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Clicks, Carts and Calculations: A Bibliometric Analysis of Operations Research and Analytics in E-commerce Consumer Behaviour (2013–2026)

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Abstract: A huge amount of every search, click, cart addition and review can be recorded on ecommerce platforms, and businesses today are turning to analytics and operations research (OR) to take action based on these impressions. This study traces the evolution of research on online consumers' behavior from analytics and OR perspective. Using PRISMA framework, 1,382 records from Scopus were identified on 16 September 2026, and then screened to 595 English-language journal articles and reviews published from 2013 to 2026 from 377 sources, authored by 1,810 authors. The literature review was supplemented by a cluster map in VOSviewer, based on co-occurrence of keywords, and a thematic mapping and a three field plot in the software Biblioshiny were examined to gain insight into the performance. The number of articles produced increased from 6 articles in 2013 to 87 articles in 2025 at an annual growth rate of 20.8%. The three most prolific countries are USA, India and China and 31.93% of papers are written by international co-authors. The motor themes in it are sales and consumer behaviour, machine learning, and the basic themes are sentiment analysis, data analytics, and big data. Only 37 of the 595 papers (6.2%) use prescriptive OR methods such as optimisation, game theory or multi-criteria decision-making. The results demonstrate a field that has shifted from consumer description to consumer prediction, but has not leveraged prediction to optimize business decisions very often. The proposed future research focuses on prescriptive analytics, real consumer data to validate OR models, new shopping channels, privacy preserving analytics and emerging markets.

Keywords*: Online Consumer Behaviour, E-Commerce, Operations Research, Analytics, Bibliometric Analysis, Biblioshiny.*

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I. INTRODUCTION

Much of the shopping is no longer on the street, but on the screen. Now, consumers want to find the products they want to buy using mobile apps, compare prices on different apps, read reviews from people they don't know and buy in very little time. This evolution was accelerated considerably during the COVID-19 pandemic. According to a study made during the period 2018-2024, the pandemic has made e-commerce not only a necessity but also a constant purchase pattern for both businesses and consumers, and it has emerged as a necessity over all product categories (Popescu et al., 2025). As consumers interact with online platforms, virtually every click, search performed, cart addition and review are recorded, meaning that online platforms have significant amounts of data about consumer behavior. These data can be analysed effectively and companies can identify what makes customers return. For example, a large data analysis of e-commerce sites revealed that each of personalised recommendations, delivery service and mobile engagement has an impact on consumer loyalty (Li & Hu, 2026). Consumers also pay attention to the way products are delivered and a recent study correlated e-commerce buying behavior with the adoption of sustainable supply chain strategies, and big data analytics emerged as a key ingredient in understanding and driving consumer buying behavior (Al-Olfi, 2026). Consumer behaviour in e-commerce has therefore become an important research area that is being studied by marketing, technology and operations.

Operations research (OR) is an area of management science that incorporates mathematical models, statistics and analytical methods to assist managers in decision making. In simple terms, OR is a method of solving a real-world problem

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by developing a model to solve it with an objective and constraints, and then finding the optimal solution. Typical OR tools are optimisation tools like linear programming, forecasting, game theory, queuing models, simulation and multi-criteria decision making (MCDM). These tools have been applied primarily in factories and transport & supply chains for years now to cut costs and plan for resources. They have, however, been adopted over the years as consumer research and marketing tools as well. Companies use them to, for instance, decide on product selection, pricing, distribution and target groups.

In e-commerce, OR takes the understanding of a consumer one step further: predicting their behaviour and then acting on that. Some important illustrations are forecasting and factor-based modelling, as Kalaivani and Sumathi (2019) applied factor based principal component model to derive key buying factors affecting the behaviour of online customers and make prediction about online sales. The other instrument used to analyse the decisions and strategies of online platforms, sellers and consumers is game theory. J. Wang et al. (2026) analyzed the potential of blockchain to enable online retailers to compete with sellers on live-streaming platforms and Song et al. (2026) investigated the impact of consumer privacy concerns on the platform's decision to trade consumer information. Optimisation models are also useful for making key decisions for businesses; Deng et al. (2026) created a two-tier supply chain model to assist multi-nationals when they decide how to enter e-commerce markets. The MCDM methods can consider multiple factors simultaneously and can be used to determine consumers' opinions in the ranking system supporting business decisions. Kyriakidis and Tsafarakis (2025) in an operational research journal, carried out aspect-based sentiment analysis, MCDM and fuzzy rule-based approach to derive useful insights from customer reviews and Jia et al. (2026) ranked electric vehicles for buyers using the sentiment found in online reviews. More than 9,000 online orders have been used in data mining techniques to demonstrate how customers' behaviour evolves over time using techniques like decision trees and association rules (Pitka et al., 2025). All these studies illustrate that OR now serves as a viable link between user information and business decisions.

The authors of this paper are the second-year Bachelor of Business Administration (BBA) students of NMIMS Anil Surendra Modi School of Commerce, Mumbai studying operations research as a part of their curriculum. The authors are young consumers and use the internet often, and can see the effects of these models in the world around them: product recommendations that appear to know their taste; prices that fluctuate; promised delivery dates that are accurate; and product reviews that guide their buying decisions. As students studied operations research in the classroom, the authors discovered that many of these concepts are probably employed by the shopping apps they use daily. This curiosity led them to learn about the previous studies that have been conducted in this area and what is known about it. The authors also have a personal interest in the topic for their future occupation. Since business students might be going into marketing, analytics, retail or operations, it is important that they understand how data is used to learn about consumer behavior, and how businesses use the information to make decisions; the study will also tell business students the direction that marketing is going and what skills it will be wanting. The authors feel this research could be of benefit to other learners and young managers interested in the same topic in an organized fashion.

Although research in this area is growing quickly, it is spread across different fields such as computer science, marketing, information systems, hospitality and operations management. Such studies also appear in various journals, making it hard to have a clear overview of the field. Previous reviews have mostly concentrated on specific aspects. For instance, Khan et al. (2026) analyzed all the studies on online reviews, and Sumanth and Somasekhar (2026) explored the evolution of artificial intelligence in online customer experience. Very few studies have related the analytical and OR aspects with the consumer behaviour aspects in order to provide a wider perspective about the topic. However, several studies have identified some research gaps that should be addressed, such as fake reviews which are difficult to identify (J. Tao et al., 2026), the use of generative AI chatbots in online shopping (Suman et al., 2026) , and the ethical concerns regarding algorithmic personalization (Nguyen et al., 2026) . To address this, the present study conducts a bibliometric study of the research on consumer behaviour and analytics related to e-commerce. Rather than reading a few papers in detail, it examines the body of work relating to this field. The goal of the field is to get to know its history, its driving topics and the dominant themes and where research is going.

Three research objectives guide this study:

- RO1: To know the trends in the study area, such as growth rate of publications over time, countries and most relevant journals.
- RO2: To determine the specific results of the field, which consist of the main research themes, the clusters of keywords and the methods it uses.
- RO3: To propose future research directions based on gaps and emerging themes identified.

For achieving these goals, the study used information from the Scopus, one of the biggest peer-reviewed research databases in the world. The search was conducted on 16 September 2026 with the words “online”, “consumer” and “analytics” in the title, abstracts, and keywords of the articles. After that, the records were screened following the PRISMA methodology, which filters a large number of papers in a systematic process. Papers which were published between 2013 and 2026, were journal articles or reviews, and were written in English were retained. Following this screening and data cleaning process, 595 articles with 1810 authors sourced from 377 journals were used. Since e-commerce consumer research is quite wide-ranging, the papers span the spectrum from online retail to quick commerce to hotels, airlines, food delivery and health platforms.

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The study adopts the bibliometric approach, which is based on numbers and maps to study a literature that is too large to be analyzed by hand. It features both performance analysis (counting publications, authors, countries and journals) and science mapping (representing the mapping of topics to each other). The mapping approaches were as follows: keyword co-occurrence analysis, thematic mapping, and a three-field plot linking between countries, authors and keywords. The data was cleaned and analysed in Microsoft Excel and then in the point-and-click interface of the Bibliometrix package in R. VOSviewer was used to build the keyword co-occurrence map of the 2026 publications for the literature review, and Mendeley was used to manage references.

The analysis yielded a number of key findings. Publications climbed from 6 in 2013 to 87 in 2025, which is an annual growth rate of 20.8%, and the linear trend line is fairly close to the data ($R^2 = 0.9052$). The USA and India are the first two contributors with nearly one-third (31.93%) of papers authored by more than one country. The Journal of Retailing and Consumer Services, IEEE Access and Decision Support Systems are the most relevant sources. The motor themes of the field are sales, consumer behaviour and machine learning, whereas the basic themes are sentiment analysis, data analytics and big data. The field has been clustered into three groups by the use of the keyword: machine learning, consumer behaviour and sales, social networking, sentiment analysis and data mining, social media and general marketing and consumer attitude.

