the study
Sales	Sales refer to the process of identifying potential customers, understanding their purchasing needs, and converting purchase opportunities into revenue for a business. (Lawrence et al., 2007) highlight the role of analytics in identifying potential buyers and predicting their likelihood of purchasing, which helps businesses target customers more effectively and improve sales performance.
Sentiment analysis	Sentiment analysis refers to analysing customers' written opinions to understand the sentiments expressed in online reviews and feedback. (Lau et al., 2018) describe their approach as "for mining consumer intelligence from a huge number of online product comments", while (Puustinen et al., 2025) discuss "topic discovery and sentiment analysis for a fixed time period" when analysing textual information. In e-commerce, sentiment analysis helps businesses understand customer opinions, monitor changes in feedback, and improve sales forecasting and customer satisfaction.
Big data	Big data refers to large volumes of information that can be analysed to understand customer behaviour and improve business decision-making. (Yang & Peng, 2026) emphasise the importance of developing marketing strategies that are "data-driven, adaptive, and customer-focused". They also explain that businesses can personalise advertising by "analysing consumer behavior, interests, and past purchases".This shows how big data can help e-commerce businesses understand customer needs, improve marketing strategies and enhance customer satisfaction.
Resource Allocation	Resource allocation refers to the process of distributing limited resources, such as money, staff and time, among different activities to achieve organisational goals efficiently. (S. Zhang & Cornell, 2026) examine "resource allocation patterns" involving "land, human resources, and capital allocation". In a digital business context, (Liu et al., 2027) propose a framework "to optimize strategic resource allocation for hotel mobile app development". In e-commerce, this approach can help businesses decide how to allocate resources among website improvement, delivery services and customer support to enhance customer satisfaction.
Artificial Intelligence	Artificial intelligence (AI) refers to the use of computer systems to perform tasks such as learning, analysing information and making decisions. (Tabaku, 2024) examines the use of AI in e-commerce, highlighting applications such as product recommendation systems, chatbots and virtual assistants to improve customer experience. In e-commerce, these technologies can help businesses personalise product suggestions, provide faster customer support and make online shopping more convenient, thereby contributing to improved customer satisfaction.
Predictive analytics	Predictive analytics refers to the use of historical data, statistical techniques and machine learning to predict future trends and outcomes. (Pathak et al., 2026) explored how predictive analytics can improve inventory management by forecasting stock shortages and optimising procurement processes. In e-commerce, this approach can help businesses predict customer demand, maintain adequate stock levels and reduce order delays, thereby improving operational efficiency and customer satisfaction.
Customer Experience	Customer experience refers to the overall perceptions and evaluations customers develop through their interactions with a business and its products or services. (X. Zhang & Kim, 2021) examined the different dimensions of customer experience reflected in online customer reviews and their relationship with customer satisfaction. In e-commerce, customer experience can involve website usability, product information, payment processes, delivery and customer support.
Online Reviews	Online reviews refer to feedback shared by customers about their experiences with products or services. (Gruss et al., 2024) analysed online customer reviews to identify factors influencing customer satisfaction and understand how positive and negative experiences affect customer evaluations. In e-commerce, customer reviews can help businesses understand opinions about product quality, pricing, delivery and customer service, allowing them to identify areas for improvement and enhance customer satisfaction.
Service Quality	Service quality refers to how well a business's services meet customer expectations and needs. (Chotisarn & Phuthong, 2025) examined logistics service quality in cross-border e-commerce, focusing on factors such as delivery timeliness, communication, shipping information and price fairness. Their findings showed that price fairness, communication quality and shipping information significantly influenced customer satisfaction. In e-commerce, maintaining good service quality can help businesses build customer trust, encourage repeat purchases and improve overall customer satisfaction.

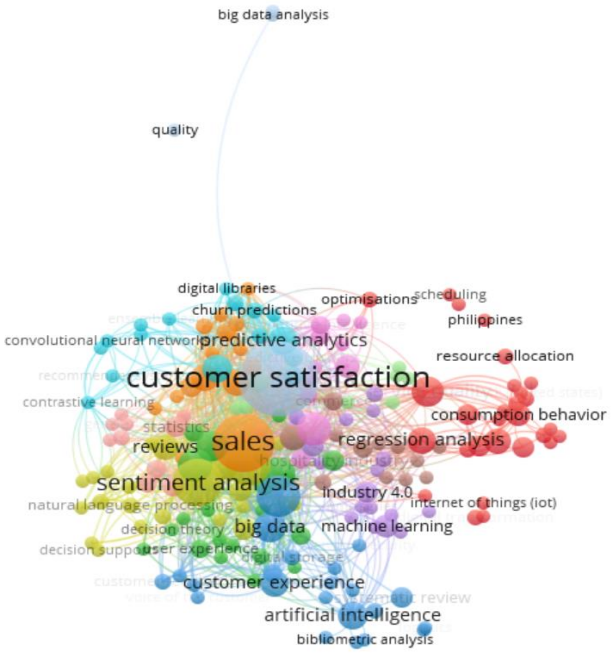

Figure -1: Co-occurrence analysis of the keywords in literature (VOS Viewer)

3. RESEARCH METHODOLOGY

One of the most well-known tools for assessing and understanding the rapidly changing trends is systematic literature review (SLR) and bibliometric analysis. The benefit of these tools is that a literature review article provides a comprehensive overview of literature related to a theme/theory/method and synthesizes prior studies to strengthen the foundation of knowledge (Paul & Rialp, 2020) while a bibliometric analysis is a popular and rigorous method for exploring and analysing large volumes of scientific data. It enables us to unpack the evolutionary nuances of a specific field, while shedding light on the emerging areas in that field (Donthu, Kumar, Mukherjee, Pandey, & Lim, 2021).

Bibliographic databases play an important role in evaluating research publications within a particular subject area, discipline, geographical region or country. One of the major databases used for this purpose is Elsevier's Scopus, which was selected as the primary source of literature for the present study. To ensure that the literature was collected in a systematic and transparent manner, the study adopted the Preferred Reporting Items for Systematic and Meta Analysis (PRISMA) technique suggested by Moher, Liberati, Tetzlaff, and Altman (2010) that aims at a methodological identification and screening of literature, which is free from the author's bias (Saxena, 2023). PRISMA provides a structured process for identifying, screening and selecting relevant research studies. In the present study, the selection process consisted of four major stages: Identification, Screening, Eligibility and Inclusion. These stages helped in narrowing down the initial pool of records to a relevant and manageable set of research articles for further analysis.

