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ARTIFICIAL INTELLIGENCE IN E-COMMERCE: A BIBLIOMETRIC ANALYSIS

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Abstract— **Artificial intelligence (AI) is reshaping e-commerce, yet the research that describes this change is scattered across computing, marketing, operations and consumer studies. This paper maps that literature through a bibliometric analysis of 1,497 English-language journal articles and reviews on AI in e-commerce retrieved from Scopus on 16 September 2026 (2011–2026), of which 1,496 records were analysed in Bibliometrix. Annual output rose from 5 documents in 2011 to 394 in 2026, and the last three years contain about 65% of all records. The literature is spread over 717 sources and 4,113 authors, and 27.61% of documents involve international co-authorship. Keyword mapping identified three clusters: AI methods, personalisation and consumer trust; digital transformation, supply chains and decision-making; and customer experience, immersive technologies and review-based synthesis. The thematic map places machine learning at the core of the field, while big data, blockchain, sentiment analysis and natural language processing occupy less developed positions. A literature-based Input–Process–Outcome framework and five research priorities are proposed, and implications for managers, policy makers and researchers are discussed.**

Keywords— **Artificial Intelligence; E-Commerce; Bibliometric Analysis; Bibliometrix; VOSviewer; Thematic Map; Research Agenda**

I. INTRODUCTION

Artificial intelligence (AI) has transformed the online business landscape, and e-commerce is among the areas in which the change is most visible. Every click, search, purchase, return and review on a website generates data. These data are varied and continuously evolving, which makes prediction, personalisation, trust and decision-making difficult for businesses [1]. AI offers a response to this difficulty. It supports product recommendation, answers to customer inquiries, fraud identification, demand forecasting and pricing. Dynamic pricing is a clear example, since firms can now forecast demand and adjust prices in real time [2]. Scholarly attention has followed this development. The Scopus data analysed in this study contain 5 articles on AI in e-commerce published in 2011, 126 in 2022 and 394 in 2026. The final three years (2024–2026) account for 972 of the 1,496 analysed documents, approximately 65% of the total. A topic that was once marginal has become one of the most active areas of research in both business and computing, and it is time to step back and establish what has been studied and how the pieces fit together. The work is also not confined to a single discipline, because the largest subject areas are Computer Science, Engineering, and Business, Management and Accounting, which shows that technical and managerial researchers are both involved.

The breadth of the field becomes clearer once the underlying technology is considered. Machine learning (ML) is the principal knowledge area for studying and using e-commerce data. It comprises supervised, unsupervised and reinforcement learning, each of which performs better on a different type of task [3]. Supervised models can predict the probability that a customer will purchase or cancel, unsupervised models can group shoppers with similar habits, and reinforcement learning can learn what to charge or what to deliver through experimentation. Layered on these methods are tools with which customers interact directly, such as recommender systems, chatbots and voice assistants. More recently, generative and agentic AI have entered the field, with the ability to write product descriptions, sustain longer conversations and complete tasks with less human involvement [4]. Chatbots illustrate the consumer side: human-like cues in a chatbot make users more willing to follow its advice [5]. Recommender systems show a similar pattern, since the user experience of a system depends on more than the accuracy of its predictions [6].

The technology also creates new problems. Many models are "black box" models, which makes it difficult for users or

managers to understand why a decision was made and slows adoption [7]. AI has also been studied in supply chains, where it is associated with greater resilience and visibility [8], and in small businesses, where digital tools can improve efficiency and extend reach to more customers [9]. The field is therefore not defined by a single tool. It combines elements of computer science, marketing, operations and consumer behaviour, each of which has its own journals. A bibliometric study can quantify and visualise publications, authors, journals and keywords, and thereby reveal the links between these elements without the need to read thousands of papers individually [10].

The motivation for this study arises from practical observation. Direct involvement of the research team in content creation and customer communication for a small online flower shop, and in a digital marketing internship that used AI tools, showed how quickly such tools had become part of daily work even in a very small business. Captions, answers to frequently asked questions and campaign plans were increasingly produced with AI assistance. At the same time, it was unclear how a student or a small seller could begin to read about these developments, because the literature is distributed across many journals and subject areas. A consolidated overview of what has been written, who is writing it and which ideas recur was therefore needed. The gap between the speed of AI adoption in e-commerce and the lack of cohesion in the research prompted this study. The tools observed in a small business are also those deployed at scale by large firms, which indicates the relevance of the topic to future managers.