The following is a map of the rest of the paper. The existing literature is reviewed and themed in the Literature Review section. In the Research Methodology section, the research methodology is explained, detailing the screening according to PRISMA and the bibliography techniques used. The data analysis and findings are given in the Data Analysis and Findings section. The results are summarized in the Future Research Agenda section, which outlines a future research agenda. The results are finally linked to the objectives of the research in the Conclusion section, the implications for the literature, management and society, and the limitations of the study are discussed.

II. LITERATURE REVIEW

➢ *Introduction*

Online consumer behaviour looks at how people search for products, compare them, buy them and discuss them on the internet, whether on shopping websites, social media or review sites. Nearly every action consumers take online leaves behind a record of data, which is why analyzing this data now matters a great deal to marketers and operations managers alike.

Operations research (OR) offers a way to turn that data into better choices. Koçak (2026), for example, predicts box-office revenue using online search data, while Jia et al. (2026) rank electric vehicles based on the sentiment found in online reviews. Game theory appears in other studies of platform choices: how worries about privacy shape the selling of consumer data (Song et al., 2026), and how blockchain can give online retailers an edge against live-streaming sellers (J. Wang et al., 2026a) . Yang et al. (2026) further demonstrate that social media posts which spark a desire to buy can signal demand and lift sales. Put simply, this field joins marketing, information systems and operations. Behavioral theory explains why consumers behave as they do, whereas analytics and OR let firms forecast that behaviour and react to it.

The reviewed literature relies on specialized terms drawn from analytics, operations research and consumer psychology. Table 1 defines the most important of these and explains their relevance to the present study.

Table 1 Critical Terms and their Relevance

Critical term	Definition and relevance to the study	Key reference
Predictive analytics	Using past behavioural data to forecast outcomes such as loyalty or purchasing intensity; the core aim of the largest cluster.	Li & Hu (2026)
LSTM	A deep learning model for sequential data that outperforms traditional models in forecasting loyalty.	Li & Hu (2026)
Sentiment analysis	Classifying opinions in text as positive, negative or neutral; the most frequent keyword in the 2026 subset.	Liu & Pareti (2026)
Aspect-based sentiment analysis	Measuring sentiment for each product attribute, linking reviews to perceived quality of specific features.	Ray et al. (2026)
Topic modelling	Unsupervised methods (e.g., LDA) that reveal hidden themes in large collections of reviews.	Khan et al. (2026)
Multi-criteria decision-making	OR methods that rank alternatives across several attributes, turning review sentiment into product rankings.	Ng et al. (2026)
Game-theoretic model	A model of strategic interaction between platforms, sellers and consumers used to find optimal strategies.	Han & Guan (2024)
Federated learning	Training a shared model without pooling raw consumer data, protecting privacy.	Haripriya et al. (2026)
S-O-R model	Stimuli shape internal states such as emotion and trust, which in turn drive purchase behaviour.	Mei et al. (2026)
Electronic word of mouth	Consumer-to-consumer communication online, mainly reviews and posts, that influences other buyers.	Lee et al. (2026)

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Live-streaming commerce	Selling through real-time video with streamer–viewer interaction; an emerging online channel.	J. Wang et al. (2026)
Eye-tracking	Measuring visual attention directly rather than relying on self-reports.	Modi & Kumar (2026)

➢ *Historical Perspective*

Online consumer research is newer than OR, but it has grown fast, and the way researchers collect data has changed with it. Instead of relying on surveys in which people report on themselves, researchers now use eye-tracking (Modi & Kumar, 2026) , EEG (Okyere Sefa et al., 2026), web mining (G. Kumar & Rishiwal, 2020) and synthetic consumers created with large language models (Jin et al., 2026) . Recent reviews show this growth clearly: Khan et al. (2026) found 1,469 documents on online reviews in marketing alone, while Sumanth and Somasekhar (2026) note a steep increase in studies on artificial intelligence and online customer experience from 2018 onwards.

Studies also note clear gaps: little is known about customer dissatisfaction with quality (R. Kumar et al., 2026) , cross-cultural sentiment analysis is rarely studied (Liu & Pareti, 2026), few studies predict who writes reviews (Lee et al., 2026), and the role of generative AI chatbots in online shopping is not yet mapped(Suman et al., 2026). Likewise, there is little evidence on how ESG performance leads to digital engagement (Toudas et al., 2026). These gaps call for a review of the field as a whole.

➢ *Thematic Clusters*

To capture the most recent research front, a VOSviewer keyword co-occurrence map was built from the 70 articles in the sample published in 2026. This map produced five interconnected clusters. The clusters group keywords and represent research themes rather than sets of documents. Because the map covers only the 2026 subset, its clusters differ from the three-cluster Biblioshiny network of the full 2013–2026 sample presented in the Co-Occurrence Network Analysis section.

- *Cluster 1: AI and Predictive Analytics*

The largest cluster centers on consumer behaviour, machine learning and predictive analytics. LSTM outperforms traditional models in predicting loyalty (Li & Hu, 2026) , ensemble learning has been used to recognise consumer purchase behaviour (P. Wang & Xu, 2020), and composite behavioural indices predict purchasing intensity better than single cues such as clicks (Anju & Veni, 2026). AI personalisation also raises engagement and purchase intention (Al-Zagheer et al., 2026). However, studies judge success mainly by accuracy, and Zillow's failed pricing algorithm shows how poor predictions erode trust (Susarla et al., 2026).

- *Cluster 2: Consumer Cognition and Decision-Making*

This cluster covers consumer attitude and decision-making. Eye-tracking shows that reviews, ratings and price attract attention on travel sites (Modi & Kumar, 2026), while Gen Z consumers ignore nutrition information despite claiming to value it(Khubchandani & Raman, 2026). Perceived product risk drives pre-purchase safety checks (Miura et al., 2026). Combining EEG with sentiment analysis, however, predicts poorly (Okyere Sefa et al., 2026), and samples are mostly small and local, so it is unclear whether these findings hold in large-scale platform data.

- *Cluster 3: Social Media Analytics and Purchase Intention*

Social media posts that evoke purchases boost sales (Yang et al., 2026), and double machine learning reveals that Instagram Reels raise engagement (Almashaleh & Fatahi Valilai, 2026). On Douyin, social presence carries the effect that live-streamers have on purchase intention (Mei et al., 2026a). Yet Nguyen et al. (2026) point to a group of consumers who skip judgement altogether, which raises ethical concerns about personalisation.

- *Cluster 4: E-Commerce Operations and Platform Strategy*

This is the area where classical OR appears most clearly. Game-theoretic models reveal how blockchain helps online retailers stand up to live-streaming encroachment (J. Wang et al., 2026a) and that consumer welfare could be greater without privacy protection(Song et al., 2026) , while blockchain-based quality verification supports a composite e-commerce entry model for multinationals (Deng et al., 2026a). Federated learning makes marketing analytics possible without combining consumer data (Haripriya et al., 2026). Still, these models are seldom checked against real consumer data.

- *Cluster 5: Sentiment Analysis of Online Reviews*

Sentiment analysis is the most frequent keyword in the 2026 subset. Negative emotions carry the path from quality problems to product discouragement (R. Kumar et al., 2026), aspect-level sentiment predicts how consumers see product quality (Ray & Singh, 2025), and review sentiment supports multi-criteria decision models that rank products (Jia et al., 2026a). But star ratings do not always match the review text (Liu & Pareti, 2026), and fake reviews remain a problem (J. Tao et al., 2026).

➢ *Synthesis and Research Gaps*

On the whole, the field is shifting from describing online consumers to predicting their behaviour, with generative AI, live-streaming, privacy and sustainability appearing as new themes. Four gaps are clear: models prefer accuracy over explanation, the evidence is mostly correlational, OR models are rarely tested with consumer data, and the ethics of personalisation remain underexplored. This study addresses these gaps by mapping the field as a whole; Table 2 summarizes the key studies.

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Table 2 Summary of Key Studies

Author(s) (year)	Cluster	Key findings
Li & Hu (2026)	1	LSTM beat traditional loyalty-prediction methods; personalized recommendations, delivery and mobile engagement shape loyalty
Anju & Veni (2026)	1	92.7% accuracy, 8–12 points above strong ensembles; single behavioural measures (e.g., clicks) are insufficient
Modi & Kumar (2026)	2	Reviews, layout, location data and emotionally relevant cues (ratings, price) drive attention
Khubchandani & Raman (2026)	2	Nutrition information ignored even by the nutrition-conscious: an attitude–behaviour gap
Yang et al. (2026)	3	Purchase-evoking frequency raises sales, more for search goods and online channels
Mei et al. (2026)	3	Social presence is the dominant mediator; AI emotion metrics add 5.6% explanatory power
J. Wang et al. (2026)	4	Blockchain helps online retail resist live-streaming; blockchain investment can benefit platform and farmer
Song et al. (2026)	4	Consumer welfare can be higher without privacy protection; light regulation of non-sensitive data advised
R. Kumar et al. (2026)	5	Negative emotions mediate the path from quality problems to product discouragement
Liu & Pareti (2026)	5	Star ratings diverge from text sentiment; China functional vs Italy experiential

III. RESEARCH METHODOLOGY

A systematic literature review (SLR) is a structured, comprehensive technique that helps to identify, select and synthesize existing research to generate meaningful insights in a subject area. The present study uses bibliometric review techniques to understand how research on online consumer behaviour in e-commerce has used analytics and operations research, and how this research has developed over time.