3.1 Article selection, inclusion, and exclusion criteria

A search was conducted on 10th September 2026 on Elsevier's database Scopus. A major advantage of Scopus is that it provides comprehensive coverage of peer-reviewed literature and facilitates systematic and structured retrieval of relevant studies through advanced search and filtering features, thereby supporting the reliability and rigor of the literature review. A search was conducted using the search keywords "Customer Satisfaction AND Analytics". The selected keywords were used to identify relevant research publications that focused on customer satisfaction and the role or application of analytics in studying customer-related outcomes.

The literature selection process followed the stages of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, namely identification, screening, eligibility, and inclusion. The PRISMA approach was used to provide a structured record of how the publications were identified and progressively refined before being included in the final dataset. This helped maintain a clear and transparent process for selecting the literature used in the study.

The process began with the identification stage, where the Scopus database was selected as the source of academic literature and the search query **"**Customer Satisfaction AND Analytics**"** was entered. The initial search generated the total number of records available for the selected keywords. These records formed the initial database for the study before the application of the filtering criteria. The number of records obtained at this stage was recorded for the purpose of documenting the literature selection process in the PRISMA diagram.

Following the initial search, the retrieved publications were refined using the filtering options available in Scopus. The filters were applied to make the search results more relevant to the objectives of the study. The main criteria used for refining the records were publication period, document type, subject area, and language. The number of publications remaining after each relevant filtering stage was noted so that the changes in the dataset could be represented accurately in the PRISMA flow diagram.

The search covered the publication period from 2002 to 2027. Publications within this period were considered, and no individual year within the selected period was intentionally excluded. A broad publication period was selected to capture the development of

research related to customer satisfaction and analytics over time. This allowed the study to include earlier research as well as more recent studies and provided a wider base for understanding the development of the research area.

The next filter applied was document type. For the purpose of the study, articles and review articles were retained. Other types of documents available in Scopus were excluded from the dataset. Articles were considered important for identifying individual research studies, methodologies, and findings, while review articles provided a broader understanding of existing research and helped identify important areas of discussion within the subject.

The records were then filtered according to subject area. The study included publications from Computer Science, Engineering, Business, Management and Accounting, Decision Sciences, and Mathematics. These areas were selected because customer satisfaction and analytics involve both business and technical aspects. Computer Science and Engineering are relevant to analytical tools, technology, data processing, and digital systems, while Business, Management and Accounting provide perspectives related to customer behaviour, customer satisfaction, business performance, and managerial decision-making. Decision Sciences and Mathematics are also relevant because they provide quantitative methods and analytical approaches that can be applied to customer-related research.

The final filtering criterion applied during the Scopus search was language. Only English-language publications were retained for further analysis, while publications in other languages were excluded. This criterion was applied to maintain consistency in the interpretation and comparison of the selected literature. Since the study required detailed examination of the selected publications, restricting the dataset to English-language research helped ensure consistency during the subsequent stages of analysis.

After the identification and initial filtering of the records, the screening stage was carried out. At this stage, the publications were progressively refined according to the predefined criteria. The publication period, document type, subject area, and language filters were considered in accordance with the scope of the study. Records that did not meet the specified criteria were excluded, while the records satisfying the requirements were retained for further processing.

The number of records before and after the application of the filters was recorded at each relevant stage. This provided the information required to show the reduction in the number of publications during the screening process. Maintaining these records was important for preparing the PRISMA flow diagram because it allowed the study to clearly show how the initial collection of publications was narrowed down to the records considered for further analysis.

Once the required filters had been applied in Scopus, the resulting literature database was downloaded for further analysis. The bibliographic records were exported from Scopus in BibTeX and RIS file formats. These files contained the bibliographic information required for transferring the selected literature into the software used for the subsequent bibliometric analysis. The downloaded files also provided a structured form of the Scopus search results, making it possible to continue the analysis outside the database.

The downloaded BibTeX file was subsequently uploaded into Biblioshiny, the web-based interface of the Bibliometrix package. Bibliometrix is an R-based tool developed for comprehensive science mapping and bibliometric analysis, while Biblioshiny provides a user-friendly web interface for carrying out bibliometric analysis without requiring extensive programming knowledge (Aria & Cuccurullo, 2017). The use of these tools allowed the selected Scopus records to be organised and examined as a bibliographic dataset.

Biblioshiny was used to process the imported BIB file and support the further analysis of the selected publications. The platform provides several functions for examining bibliographic information and identifying patterns within a research field. The use of Biblioshiny also supported the systematic handling of the selected records and provided a suitable platform for the bibliometric analysis of the literature obtained from Scopus (Aria, Cuccurullo, D'Aniello, & Spano, 2026).

The RIS file downloaded from Scopus was also retained as part of the literature records and supported the management and transfer of the bibliographic information. Maintaining the exported files in these formats provided a record of the literature retrieved from Scopus and allowed the selected publications to be used for subsequent stages of the research process.

After the screening and organisation of the retrieved records, the publications that satisfied the predefined criteria were considered under the eligibility stage. The purpose of this stage was to ensure that the publications retained in the dataset were within the defined scope of the study. The selected records had to fall within the publication period of 2002–2027, belong to the relevant document types, fall within the selected subject areas, and be available in English.

The eligibility stage therefore provided an additional basis for ensuring that the final dataset was consistent with the research objectives. Publications that did not satisfy the established criteria were not considered for the final analysis. The number of records retained after this process was documented to establish the final set of publications used in the study.

The final stage was the inclusion of the eligible publications in the research dataset. The publications that remained after the application of the predefined criteria were considered suitable for the subsequent analysis of literature relating to customer satisfaction and analytics. The final number of publications was recorded as the number of studies included in the review.

After completing the identification, screening, and eligibility process, the PRISMA flow diagram was prepared to present the complete article selection procedure. The diagram shows the initial number of records identified through the Scopus search and the reduction in records following the application of the different filtering criteria. It also presents the number of records excluded during the screening and eligibility stages and the final number of publications included in the study. In this manner, the PRISMA diagram provides a clear visual representation of the complete selection process and explains how the final research dataset was obtained (Page et al., 2021).

The overall methodology therefore combined Scopus for the identification and retrieval of relevant literature, predefined filtering criteria for screening, BibTeX and RIS files for exporting the retrieved records, Bibliometrix and Biblioshiny for bibliometric analysis, and the PRISMA framework for documenting the selection process. Following these stages in a defined sequence helped establish a systematic and transparent method for collecting and analysing the literature related to customer satisfaction and

analytics. The final dataset obtained through this process was subsequently used for the detailed analysis of the existing literature and for examining the development and research trends within the selected area.

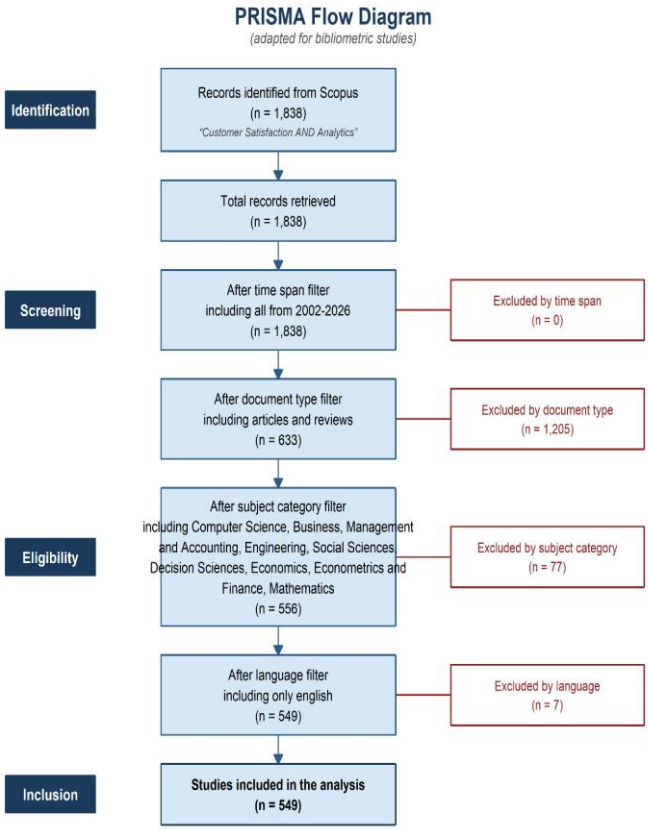

Figure -2: Prisma Diagram

4. DATA ANALYTICS

4.1 Overview

Bibliometrics studies research through numbers. It is based on the statistical measurement of science, scientists, or scientific activity (Broadus, 1987; Diodato, 1994; Pritchard, 1969). It can show trends over time, the themes that are studied, and the most active scholars and institutions. The aim of this report is to describe the research on data analytics and customer satisfaction. The first set of analyses examined the main information and the output over time. The next analyses looked at sources, countries, and authors. The last analyses used keywords to map the main themes.

4.2 Data and method

The data comes from Scopus and has 548 documents. Of these, 518 are articles (94.5%) and 30 are reviews (5.5%). The data was analysed with the bibliometrix R package (Aria & Cuccurullo, 2017), and the keyword networks were drawn in VOSviewer (van Eck & Waltman, 2010). The work followed the usual five stages of study design, data collection, data analysis, data visualisation, and interpretation. All figures are numbered and given a title.

4.3 Results

4.3.1 Main information

Figure 3 provides an overview of the dataset. The documents cover the years 2002 to 2027 and appear in 375 sources. They were written by 1,710 authors, of whom 60 wrote a document alone. What stands out in the figure is the amount of teamwork. There are 3.43 co-authors per document, and 29.56% of the documents have authors from more than one country. The data has 1,907 author keywords. The average document age is 4.03 years, and each document has 23.41 citations on average, which gives 12,831 citations in total. The most active authors are Kim HS (15 documents), Lee M (10), Kim S (7), and Shokouhyar S (6).

Figure -3: Main information about the dataset

The annual growth rate is shown as -4.3%. This figure should be read with care. The time span ends in 2027, and that year has only one document, so the small last value pulls the rate below zero. Using the full years 2002 (3 documents) and 2025 (115 documents), growth is about 17% a year.

The topic is spread over many sources. The largest are IEEE Access (14 documents), International Journal of Advanced Computer Science and Applications (10), Sustainability (9), Expert Systems with Applications (9), and Journal of Retailing and Consumer Services (8). The top source holds only 2.6% of all documents. The most cited paper is on Industry 5.0 in the Journal of Cloud Computing, with 905 citations. It is followed by a paper on social media analytics in Communications of the ACM, with 517 citations.

4.3.2 Annual scientific production

Figure 4 shows the number of articles per year from 2002 to 2027. From the graph, we can see that output was very low until 2017, with 1 to 7 documents a year and 58 documents in total over 16 years. Output then rose to 16 in 2018, 28 in 2019, and 32 in 2020. It stayed at 42 and 41 in 2021 and 2022, then increased to 59 in 2023, 86 in 2024, and 115 in 2025, which is the peak. What stands out is the rapid increase after 2017. The 490 documents from 2018 onward are 89% of the dataset.

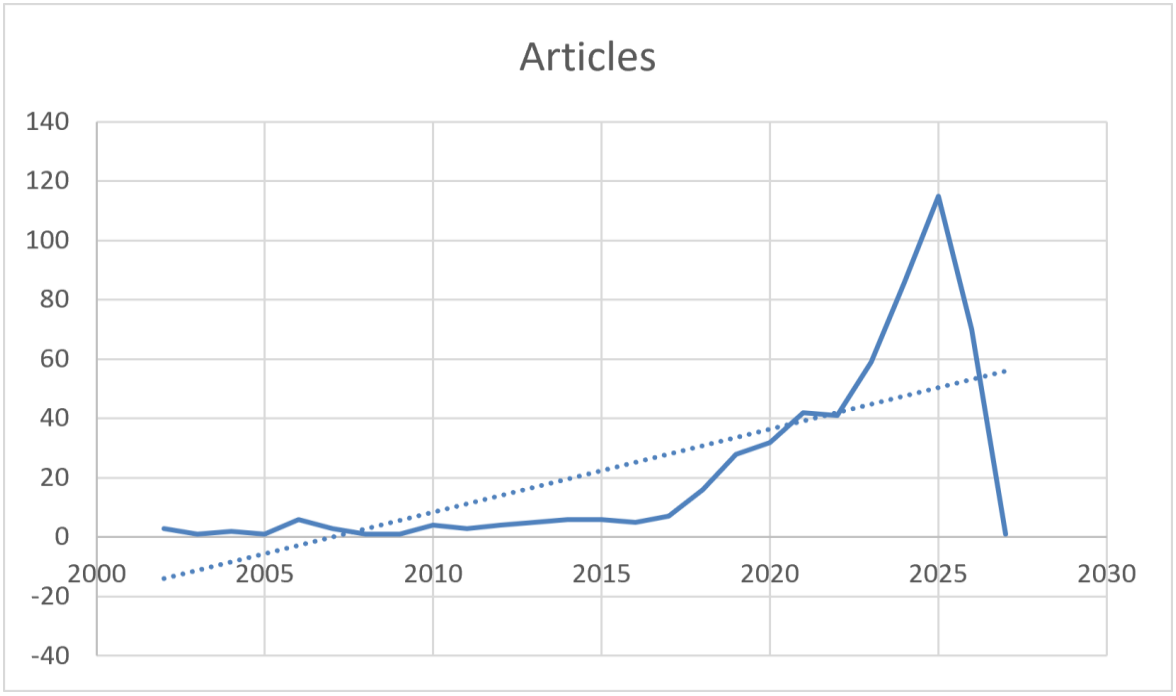

Figure -4: Annual scientific production

The fall to 70 documents in 2026 and 1 document in 2027 reflects incomplete years, since the data was collected in September 2026. The dotted line is a straight trend line. It sits above the real values for most years before 2022 and below them in the peak years 2023 to 2025. It fits poorly because growth is faster than a straight line.