➢ *Article Selection, Inclusion and Exclusion Criteria*

Considering the amount of research, the authors used the PRISMA framework in the shortlisting of the sample. PRISMA offers a reproducible, repeatable and documented methodology for data collection and reporting, which facilitates its replicability (Moher et al., 2010). The framework has four subsequent stages of identification, screening, eligibility/inclusion (Moher et al., 2010), and is suitable for a high number of literatures retrieved after performing an initial database search. The data were obtained from Scopus on 16th September 2026 with the following Boolean query: (online AND consumer AND analytics) [title, abstract, keywords]. The initial search returned 1,382 records. An initial analysis of the subject area classification of the papers in the dataset indicated a high level of concentration in Computer Science (823 papers), Business, Management and Accounting (758 papers) and Engineering (441 papers). Again, some papers were classified in more than one subject area, so these figures overlap. Consumer decision making in e-commerce is a multidisciplinary subject, therefore there was no subject that was omitted. The search string did not contain words specific to OR, such as optimisation, game theory or MCDM, and hence OR studies only appear where they also refer to online consumers and/or analytics, as is recognized as a limitation in the Conclusion section.

The records were subsequently screened. The 1,382 identified records were initially screened by publication year and then those between 2013 and 2026 were retained, yielding 1,353 papers. The articles included in the database had the earliest date of 2003, although articles prior to 2013 were excluded as publication increased significantly from that date onwards, and the articles from 2013–2026 were to capture the speedy change in the world of e-commerce and digital consumer analytics.

The data was then narrowed down to articles and reviews, with the exclusion of conference papers, conference reviews, book chapters, books, errata, retracted papers and notes. This filter eliminated 749 records, leaving 604 papers.

Of these 604 papers, the remaining papers were screened for language, and only English-language papers were used for consistent interpretation and thematic analysis. The available 604 papers were all in English except for 5 (2 in Chinese, 2 in Spanish and 1 in Thai) which were not included. After applying the last eligibility filter, only academic journal papers were included, excluding 2 papers from other sources, resulting in 597 papers. These 597 records were imported into Biblioshiny, with 2 records having incomplete abstract information, and thus excluded, resulting in an analyzed sample of 595 records. A progressive filtering from 1,382 to 595 records allowed the final sample to contain only English language journal articles and reviews indexed in Scopus.

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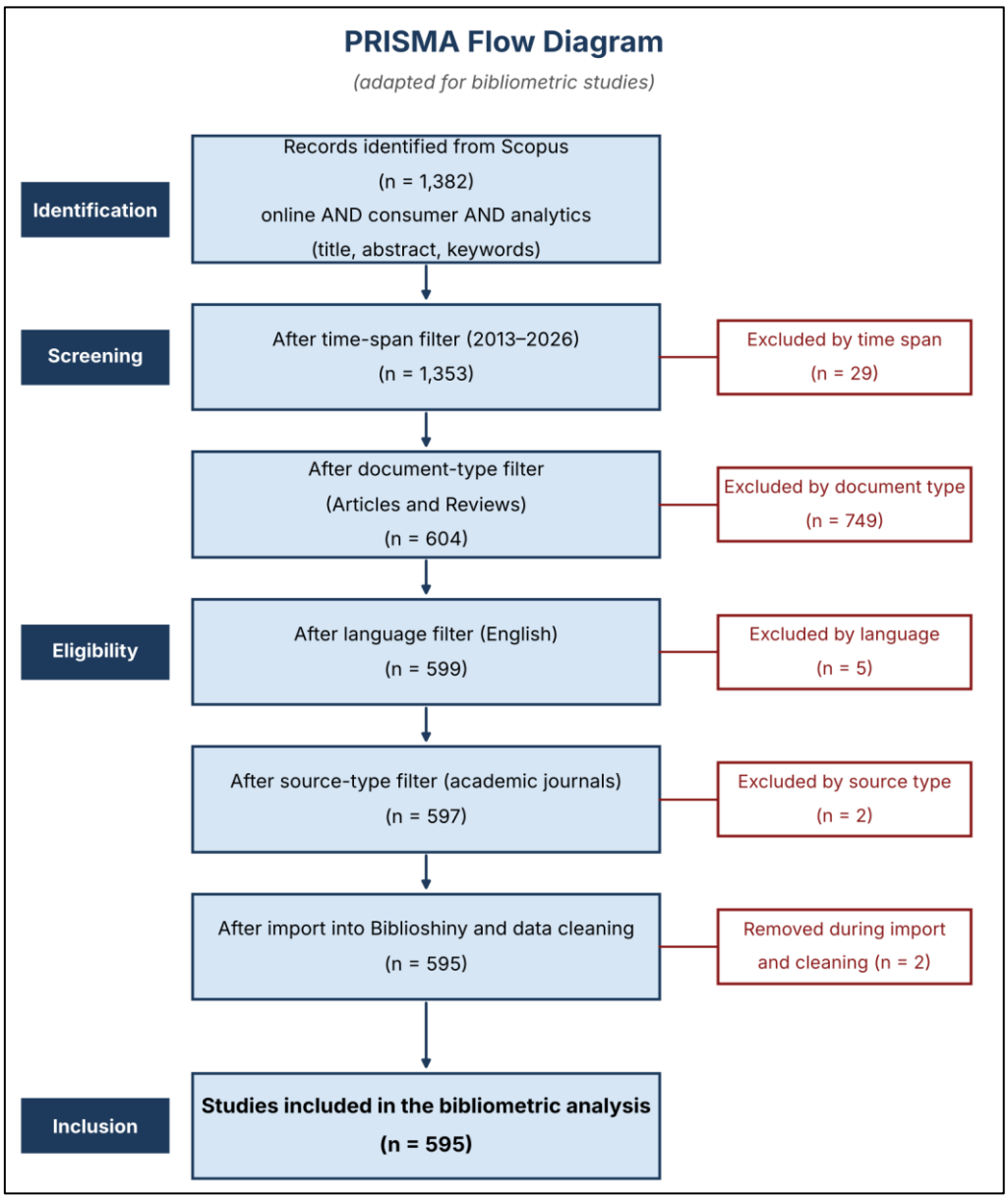


Fig 1 PRISMA Flow Diagram

➢ *Bibliometric Analysis*

There are a number of ways to analyze a corpus of literature, but when a dataset reaches hundreds or thousands of articles it is no longer practicable to analyze it manually. Therefore, it is not possible to rely solely on the traditional literature review approach because the amount of research on the topic is considerable and it covers a wide range of disciplines.

The need to handle vast amounts of publication information in a systematic, quantitative, and repeatable manner led to the introduction of bibliometric analysis in the present study, which is able to identify the dominant theme(s) and its evolution (Donthu et al., 2021). This study adopts the proposed four-step procedure of Donthu et al. (2021) for bibliometric analysis.

- Step 1: Determine Objectives and Scope. The purpose and scope of the study have been defined prior to selecting any technique or data collection method, as it is challenging to have a data analysis method that matches the research questions the study was designed to answer, if these research questions were not defined at the outset of the study (Donthu et al., 2021). This study analyses the state of the art in the research of e-commerce consumer behaviour and analytics, and elucidates the themes to which it adheres – the people behind it (countries, journals) and the structure of the key topics. The final sample of 595 articles falls within the range of hundreds to thousands of papers for which Donthu et al. (2021) recommend for bibliometric analysis instead of manual review.
- Step 2: Choose the Techniques. The study aimed to employ bibliometric techniques, which were chosen with respect to the goals of the study. In addition to the performance analysis, the study uses three science-mapping techniques namely keyword co-occurrence (co-word) analysis, thematic mapping and a three-field plot of

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countries, authors and keywords. The study does not employ techniques that examine how documents are connected (co-citation analysis, bibliographic coupling, co-authorship analysis or network centrality analysis), as its aim is to show the overall structure and trends of the field rather than to identify the individual papers or collections of papers which are at the heart of the field.

- Step 3: Collect the Data. The following process, based on PRISMA, was utilized. Only one database (Scopus) was used, and search terms were developed based on the scope of the study. The inclusion criteria were: publication period, document type, English language and academic journal source. After import and cleaning, 595 papers were used as the final dataset.
- Step 4: Conduct Analysis and Provide a Report. Performance analysis and science mapping were conducted as a single task instead of two different tasks. Donthu et al. (2021) note that in practice, analysing and describing results often go hand-in-hand: Researchers realise that they need one more chart or table to make a point, so they go back to the data and get more results. Thus, in this study the analysis and write-up are considered as one continuous process, each and every result is explained in terms of what it means in the field and not just shown.