4.3.3 Country scientific production

Figure 5 presents the country scientific production, where a darker shade means more production. India has the darkest shade, followed by the United States and then China. The counts of author affiliations confirm this order: India (211), the United States (187), China (82), South Korea (68), the United Kingdom (42), Australia and Jordan (38 each), and Saudi Arabia (37).

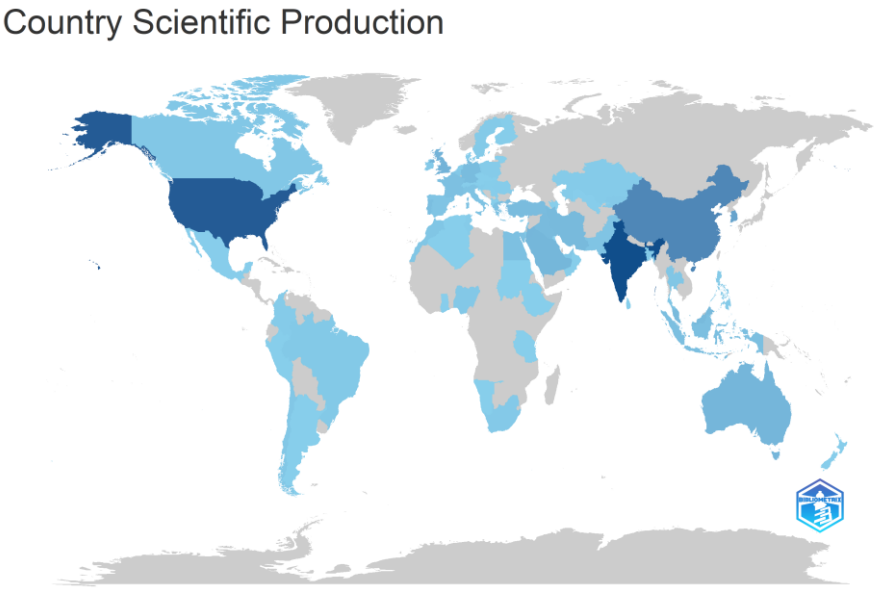

Figure -5: Country scientific production

Interestingly, the United States has more documents with at least one author from the country (106) than India (96). India has more author affiliations spread over slightly fewer documents. Five of the top eight countries are in Asia: India, China, South Korea, Jordan, and Saudi Arabia. The grey areas, such as Russia, Greenland, and much of Africa, show no data. Overall, these results suggest that research is spread across many countries but centred on a few.

4.3.4 Three field plot

Figure 6 is a three field plot that links countries (left), authors (middle), and author keywords (right). It uses the top 12 countries, 15 authors, and 15 keywords. Cited references were not used because the file has none. A line joins two items when they appear in the same documents, and the height of a box shows how many links the item has.

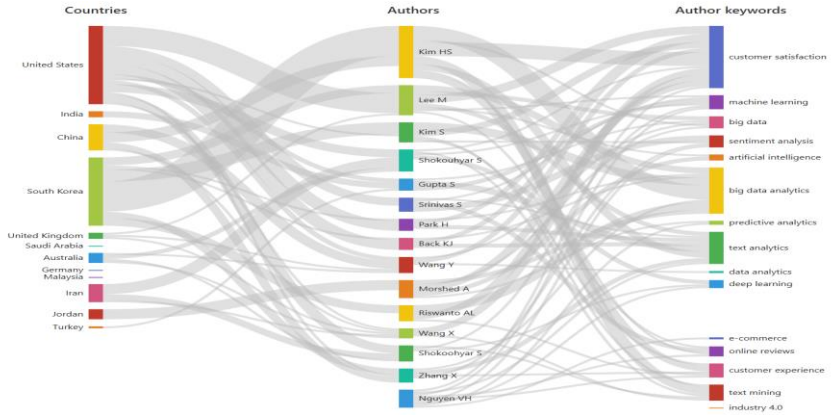

Figure -6: Three field plot of countries, authors, and author keywords

What stands out in the plot is the tie between authors and countries. All 15 documents by Kim HS include a South Korean affiliation, and 5 of them also include a Chinese one. All 10 documents by Lee M include a United States affiliation. Shokouhyar S links mainly to Iran (5 of 6 documents), and Morshed A links to Jordan (5 documents). Kim HS writes most often on customer satisfaction and big data analytics (7 documents each), followed by text mining (4).

On the right, customer satisfaction is the largest keyword (81 documents). It is followed by machine learning (60), big data (49), sentiment analysis (46), and artificial intelligence (45). The next most frequent keywords are big data analytics (43), predictive analytics (34), text analytics (32), data analytics (24), and deep learning (23). One warning is needed. Scopus lists authors as surname and initials, so one name can hide several people. Shokouhyar S and Shokoohyar S may be the same person, and the plot shows them as two authors.

4.3.5 Keyword co-occurrence

Turning now to the keywords, Figures 7 and 8 show VOSviewer co-occurrence maps with a minimum of 5 and 10 occurrences. In these maps, each circle is a keyword, its size shows how often it appears, a line links keywords that appear together, and a colour marks a cluster (van Eck & Waltman, 2010). Figure 7 has many more keywords than Figure 8.

Further analysis of Figure 7 shows about seven clusters, so the main groups split into smaller topics. Customer satisfaction is again the largest circle, now in the purple cluster with customer relationship terms, such as crm and the telecommunication industry. The cyan cluster covers prediction: predictive analytics, learning systems, deep learning, predictive modeling, customer retention, and support vector machines. The green cluster covers text: sentiment analysis, text analytics, text mining, topic modeling, online review, and service quality. The orange cluster links sales with natural language processing, social media, customer feedback, and surveys. The yellow cluster holds artificial intelligence, data analytics, industry 4.0, supply chain

management, blockchain, and smart manufacturing. The red and blue clusters are smaller and include information management, logistics, performance, random forest, and data visualization.