➢ *Software and Resources*

- Scopus (Elsevier) is a leading academic database covering peer-reviewed articles, papers and books. It was used to search and filter the literature, reducing the dataset from 1,382 records to 597 papers.
- Microsoft Excel was used to clean the exported dataset before analysis.
- RStudio runs R, the language behind Bibliometrix (Aria & Cuccurullo, 2017), the package used for the bibliometric analysis. Because Biblioshiny sits on top of Bibliometrix and hides the coding, RStudio was not used directly.
- Biblioshiny is the point-and-click interface of Bibliometrix. The cleaned dataset was loaded into it to produce publication trends, country and source analyses, the three-field plot, the keyword co-occurrence network and the thematic map.
- VOSviewer was used to build the keyword co-occurrence cluster map of the 2026 publications that structures the literature review (see the Thematic Clusters section).
- Mendeley is reference management software used to organize the literature and generate formatted citations and references. It played no role in the bibliometric analysis itself.

IV. DATA ANALYSIS AND FINDINGS

➢ *Data Preparation and Main Information*

Before analysis, the Scopus export was cleaned in Microsoft Excel: errors and missing (NA) entries were cleared, and fields not required for the analysis were removed. Table 3 summarizes the main information of the final dataset.

Table 3 Main Information About the Dataset

Indicator	Value
Timespan	2013–2026
Sources (journals)	377
Documents	595
Annual growth rate	20.8%
Authors	1,810
Co-authors per document	3.46
International co-authorship	31.93%
Average citations per document	29.45

The 595 documents have been identified in 377 sources indicating a spread of the available literature on the subject in a variety of journals. The literature came from a total of 1,810 authors, indicating an increasing research community. Co-authorship and authors per document are frequently used in bibliometric analysis to look at the patterns of collaboration (Donthu et al., 2021). International co-authorship rate of 31.93% indicates that there is a high degree of international collaboration, with almost one-third of publications having international co-authorship. The average number of co-authors per document is 3.46, indicating that the documents are created primarily in collaborative rather than individual efforts. Lastly, the mean of 29.45 citations per document suggests that the literature is well received in scholarly circles. The analysis covers the evolution of publications, the most important publications sources and countries, the most frequent keywords used, the most important research topics and the relationships between them. This method is similar to the one employed in the previous bibliometric analysis of consumer behaviour research, which utilized bibliometric and text-mining methods to document the development of consumer behaviour research.

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➢ *Annual Scientific Production*

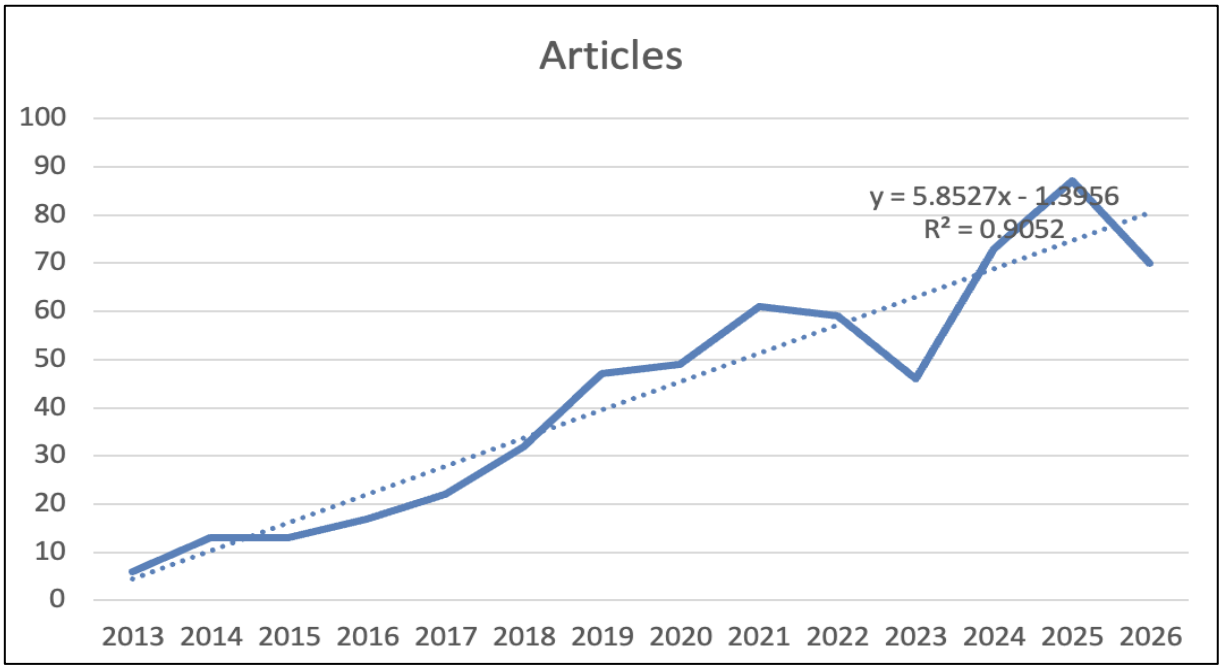


Fig 2 Annual Scientific Production, 2013–2026

Figure 2 shows the number of publications per year between 2013 and 2026, with the overall trend of publications increasing. In the early years output was low, with only 6 articles in 2013, 13 in each of 2014 and 2015, and 17 in 2016. It then continued to grow to 22 articles in 2017 and 32 articles in 2018. A more noticeable rise can be seen from 2019 onwards, with 47 publications in 2019, 49 in 2020 and 61 in 2021. The output slightly reduced in 2022 to 59 and further decreased to 46 in 2023. Publication activity increased rapidly to 73 articles in 2024, before climbing to its peak of 87 articles in 2025. The 2026 figure of 70 articles is below the 2025 high because the data were collected in mid-September, but is significantly higher than in the early years. The dotted linear trendline indicates that there is a strong positive correlation between time and the number of publications, with an R^2 of 0.9052. Since the R^2 value for the linear trendline was greater than the R^2 value of the exponential trendline, the linear trendline was chosen because it gave a better fit of the observed data. Because 2026 only includes papers up to mid-September, the growth rate was also worked out for the complete years 2013–2025, which comes to 25.0% a year.

➢ *Country Scientific Production*

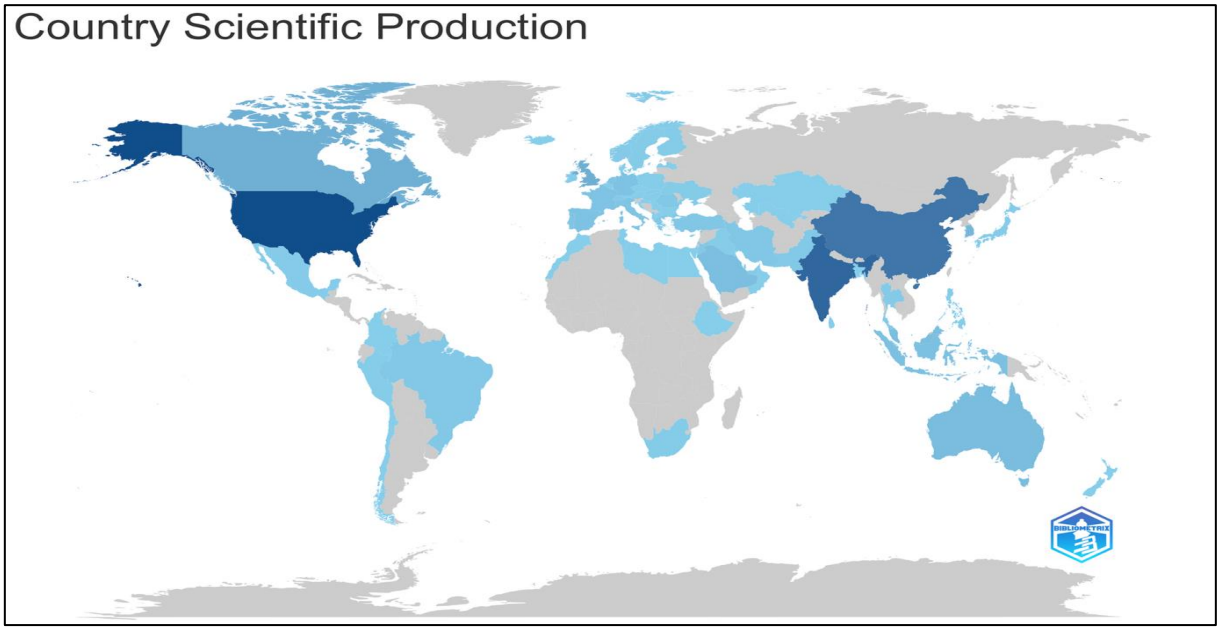


Fig 3 Country Scientific Production

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As illustrated in Figure 3, the research on this topic has been carried out in various parts of the world, with North America, Europe and Asia leading the pack. The darkest shading on the map represents the leading contributors, which are USA, India and China, and there has been a significant contribution from other European and Asian countries. It is also evident from the map that research is ongoing all over the world, with research contributions from Europe, Middle East, Southeast Asia, Oceania and Americas. This demonstrates that the subject has been studied by researchers all over the globe. In keeping with this distribution, 31.93% of the publications are co-authored by researchers from other countries, as befits a global and very collaborative field.