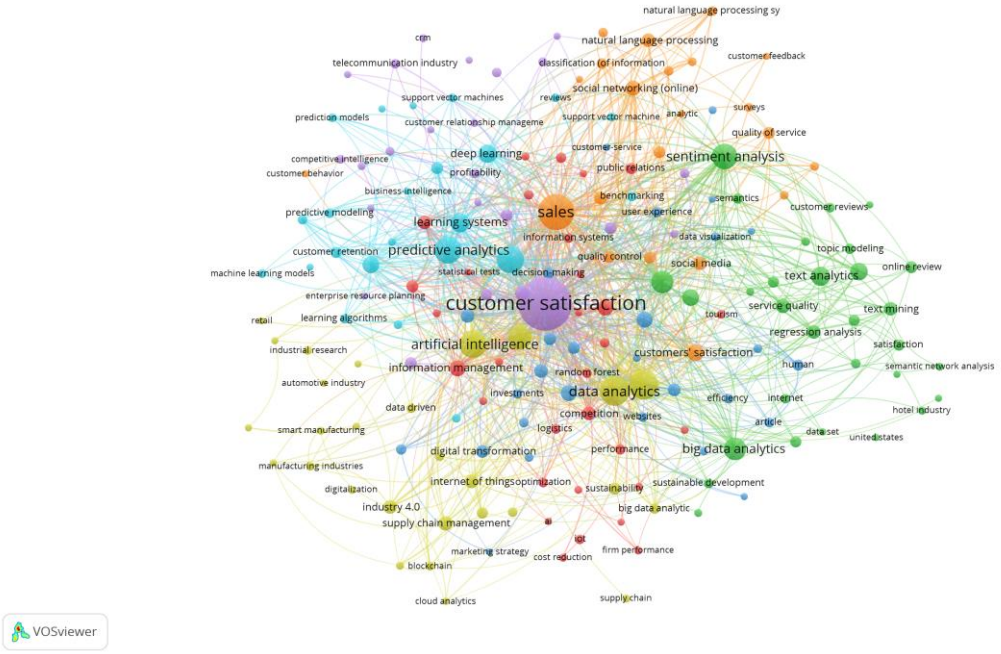

Figure -7: Keyword co-occurrence network, minimum 5 occurrences

Figure 8 shows five clusters. Customer satisfaction is the largest circle and sits in the middle, in the green cluster. This cluster also holds decision making, forecasting, information management, supply chain management, internet of things, and industry 4.0. The purple cluster is about data: big data, big data analytics, data analytics, advanced analytics, and e-commerce. The red cluster is about text and reviews: sentiment analysis, text analytics, text mining, online reviews, customer experience, service quality, and marketing. The blue cluster is about prediction methods: predictive analytics, machine learning, learning systems, deep learning, random forests, and decision trees. The yellow cluster holds sales, social media, social media analytics, natural language processing, and decision support systems.

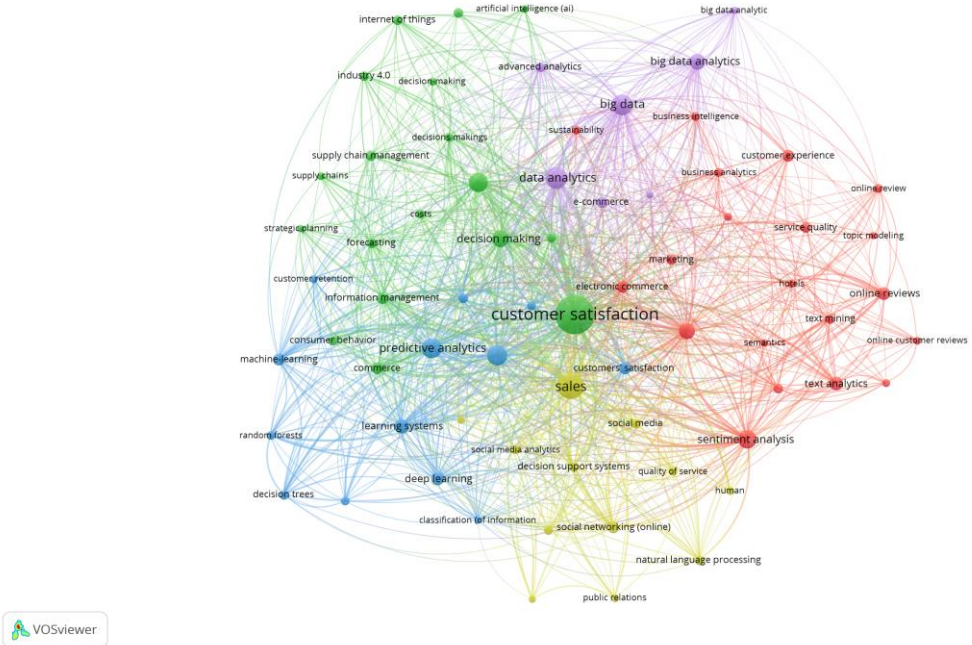

Figure -8: Keyword co-occurrence network, minimum 10 occurrences

A comparison of the two figures shows that the lower limit adds small topics, such as blockchain, telecommunication, and hotel industry. The higher limit keeps the main structure. In both maps, customer satisfaction is in the centre, and the same groups appear around it: data, text and reviews, prediction methods, and sales or social media. The maps also list terms for the same idea apart, such as decision making and decision-making, so their counts are split.

4.4 Summary of results

Taken together, these results suggest that research on data analytics and customer satisfaction is young and growing fast. Output rose from 3 documents in 2002 to 115 in 2025, and 89% of the documents were published from 2018 onward. India and the

United States lead in country production, followed by China and South Korea, and about three in ten documents have international authors. The keyword maps show customer satisfaction at the centre, linked to data analytics, text and review analysis, and prediction methods.

5. FUTURE RESEARCH AGENDA

The bibliometric evidence shows research on analytics and customer satisfaction as young, fast-growing and international. The Scopus corpus holds 548 documents, rising from 3 in 2002 to 115 in 2025, with 89% published from 2018 onward. However, the field is organised around measuring and predicting satisfaction rather than around deciding what to do about it. The most frequent keywords are customer satisfaction (81), machine learning (60), big data (49), sentiment analysis (46) and artificial intelligence (45), and the keyword maps cluster around data, text and reviews, prediction methods, and sales or social media. None of the keyword lists reported in the data analytics section contains the core vocabulary of operations research (OR), such as optimisation, linear programming, queueing, simulation or inventory models. OR appears mainly in isolated studies: genetic algorithms for marketing strategy (Yang & Peng, 2026), game theory and deep learning for resource allocation (Liu et al., 2027), predictive analytics for procurement (Pathak et al., 2026), and analytics for customer targeting and sales-force allocation (Lawrence et al., 2007).

The central question for future research is therefore how the large body of analytics evidence on what satisfies customers can be turned into optimised operational decisions that measurably improve satisfaction in e-commerce. One caution applies throughout: the corpus was built with the search string "Customer Satisfaction AND Analytics", so the thin presence of OR is partly a product of search design. Priority 6 addresses this directly.

Table 2 lists six priorities. Priorities 1 to 3 address the core gaps between analytics and OR decision-making, Priorities 4 and 5 test whether such models are fair and generalisable, and Priority 6 supplies the conceptual and methodological infrastructure the others depend on.

Table -2: Summary of the research agenda

Priority	Observation from the corpus	Core research question	Proposed approach	Expected contribution
1. From predictive insight to prescriptive decisions	Machine learning (60), big data (49), sentiment analysis (46) and predictive analytics (34) dominate; OR terms are absent from the reported keyword lists	Can review-derived insights be converted into optimised resource allocations that beat managerial heuristics?	Full-text coding of the corpus; predict-then-optimise pipeline; robust optimisation	A tested route from customer feedback to budget and capacity decisions
2. Satisfaction inside operational OR models	Logistics, supply chain and information management appear as clusters, but satisfaction is mostly treated as an after-the-fact outcome	How do delivery, stock and support levers change satisfaction, and does optimising for it change decisions?	Causal response-function estimation; multi-objective and chance-constrained models; queueing simulation	Satisfaction-aware inventory, fulfilment and service-capacity models
3. Satisfaction dynamics, retention and lifetime value	Customer retention and CRM appear in the keyword maps, yet satisfaction is mostly studied at a single point in time	When and for whom should a firm intervene to protect satisfaction and retention?	Markov decision processes; survival analysis; randomised service-recovery experiments	Dynamic policies linking satisfaction to long-term value
4. Fairness, trust and responsible optimisation	Privacy, ethics and fairness are absent from the reported top keywords, while AI personalisation and chatbots are discussed	What does equity cost in satisfaction terms, and how do customers react to prioritisation and data use?	Full-text synthesis; fairness-constrained optimisation; survey experiments	Evidence on efficient and acceptable customer-facing algorithms
5. Context, geography and generalisability	India (211), the United States (187) and China (82) lead; 4 of 12 literature-review sources come from hospitality or agriculture; only 29.56% of documents are multi-country	Which findings hold across markets and e-commerce formats?	Harmonised cross-market replication; multilingual review mining	Clarified boundary conditions for e-commerce
6. Conceptual coherence, scope and evidence infrastructure	OR vocabulary was not in the search string; one database, English only, no cited references; duplicated keywords and ambiguous author names	What counts as OR-based satisfaction research, and how much of the observed growth is substantive?	OR-extended multi-database search; co-citation analysis; shared taxonomy; living review	A cumulative, reproducible evidence base

5.1 Priority 1: From Predictive Insight to Prescriptive Decisions

Gap: Review mining and sentiment analysis form a large part of the corpus, and the red cluster in the keyword map links sentiment analysis, text mining, online reviews, customer experience and service quality. These studies tell managers what customers like and dislike. Lau et al. (2018) use aspect-level sentiment to improve sales forecasting, and Puustinen et al. (2025) detect changes in sentiment over time. Few go on to the next step, which is deciding how a limited budget or capacity should be spent in response. The clearest exceptions are Liu et al. (2027), who link user reviews to budget allocation through deep learning and game theory, but for hotel apps rather than e-commerce, and Yang and Peng (2026), who use genetic algorithms for e-commerce marketing. There is also a methodological warning: models tuned for predictive accuracy do not necessarily produce

the best decisions (Elmachtoub & Grigas, 2022), so a more accurate sentiment classifier cannot simply be assumed to give better outcomes.

Research questions: What share of the corpus moves beyond describing and predicting to prescribing? Does a predict-then-optimise approach to splitting a fixed budget across website improvement, delivery and customer support raise satisfaction relative to heuristic allocation? How sensitive are the resulting allocations to errors in sentiment estimates?

Proposed approach: First, a full-text coding of the corpus (or a stratified sample) should classify each study by analytics stage (descriptive, predictive, prescriptive), OR technique (optimisation, simulation, queueing, game theory, multi-criteria decision-making, data envelopment analysis) and satisfaction measure, using two independent coders. Second, a pipeline study using public e-commerce review data or a partner retailer's data should extract aspect-level sentiment (delivery, product quality, price, support), estimate how satisfaction responds to improvement in each aspect, and solve the allocation as a constrained optimisation problem. Robust optimisation (Bertsimas & Sim, 2004) can protect decisions against noisy estimates. Results should be compared with equal-split, last-period and manager-judgement allocations, ideally through a field test or offline policy evaluation (Bertsimas & Kallus, 2020).

Contribution: This would show whether the analytics evidence base can actually change decisions, and would give e-commerce managers a tested route from customer feedback to budget and capacity choices.

5.2 Priority 2: Building Customer Satisfaction into Operational OR Models

Gap: The corpus does include operations-side work. Pathak et al. (2026) show that predictive analytics can improve procurement visibility and, through it, customer satisfaction, and Chotisarn and Phuthong (2025) find that price fairness, communication quality and shipping information significantly influence satisfaction in cross-border e-commerce. Supply chain management, logistics and information management also appear as clusters in the keyword maps. Even so, satisfaction is mostly treated as an outcome observed after the fact. Classical OR models for inventory, fulfilment, routing and staffing typically minimise cost subject to a fixed service target, and rarely use an empirically estimated customer response as part of the model. Without that link, an operationally optimal plan may not be the one customers actually prefer.

Research questions: What is the shape of the relationship between operational levers (delivery speed and reliability, stock-outs, order-tracking information, support response time) and satisfaction or repeat purchase? Are there thresholds, such as a sharp drop once a promised delivery date is missed? How much does optimising for expected satisfaction, rather than cost alone, change the decisions, and at what cost?

Proposed approach: Response functions should be estimated from order-level data merged with ratings, reviews and repeat purchases, using causal designs such as natural experiments (for example, courier disruptions), difference-in-differences or instrumental variables rather than simple correlation. These functions can then be embedded in multi-objective optimisation (cost against expected satisfaction, shown as a Pareto frontier), chance-constrained models for setting delivery promises, and queueing or simulation models for customer-support capacity. The models should be validated through simulation calibrated on real data and A/B tests of delivery-promise and staffing policies.