Table 4 gives the numbers behind the map. These count how many times each country appears in the author affiliations, so a paper with three authors from India counts three times for India. The USA comes first with 292 appearances, followed by India with 231 and China with 161. Together these three make up almost half (46.8%) of all 1,462 appearances, which are spread across 80 countries. After them there is a big drop, with the United Kingdom at 68 and Canada at 66.

Table 4 Most Productive Countries

Country	Frequency
USA	292
India	231
China	161
United Kingdom	68
Canada	66
South Korea	50
Australia	37
Taiwan	35
Malaysia	33
Saudi Arabia	32

➢ *Most Relevant Authors*

Table 5 lists the ten authors with the most papers in the dataset. Wang Y is at the top with nine papers, and Liao S and Widowati R follow with seven each. The fractionalized count splits every paper equally between its co-authors, which gives a fairer idea of each person's share. What stands out is how spread out the field is: 1,661 of the 1,810 authors (91.8%) have only one paper in the dataset, and just 25 have four or more. So, no single group of researchers is driving this area. One thing to keep in mind is that Scopus records authors by surname and initials, so a common name like Wang Y may combine more than one person.

Table 5 Most Relevant Authors

Author	Documents	Fractionalised count
Wang Y	9	2.23
Liao SH	7	2.50
Widowati R	7	2.33
Zhang Z	6	1.74
Singh A	5	1.67
Li H	5	1.15
Wang X	5	0.95
Oh YK	4	2.33
Borghi M	4	1.83
Shokouhyar S	4	1.58

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➢ *Three-Field Plot*

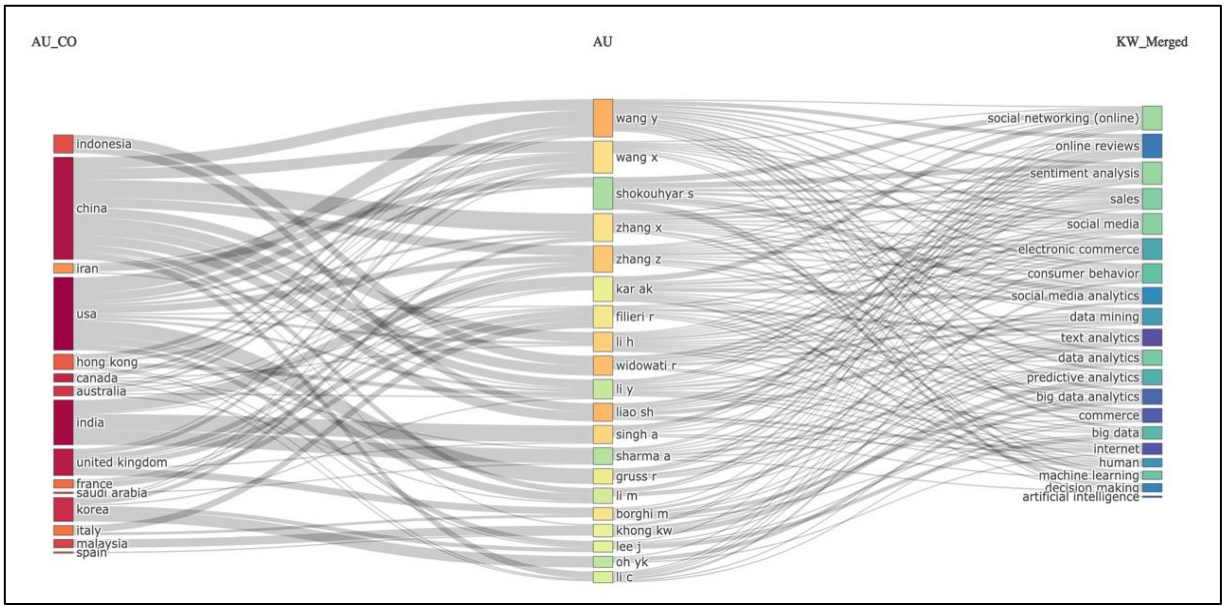


Fig 4 Three-Field Plot of Countries (Left), Authors (Middle) and Keywords (Right)

Figure 4 is the plot of the three fields, the relationship between countries, researchers and research keywords in the dataset. It aids in revealing which authors do the research, where the research is done, and what topics these authors focus on. Countries are listed on the left column, authors on the middle column, and keywords on the right column, while the links between the three indicates their relationship, with the broader the connection, the stronger it is. The plot is meshed with countries like China, USA, India, with a lot of authors, who are linked with a lot of research topics like social networking (online), online reviews, sentiment analysis, social media, electronic commerce, consumer behaviour, data analytics. Overall, the three plots show the global nature of the research and focus on the social media, consumer behaviour, e-commerce and data analytics themes.

➢ *Thematic Map*

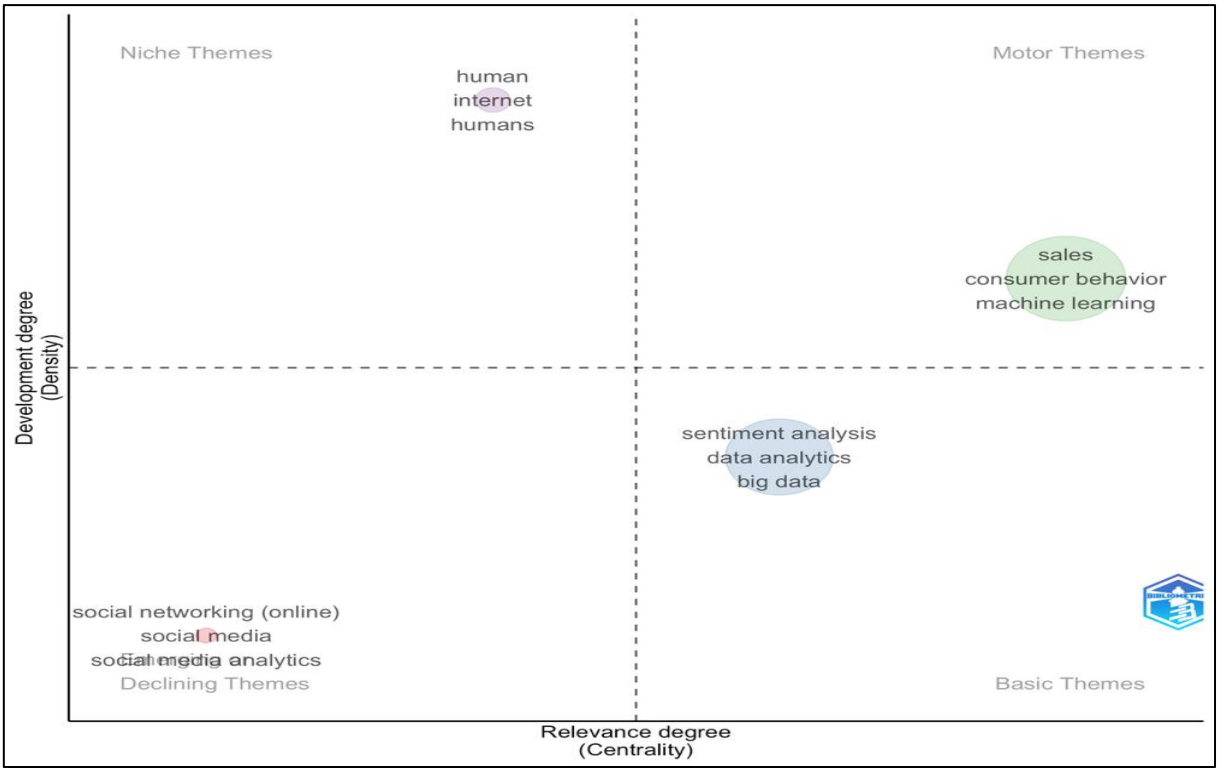


Fig 5 Thematic Map

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The thematic map (Figure 5) situates the major research themes in terms of centrality (relevancy to the overall research area) and density (development of the theme). The analysis shows well developed, developing and declining or emerging research themes. The motor-themes quadrant includes sales, consumer behaviour and machine learning. They are high in centrality and density indicating that they are well developed themes and are closely related to the general research area. Sentiment Analysis, Data Analytics and big data are in the basic-themes quadrant. Themes with high centrality and low density are important to the research area, but do not have the same level of internal development as the motor themes. human, internet and humans are in the niche-themes quadrant. These are indexing terms without substantive content, not research themes, and the use of 'human' and 'humans' is due to an almost identical keyword not being merged in the process of cleaning. Social networking (online), social media and social media analytics are considered emerging or declining. They are of low centrality and low density; this indicates that they are not very well connected within the thematic structure.