Contribution: This would move satisfaction from an outcome that is merely reported to a quantity that operational models explicitly trade off, and give retailers a clear picture of what each unit of service improvement costs and returns.

5.3 Priority 3: Satisfaction Dynamics, Retention and Lifetime Value

Gap: Customer retention, customer relationship management and predictive modelling appear in the keyword maps, and the literature review notes that satisfaction supports loyalty, repeat purchases and favourable word of mouth (Irshad et al., 2024). Yet most studies examine satisfaction at one point in time or over a fixed window. Sequential decisions, such as whether to offer a refund, coupon or priority support after a bad experience, are rarely modelled as a dynamic problem in which today's action changes tomorrow's satisfaction and future purchases. Lawrence et al. (2007) show the value of analytics for targeting and allocation decisions, but the link between satisfaction states and long-run customer value remains thin in the e-commerce setting.

Research questions: How does satisfaction evolve across a customer's sequence of orders and service contacts? Which customers should receive service-recovery actions, when, and at what cost relative to lifetime value? Do dynamically optimised recovery policies outperform fixed rules?

Proposed approach: Longitudinal customer data should be used to estimate transitions between satisfaction states and to run survival analysis of churn. Markov decision process formulations (Puterman, 1994), solved by dynamic programming or reinforcement learning, can then identify when intervention is worthwhile. Policies should be tested through randomised field experiments in which comparable customers receive different recovery offers, with satisfaction, retention, cost and margin recorded as outcomes.

Contribution: This would connect satisfaction research to long-term value and give firms a principled basis for deciding who to intervene for and when.

5.4 Priority 4: Fairness, Trust and Responsible Optimisation

Gap: The corpus discusses AI-based recommendation systems, chatbots and virtual assistants (Tabaku, 2024) and personalised advertising built on consumers' past purchases (Yang & Peng, 2026). Optimising service by customer value or predicted satisfaction can also mean that some customers are systematically served first. Despite this, privacy, ethics and fairness do not appear among the keywords reported in our analysis. As keyword counts cannot separate genuine neglect from different labelling, this gap should be tested rather than assumed. Relevant foundations include fairness norms in pricing and service (Kahneman et al., 1986), the privacy calculus in e-commerce (Dinev & Hart, 2006), and the OR concept of the price of fairness, which measures how much total benefit is lost when allocations must be equitable (Bertsimas et al., 2011).

Research questions: How much overall satisfaction is lost when allocation rules are constrained to be equitable across groups such as new and loyal customers, regions or order values? How do customers perceive prioritisation and data use, and do these perceptions affect trust, satisfaction and repeat purchase?

Proposed approach: A full-text synthesis should tag whether fairness, privacy and ethics are measured empirically, modelled, or only discussed. Fairness-constrained versions of the models in Priorities 1 to 3 should report the price of fairness explicitly. Survey experiments can then vary the disclosed prioritisation rule, data use and opt-out options, and link perceptions to behavioural outcomes.

Contribution: This would establish whether optimised customer-facing systems can be both efficient and acceptable, and give practitioners design rules that balance satisfaction gains with equity and trust.

5.5 Priority 5: Context, Geography and Generalisability

Gap: India leads in author affiliations (211), followed by the United States (187), China (82) and South Korea (68), and five of the top eight countries are in Asia. Much of Africa, Russia and Greenland shows no data. Only 29.56% of documents have authors from more than one country, and the three-field plot shows strong author-country ties (all 15 documents by Kim HS include a South Korean affiliation, and all 10 by Lee M a United States one), which suggests research silos. Context is also thin within the literature review: four of the twelve sources come from hospitality or agriculture (Gruss et al., 2024; Zhang & Kim, 2021; Liu et al., 2027; Zhang & Cornell, 2026), and the keyword map includes hotel and telecommunication clusters. Findings on food trucks, hotels or farms may not transfer to e-commerce, where returns, last-mile delivery, marketplace sellers and payment methods shape satisfaction differently.

Research questions: Which satisfaction drivers and operational response functions hold across markets and across e-commerce formats (marketplace, direct-to-consumer, cross-border)? Which depend on infrastructure, regulation or consumer norms?

Proposed approach: Cross-market replications should use the same aspect taxonomy, satisfaction measures and analysis plans. Comparisons across formats are needed, and emerging-market features should be tested as hypotheses rather than assumed, for example payment mode (such as cash on delivery), return policies, festive-season demand peaks and last-mile reliability outside large cities. Because the corpus is restricted to English, multilingual review mining is needed to capture regional-language feedback. Cross-country co-authorship should be encouraged so that studies are not tied to a single national setting.

Contribution: This would establish boundary conditions and prevent results from one sector or country from being treated as universal.

5.6 Priority 6: Conceptual Coherence, Search Scope and Evidence Infrastructure

Gap: Several features of the present corpus limit what can be concluded about OR specifically.

- **Search scope.** The query "Customer Satisfaction AND Analytics" does not include OR vocabulary, so OR studies that do not use the word analytics are missed. The corpus is also limited to Scopus, English-language articles and reviews, which excludes conference papers and preprints where OR methods often appear first.
- **Missing references.** The exported file contained no cited references, so co-citation and bibliographic coupling could not be run, and the intellectual structure of the field remains unmapped.
- **Data quality.** One name can hide several authors (Shokouhyar S and Shokoohyar S may be the same person), and the same idea is counted twice under variants such as decision making and decision-making.
- **Measurement.** Satisfaction is measured in different ways (ratings, surveys, sentiment scores), and it is unclear whether review-based sentiment tracks survey satisfaction.
- **Interpreting growth.** The reported annual growth rate of -4.3% is an artefact of the incomplete years 2026 and 2027, while growth between the full years 2002 and 2025 is about 17% a year. It is also unclear whether the surge reflects growth specific to this topic or growth in analytics research generally.

Research questions: What conditions make a study count as OR-based customer satisfaction research? How much of the apparent growth is specific to this topic? Do review-derived sentiment scores converge with survey-based satisfaction?

Proposed approach: The search should be repeated with OR terms (for example optimisation, linear programming, queueing, simulation, game theory, data envelopment analysis, multi-criteria decision-making) combined with customer satisfaction or customer experience and e-commerce or online retail, across Scopus and Web of Science, and compared with the present corpus. Re-exports should include cited references. A keyword thesaurus and author identifiers such as ORCID should clean the data, and a shared taxonomy with explicit inclusion rules should be validated through independent double coding. Growth should be compared with adjacent analytics fields using segmented regression or changepoint models (Muggeo, 2003). A living review with a registered protocol, periodic updates and a shared replication package (export files and analysis scripts) would keep the evidence current.