➢ *Most Relevant Sources*

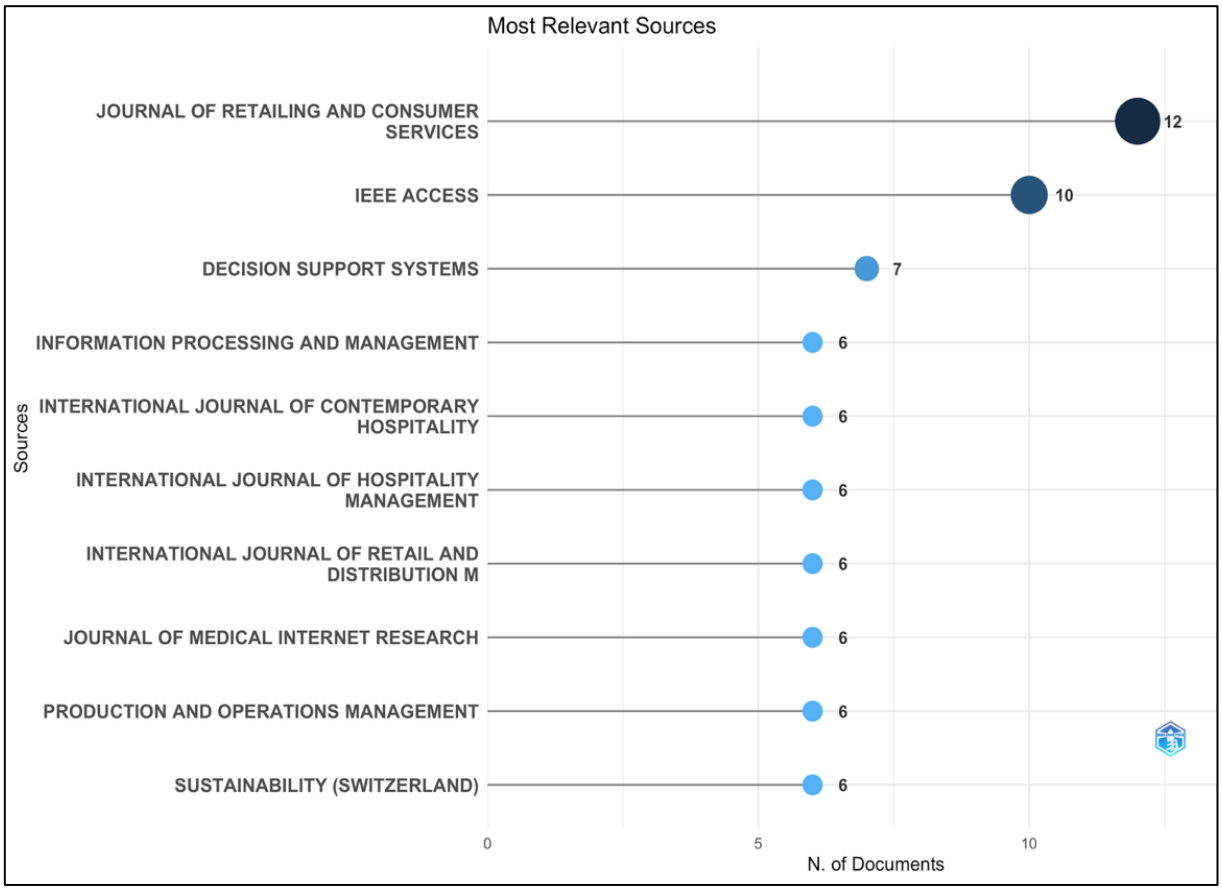


Fig 6 Most Relevant Sources

The most relevant sources analysis (Figure 6) allows us to know which are the journals that have published the most papers on the research area. The Journal of Retailing and Consumer Services has the highest number of publications with 12, followed by IEEE Access with 10 and Decision Support Systems with 7 publications. Other journals that contribute 6 publications each are: Information Processing and Management, International Journal of Contemporary Hospitality Management, International Journal of Hospitality Management, International Journal of Retail and Distribution Management, Journal of Medical Internet Research, Production and Operations Management and Sustainability (Switzerland). This analysis demonstrates that the research is not confined to a specific journal, but appears in journals focused on retailing, consumer behaviour, information technology, hospitality, operations management and sustainability. This variety of publication sites reflects the multidisciplinary aspects of the research, as the researchers approach the subject of consumer behaviour in a marketing and technologic sense. The Journal of Retailing and Consumer Services is of particular interest to this study, as the research topic is tightly related to the decision-making process of both retailers and consumers, providing valuable information on the choice of products. Meanwhile, IEEE Access and Decision Support Systems indicate that technology and approaches to analytics and decision support are becoming more critical to this area and are helping businesses use data to make choices and improve the customer decision making experience.

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➢ *Sources' Production Over Time*

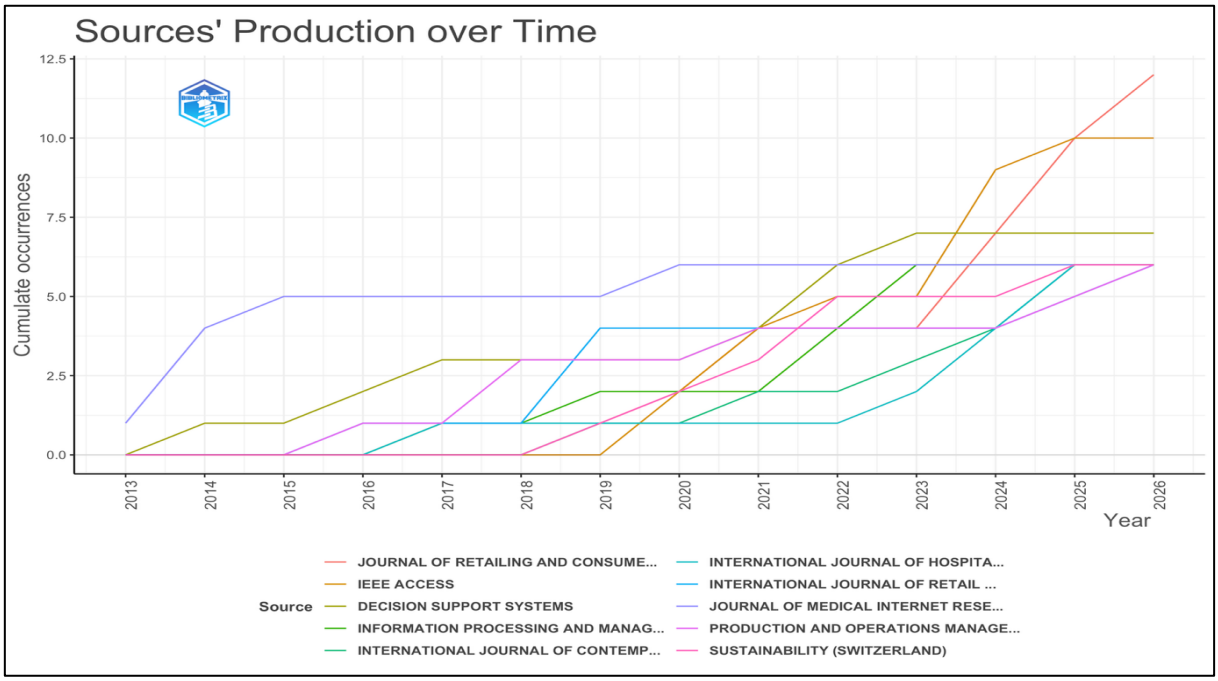


Fig 7 Sources' Production Over Time (Cumulative)

Figure 7 shows the cumulative publications of the top journals in the period 2013–2026. Over time all of the major journals collect publications, but at different rates and times. The Journal of Medical Internet Research is the first journal to appear in the sample, in 2013. By 2015, it reaches five publications and by 2020 it reaches six publications and stays at that level thereafter. Around 2019-2020, IEEE Access appears, and increases steadily to 2023, after which it suddenly grows to nine publications in 2024, with ten publications in 2025. The Decision Support Systems is developed gradually: it's growing from three publications in 2017 up to seven in 2023 and further. The growth of Information Processing and Management is also uneven, with the majority of the growth between 2021 and 2023. The Journal of Retailing and Consumer Services has increased in line quickly since 2023, and has reached a total of twelve publications by 2026, indicating that it has recently become a pillar of the retail and consumer journals. Other journals, including the International Journal of Retail and Distribution Management, International Journal of Hospitality Management, Production and Operations Management and Sustainability (Switzerland), experience gradual growth, each reaching six publications by 2025–2026.

➢ *Co-Occurrence Network Analysis*

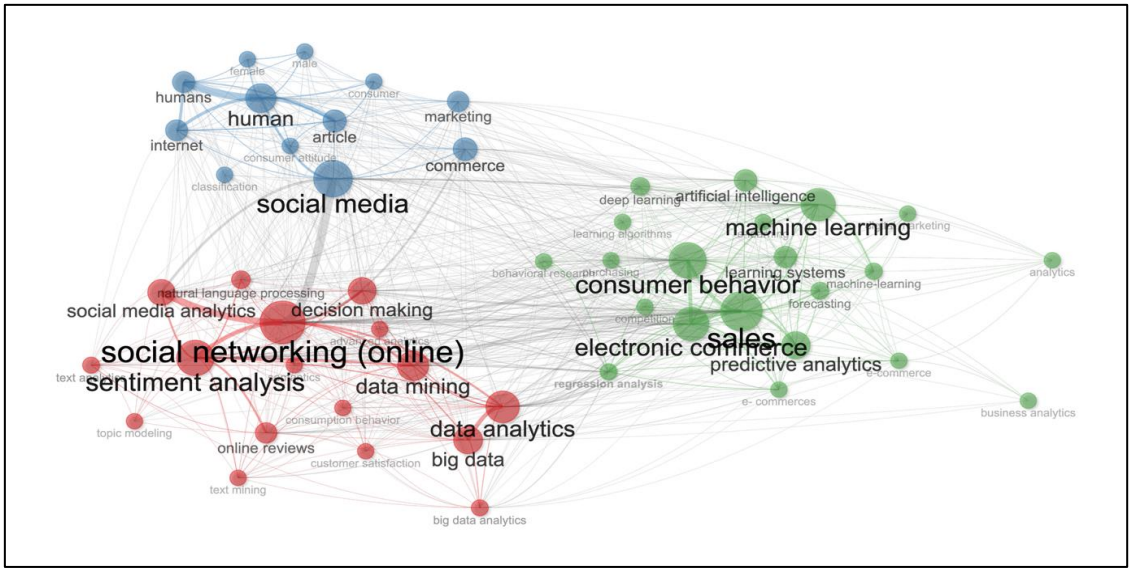


Fig 8 Keyword Co-Occurrence Network

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The co-word network (Figure 8) illustrates the quantity of co-occurrence between the various keywords in the same publications. It shows the main trends of research and the links between the trends. The bigger the node the more often the word was used, the lines represent connections between words and the colors represent different clusters. The green cluster focuses on machine learning, consumer behaviour, sales/electronic commerce, AI and predictive analytics. It highlights the relationship between consumer study and the use of technological techniques and methods, such as machine learning, to interpret and predict consumer behavior. Social networking (online), sentiment analysis, data mining, data analytics, natural language processing and decision making are the elements of the red cluster. It is a research field dealing with the analysis of "consumer opinion" and of consumer behaviour by analysing social networks and online text, with the aim of deriving information from digital data, using tools such as sentiment analysis and data mining. Social media is grouped with other, more broad terms, like human, commerce and marketing, in the blue cluster. These terms are more conceptually oriented, and they concern consumer attitudes, marketing/commercial aspects, and not a specific research method, as compared to the other clusters. A key aspect of the network is that the clusters are well connected and not isolated: consumer behaviour is connected with social media research; analytics and technology is connected with both. This means that the field is becoming more and more interdisciplinary, with traditional marketers and consumer behaviourists adding in analytics, machine learning and social media analysis.

Table 6 shows the author keywords that are used most often. Sentiment analysis (61) and machine learning (55) are clearly the most popular, followed by social media (48) and social media analytics (44). Most of the rest of the top ten are analytics terms, such as big data analytics, text analytics and data analytics. Interestingly, no OR method makes it into the top ten. Forecasting only comes 45th with six mentions, and optimization comes 101st with three. It should be noted that the network in Figure 8 also uses Scopus index keywords, which is why words like “sales” and “human” show up there but not in this table.

Table 6 Most Frequent Author Keywords

Author keyword	Occurrences
sentiment analysis	61
machine learning	55
social media	48
social media analytics	44
big data analytics	39
big data	38
text analytics	36
online reviews	34
e-commerce	30
data analytics	28

➢ *Most Cited Documents*

Table 7 lists the ten most cited papers in the dataset. The most cited by far is Xiang et al. (2017), with 907 citations, which compares the major online review platforms used in hospitality and tourism. Second is Salehan and Kim (2016), with 585 citations, who used sentiment mining to predict the performance of online reviews. Most of the other papers are about online reviews and text mining (Barbado et al., 2019; Tussyadiah & Zach, 2017; Xu et al., 2017), engagement on social media (Oh et al., 2017) or big data analytics (Guha & Kumar, 2018;Mariani & Fosso Wamba, 2020). This fits well with the sentiment analysis and social media themes found earlier. Two papers are a bit outside the main topic, one on smart-home IoT analytics (Yassine et al., 2019) and one on food science (D. Tao et al., 2020) , which shows how broad the search string was. None of these ten papers uses a classical OR method.

Table 7 Most Cited Documents

Document	Source	Citations
Xiang et al. (2017), A comparative analysis of major online review platforms	*Tourism Management*	907
Salehan & Kim (2016), Predicting the performance of online consumer reviews	*Decision Support Systems*	585
Yassine et al. (2019), IoT big data analytics for smart homes	*Future Generation Computer Systems*	306
Barbado et al. (2019), A framework for fake review detection	*Information Processing & Management*	273
Tussyadiah & Zach (2017), Salient attributes of peer-to-peer accommodation	*Journal of Travel & Tourism Marketing*	272
Oh et al. (2017), Consumer engagement behavior and movie box office	*Information & Management*	240
Mariani & Fosso Wamba (2020), Big data analytics companies and innovation	*Journal of Business Research*	235

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D. Tao et al. (2020), Text mining in food science and nutrition	*Comprehensive Reviews in Food Science and Food Safety*	220
Xu et al. (2017), Business intelligence in online customer textual reviews	*International Journal of Information Management*	214
Guha & Kumar (2018), Big data research in operations management	*Production and Operations Management*	212

➢ *Use of OR Methods*

Since the search string did not include any OR terms, the authors also checked how much of the dataset actually uses OR methods. To do this, the titles, abstracts and keywords of the 595 papers were searched for OR method terms. Prescriptive methods included optimisation models and metaheuristics (such as linear or integer programming, genetic algorithms and particle swarm optimisation), game theory, multi-criteria decision-making (such as AHP, TOPSIS and VIKOR), simulation and queuing, and data envelopment analysis. Forecasting and time-series terms were counted separately.

The results are shown in Table 8. Only 37 papers (6.2%) use a prescriptive OR method, while 70 (11.8%) use forecasting. Altogether, 98 papers (16.5%) use some kind of OR method. Prescriptive OR is also quite recent, as 21 of the 37 papers were published in 2023 or later, 11 of them in 2024 alone. No journal has more than four of these papers (*IEEE Access*). The most cited ones look at mining consumer perceptions from social media (Pournarakis et al., 2017), ranking products from online reviews (Awajan et al., 2021) and planning car-sharing fleets around customer flexibility (Ströhle et al., 2019). Overall, this supports the main finding of this study: the field uses OR to forecast consumer behaviour about twice as often as it uses OR to make decisions. As this was a simple keyword search and not a full reading of every paper, these counts should be seen as approximate.

Table 8 Papers Using OR Methods

OR method family	**Documents**
Optimisation (programming models and metaheuristics)	15
Game theory	9
Multi-criteria decision-making (MCDM)	8
Simulation and queuing	5
Data envelopment analysis	0
Prescriptive OR methods (unique papers)	37 (6.2%)
Forecasting and time-series models	70 (11.8%)
All OR method terms (unique papers)	98 (16.5%)

V. FUTURE RESEARCH AGENDA

➢ *Rationale for the Agenda*

The gaps in the future research agenda should not be chosen arbitrarily; rather, they should be derived from the structure created by the bibliometric mapping (Donthu et al., 2021). The agenda below has been structured around the thematic map (Figure 5) and the keyword network (Figure 8) and is based on the literature review gaps (see the Synthesis and Research Gaps section). It considers the well-developed motor themes, the central but under-developed basic themes, and the emerging or declining themes whose direction of development is still unclear, before moving on to cross-cutting directions.

➢ *Extending the Motor Themes: From Prediction to Decision-Making*

The core of this field is sales, consumer behaviour and machine learning. Most of this research applies machine learning techniques to forecast loyalty, purchasing intensity or sales (Anju & Veni, 2026; Li & Hu, 2026) and the success is mainly measured based on the predictive accuracy. Now the focus turns to prescription, with future research being needed to link machine-learning predictions with optimisation models for pricing, inventory and product recommendations, allowing forecasts to drive decisions. Such work should also pay greater attention to explainability, as the example of the Zillow pricing algorithm demonstrates, because accurate looking predictions can still erode trust when they are incorrect (Susarla et al., 2026). Last but not least, most of the evidence in this study is correlational, so there is potential to measure the impact of the drivers in this study through a double machine learning approach (Almashaleh & Fatahi Valilai, 2026) and field experiments to confirm if the drivers found by the predictive models really influence the consumer's behaviour.

➢ *Deepening the Basic Themes: Sentiment Analysis, Data Analytics and Big Data*

Sentiment analysis, data analytics and big data is at the heart of the field with less internal development. The literature of classification is still not unified and is scattered among sub-literatures. Three directions follow. First, sentiment should be more systematically related to decisions, such as by integrating aspect-level sentiment into MCDM models to score products or product alternatives (Jia et al., 2026b; Kyriakidis & Tsafarakis, 2025a; Ng et al., 2026), or to determine which products to delete (Zhu et al., 2025a). Second, despite the potential benefits of reviews, the credibility of reviews has garnered renewed attention, with fake reviews remaining difficult to identify (J. Tao et al., 2026) and there being a lack of research which extends the

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finding that eWOM credibility is a function of platform type and culture to (Verma et al., 2023) AI-generated reviews. Third, although star ratings and review text can vary in a number of different ways across markets (Liu & Pareti, 2026) , cross-cultural sentiment analysis is rare.