Contribution: This would improve construct validity, comparability and reproducibility, and provide the foundation for the cumulative evidence sought in Priorities 1 to 5.

5.7 Summary of the agenda

The agenda centres on a single practical question: under what conditions can the analytics understanding of customers be turned into optimised operational decisions that raise satisfaction in e-commerce without unfairly burdening customers or the firm? A stronger evidence infrastructure (Priority 6) is the base. Prescriptive models, satisfaction-aware operations and dynamic retention policies (Priorities 1 to 3) show whether value is actually created. Fairness and context (Priorities 4 and 5) decide whether that value is acceptable and transferable. Pursued together, these priorities could turn a fast-growing but prediction-heavy literature into a cumulative research programme that offers reliable guidance to managers, customers and policymakers.

6. CONCLUSION

The main aim of this study was to understand how customer satisfaction research uses analytics and how it can be better connected with Operations Research in e-commerce. To meet this aim, the authors carried out a PRISMA-guided bibliometric analysis of 548 Scopus documents published between 2002 and 2027. The central finding is clear. The field has grown quickly and internationally, but it is built around measuring and predicting satisfaction rather than deciding how to improve it. The paragraphs below summarise how far each objective was met.

The first objective, analysing publication trends, was met. Output grew from 3 documents in 2002 to 115 in 2025, or about 17% a year, and 89% of the documents were published from 2018 onward. This makes it a young and fast-growing field. The annual growth rate of −4.3% shown by Biblioshiny is misleading, because the years 2026 and 2027 were incomplete when the data was collected. India, the United States, China and South Korea are the leading contributors, and five of the top eight countries are in Asia. IEEE Access is the most productive source with 14 documents, yet no single source holds more than 2.6% of the dataset. Kim HS (15 documents) and Lee M (10) are the most productive authors. The most cited paper, on Industry 5.0, has received 905 citations.

The second objective had two parts. The first part, identifying the main research themes, was met. The most frequent keywords are customer satisfaction, machine learning, big data, sentiment analysis, artificial intelligence and predictive analytics. The keyword maps place customer satisfaction at the centre of five themes: data analytics, text and review mining, prediction methods, sales and social media, and decision-making and supply chains. Researchers have clearly invested heavily in learning from customer data and online feedback.

The second part, assessing the link with OR, was met in part. Typical OR terms such as optimisation, linear programming, queueing and simulation are missing from the main keywords. OR methods appear only in a few isolated studies on sales-force allocation, marketing strategy, resource allocation and procurement (Lawrence et al., 2007; Liu et al., 2027; Pathak et al., 2026; Yang & Peng, 2026). This points to a clear gap between predicting what customers want and deciding how to deliver it. Because the search phrase did not include OR terms, however, this is a gap within the selected dataset rather than proof that OR is absent from the wider literature.

The third objective, proposing a future research agenda, was met through six priorities. The first three address the core gap: turning review insights into budget and capacity decisions, building satisfaction into inventory, delivery and support models, and tracking how satisfaction and loyalty change over time. The fourth and fifth test whether such models are fair and whether they work across different markets. The sixth improves the search scope, data quality and reproducibility of future reviews. The fourth objective, drawing out the implications of the study, is addressed below.

6.1 Implications

Academic implications. The study adds to the body of knowledge in three ways. First, it maps 548 publications and shows that research on customer satisfaction and analytics focuses on measurement and prediction, with OR largely missing. Second, it brings together two streams that are usually studied separately, customer analytics and operational decision-making. Third, it turns the observed gaps into six research priorities with specific questions and methods, giving future researchers a clear starting point. It also corrects a misleading growth figure that other bibliometric studies could easily repeat.

Managerial implications. E-commerce firms can improve profitability by using customer feedback to decide where to spend, not just to report satisfaction scores. First, reviews and complaints can be sorted by issue, such as delivery, product quality, price and support. Possible fixes can then be ranked by their cost against the satisfaction they are likely to bring, so that limited budgets go where they earn the most. Second, refunds, coupons and priority support after a bad experience can be targeted at customers whose future purchases justify the cost, instead of being given to everyone. Third, queueing models can size the customer-support team, which avoids both paying for idle staff and losing customers to long waits. Fourth, delivery promises can be set from actual delivery records, because a missed promise may hurt satisfaction more than a slightly longer but reliable one. Each of these steps should be tested on the firm's own data before it is rolled out.

Social implications. Better operational decisions make online shopping more reliable for everyone. Fewer delays, more accurate product information and faster support save customers time and money. The benefits of digitalisation are still unevenly spread across countries (UNCTAD, 2024). More dependable and affordable e-commerce can help extend these benefits to smaller cities and less-served regions. At the same time, serving customers according to their predicted value may leave out people with little purchase history. Optimised systems should therefore treat customers fairly and use their data responsibly.

Policy implications. The study offers several suggestions for policymakers and regulators. First, platforms that give faster delivery or support to certain customers based on their predicted value could be required to disclose this practice. Second, the analysis of reviews and purchase histories should follow data-protection laws such as India's Digital Personal Data Protection Act, 2023. Third, platforms could be asked to report standard measures of complaint resolution and customer satisfaction, which would allow fair comparison between them. This could build on the grievance-redressal duties already placed on e-commerce platforms by India's Consumer Protection (E-Commerce) Rules, 2020. Finally, research funding bodies could support open, anonymised e-commerce datasets and studies in regional languages, since much of Africa and all non-English research are missing from the present dataset.

6.2 Limitations

The study has several limitations. First, it relied on a single database, Scopus, so relevant studies indexed only in Web of Science or elsewhere may be missing. Second, the authors had no access to company data such as order records, delivery times or customer ratings, so the proposed links between satisfaction and OR could not be tested. Third, the search phrase did not include OR terms or an e-commerce filter. Some OR studies may therefore have been missed, while some hotel, telecommunication and agriculture studies were included. Fourth, only English-language articles and reviews were included, which leaves out conference

papers and research in other languages. Fifth, the exported records had no cited references, so co-citation analysis could not be carried out. Sixth, some author names and keywords were recorded inconsistently, such as decision making and decision-making, which splits their counts. Finally, as student researchers, the authors had limited technical knowledge of advanced OR modelling and did not build or solve optimisation models. The OR applications discussed are therefore suggestions to be tested rather than proven results.

Overall, the study largely met its objectives. It described how research on customer satisfaction and analytics has grown, identified its main themes, showed the gap between prediction and decision-making, and set out an agenda to close it. Its main message is simple: customer analytics can show what customers want, and Operations Research can show how to deliver it with limited resources. Bringing the two together offers e-commerce businesses a path to decisions that are efficient, fair and focused on the customer.

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