➢ *Developing or Fading Trends: Social Media and New Shopping Avenues*

Social networking, social media and social media analytics are in the emerging/diminishing quadrant and their future direction is still unclear. A possible interpretation is that general social media is being replaced by more specific media and services. The live-streaming commerce (Mei et al., 2026b; J. Wang et al., 2026b) and generative AI chatbots are transforming the online shopping landscape, yet they (2026) have yet to be fully understood in their impact on consumer behaviour. Future research should consider AI as a subject of study (as in the case of trust in AI recommendations), as well as an instrument of research (such as sentiment classification or synthetic consumer agents, as proposed by Jin et al., 2026); and maintain the distinction between the two roles. The quadrant would also indicate decline or emergence through time by tracking these themes.

➢ *Testing OR Models with Real Consumer Data*

Classical OR tools are available, but only in a smaller proportion of the field and these are primarily used for the investigation of platform strategy. It is rare to test game-theoretic models of platforms, sellers and consumers (Han & Guan, 2024; Song et al., 2026; J. Wang et al., 2026a) and optimization models of market entry (Deng et al., 2026b) on real consumer data. Calibration and validation of these models using transaction, clickstream or review data in the future would be useful to determine whether their equilibrium results are valid for real markets.

➢ *Privacy, Ethics and Emerging Markets*

There is a lack of work around privacy-preserving methods like federated learning (Haripriya et al., 2026) as well as the ethics of algorithmic personalization (Nguyen et al., 2026) and of creating customer digital twins out of behavioural data (Okyere Sefa et al., 2026). Moreover, products and marketing strategies may have different impacts on consumers in various regions, due to their individual preferences and expectations (Liu & Pareti, 2026) . Future studies may be better directed towards Indian consumers and consumer of the emerging markets in view of India being one of the principal contributors in this field (Figure 3). Table 9 summarizes the agenda.

Table 9 Summary of the Future Research Agenda

Theme group (thematic map)	Gap identified	Suggested direction
Motor: sales, consumer behaviour, machine learning	Predictions are rarely turned into decisions; accuracy is valued over explanation	Combine ML forecasts with optimisation; explainable and causal designs
Basic: sentiment analysis, data analytics, big data	Sentiment is measured but seldom used for decisions; fake and AI-generated reviews; few cross-cultural studies	Sentiment-driven MCDM; credibility of AI-generated reviews; cross-market comparisons
Emerging/declining: social networking, social media, social media analytics	Direction unclear; new channels under-studied	Live-streaming and GenAI chatbot research; AI as object vs instrument
Cross-cutting: OR models	Game-theoretic and optimisation models rarely validated	Calibrate models with real transaction and review data
Cross-cutting: privacy, ethics, markets	Privacy, ethics and emerging markets underexplored	Federated learning; ethical personalization; Indian and emerging-market consumers

VI. CONCLUSION

This study set out to understand how research on e-commerce consumer behavior has used operations research and analytics, by carrying out a bibliometric analysis of 595 Scopus-indexed articles published between 2013 and 2026. The study was guided by three research objectives, and the findings show that each of them has been met to a large extent. This section first maps the findings to each objective, then discusses the implications of the study, followed by its limitations, and closes with final remarks.

- RO1: Understanding the trends in the research area. The first objective was fully achieved. The results show that the field is growing steadily and quickly. Publications rose from only 6 in 2013 to 87 in 2025, an annual growth rate of 20.8% (25.0% a year if the incomplete year 2026 is left out). A linear trendline explains most of this growth (R^2 = 0.9052), suggesting that interest in the topic has risen year after year. A small dip in 2022 and 2023 was followed by a sharp rise in 2024 and 2025, which may reflect the wider business adoption of artificial intelligence tools during this period. The figure for 2026 appears lower mainly because the data was collected in September 2026, before the year was over. The field is also global and collaborative: the USA, India and China lead in output, almost one-third (31.93%) of papers involve international co-authors, each paper has 3.46 authors on average, and each paper has been cited about 29 times on average. The research is spread across 377 sources, led by the *Journal of Retailing and Consumer Services*, *IEEE Access* and *Decision Support Systems*.
- RO2: Identifying the specific findings of the field. The second objective was also achieved. The thematic map shows that sales, consumer behaviour and machine learning are the motor themes of the field; these topics are

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both well developed and central. Sentiment analysis, data analytics and big data are also central but less developed. Social networking, social media and social media analytics are in the emerging or declining quadrant. The keyword co-occurrence network divides the research into three connected groups: machine learning, consumer behaviour and sales; social networking, sentiment analysis and data mining; and social media with general marketing and commerce terms. The literature review, based on a VOSviewer map of the 2026 publications, added more detail and identified five clusters covering predictive analytics, consumer cognition, social media and purchase intention, platform strategy, and review sentiment.

From these results, the main conclusion is that research in this field has moved from describing online consumers to predicting their behaviour, but it has not yet reached the stage where these predictions are routinely used to make better, optimised business decisions. Most studies use machine learning and text mining to forecast loyalty, purchase intention or sentiment(Li & Hu, 2026). Classical OR tools such as game theory and optimisation are present but form a smaller part of the field, and they are mainly used to study platform strategy. Only 37 of the 595 papers (6.2%) use a prescriptive OR method, compared with 70 (11.8%) that use forecasting (Song et al., 2026) .

- RO3: Suggesting future research agendas. The third objective was achieved by examining the emerging themes and the gaps identified in existing research. The Future Research Agenda section sets out five directions: moving from prediction to decision-making, deepening sentiment analysis so that it supports decisions, studying new shopping channels such as live-streaming and generative AI chatbots, testing OR models with real consumer data, and focusing on privacy, ethics and emerging markets such as India.

The present study makes several contributions to the literature. It brings together OR, analytics and consumer behaviour research, which are often studied separately, and shows how these areas are connected and where they remain apart. It also identifies the leading journals, countries and themes, which can be useful for future researchers who want to explore the topic further.

For e-commerce managers, the findings suggest that consumer data becomes most useful when it is used to make business decisions. Online reviews, for example, are not only feedback; they can guide which products to keep, improve or remove (Zhu et al., 2025). Managers can combine sentiment analysis with decision-making tools to rank product features and set priorities (Kyriakidis & Tsafarakis, 2025b) At the same time, managers should not trust algorithms blindly and should check model results with human judgement before making major decisions (Susarla et al., 2026).

Better use of OR in e-commerce can benefit both consumers and society. More accurate demand forecasts can reduce overstocking and waste. Better review analysis and fake-review detection can help consumers make more informed choices and protect them from misleading information (J. Tao et al., 2026). Recommendation systems that match products to real needs can save consumers time and money.

The findings are also important for policymaking. As platforms collect more consumer data, governments need clear rules on how this data is used and shared. Policymakers could also set standards for transparency in algorithmic personalisation and take strong action against fake reviews. Finally, as consumers are now more concerned about how products are made and delivered (Al-Olfi, 2026), policies that encourage honest disclosure of sustainable supply chain practices could help consumers make more informed choices.

A number of limitations should be noted. First, the study was limited by time. It was completed within a single academic term, so more advanced techniques could not be carried out, and the data for 2026 covers only part of the year. Second, the search string (“online AND consumer AND analytics”) did not include OR-specific terms, so OR studies appear in the sample only where they also address online consumers and analytics; the sample therefore reflects analytics-oriented consumer research more broadly than OR alone. Third, Scopus was the only database used, and only English-language journal articles and reviews were included, so relevant work in other databases, languages and outlets may have been missed. Fourth, the authors had limited advanced technical expertise. As business students rather than data scientists, the authors relied on the point-and-click Biblioshiny interface instead of writing code in R, which limited how far the analysis could be customised. Manual data cleaning in Excel can also leave small errors, such as near-duplicate keywords like “human” and “humans” appearing separately. Finally, the literature review clusters are based on the 2026 publications only, so they reflect the most recent research front rather than the full period. These limitations do not change the overall picture, but they should be kept in mind when reading the results.

Overall, this study shows that research on e-commerce consumer behaviour has grown into a large, global and multidisciplinary field, driven by machine learning, sentiment analysis and big data. While the field has become quite accurate at predicting online consumer actions, the next logical step is to apply operations research to determine how businesses, platforms and policymakers should respond. The authors hope that this study encourages future researchers, especially students, to explore this meeting point between consumer behaviour and decision science, where much valuable work still remains to be done.

DECLARATIONS

- Conflict of interest. The authors declare no conflict of interest.
- Use of generative AI. The authors used AI-assisted tools only to format the manuscript (layout, headings and references). All content, analysis and interpretation were

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written and checked by the authors, who take full responsibility for the work.

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