Although the area has not been neglected, earlier reviews leave several matters open. Many consider only one industry or one method, which makes it difficult to transfer their results to other fields [2]. Some concentrate on a single technical issue, such as link prediction in social networks and e-commerce, which was examined using 690 documents [11]. Others consider only the customer side. For instance, Sumanth and Somasekhar [12] analysed 257 articles on AI in the online customer experience, and Mouammine [13] explored sensory marketing with a comparable focus. A review of 82 studies on customer experience reports a shift from transactions to technology-enabled experience [14], while a review of 134 articles indicates that generative AI is reshaping consumer decisions [15]. These contributions are valuable, but none shows how the different slices relate to one another. A general bibliometric study of e-commerce exists [16], but it is not specific to AI. In addition, research on consumers, on algorithms and on supply chain decisions tends to be read separately, even though trust, explainability and governance appear in all three [17, 18]. The problem is aggravated by the speed of growth. The documents in the dataset are recent, with an average age of only 2.49 years, so older reviews miss much of what has since been published, and individual readers find it hard to form a single picture from so many papers. A new and comprehensive mapping of the whole field is therefore required.

This study attempts to close that gap. On 16 September 2026, a search was conducted on Scopus using the terms “e commerce AND artificial intelligence”, and article selection followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach in order to keep the process clear and transparent [19]. The initial search returned 5,619 documents. Restricting the years to 2011–2026 left 5,024, retaining only articles and reviews gave 1,546, of which 1,510 were in English, and the removal of book series, conference proceedings and trade journals left 1,497. Only peer-reviewed journal articles and reviews were therefore retained, which provides a solid foundation for the analysis. The final dataset comprises 1,497 journal publications (1,496 of which were retained by the analysis software), drawn from 717 sources and written by 4,113 authors, a sample large enough to reveal genuine patterns. Data were organised in Microsoft Excel, analysed in Bibliometrix through RStudio [20], mapped in VOSviewer [21] and managed in Mendeley Desktop for referencing. The remainder of the paper is organised as follows. Section II reviews the literature through the three keyword clusters identified. Section III sets out the research methodology. Section IV presents the data analysis: main information on the dataset, annual scientific production, the three-field plot, the most relevant sources and the thematic map. Section V develops a future research agenda, and Section VI concludes with implications, limitations and directions for further work.

Three research objectives follow from this motivation and gap. The first (RO1) is to understand research trends in AI for e-commerce, including publication trends over time, the most active journals and authors, and the level of collaboration between researchers from different countries. The second (RO2) is to report specific findings from the analysis: the main keywords, the links between authors, themes and journals, and the thematic map, which distinguishes central and well-developed themes from peripheral ones. The third (RO3) is to propose an agenda for future research, drawing on the less dominant or less connected themes (big data, blockchain, sentiment analysis and natural language processing) and on newer themes such as generative and agentic AI, which need further development. Together, the objectives move from describing the field, to explaining it, to questioning it. RO1 and RO2 are addressed in Sections II and IV, RO3 in Section V, and all three are revisited in Section VI. The objectives follow the same sequence as the results, so that the reader can move from numbers to themes and then to the future agenda. The study is intended to be useful both to readers who want figures and to those who want ideas, and to serve as a starting point for students, researchers and managers working in this field.

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II. LITERATURE REVIEW

A. Overview

A large and growing body of literature has investigated AI in online commerce. E-commerce platforms generate heterogeneous, multimodal and continuously evolving data, which creates challenges for prediction, personalisation, trust and decision-making [1]. Previous research has established that ML is the key knowledge area for analysing such data [3], and AI-based dynamic pricing shows the operational stakes, since firms can forecast demand and optimise prices in real time [2].

The volume of literature has increased in recent years. As Table 4 shows, the Scopus dataset rises from 5 records in 2011 to 126 in 2022 and 394 in 2026. Research on AI and online customer experience has grown sharply since 2018 [12], and link-prediction research in e-commerce grew by 22.46% annually between 2005 and 2024 [11]. The generalisability of much published research is nevertheless limited, because existing reviews typically focus on a single industry or methodological stream [2], and a longitudinal map of e-commerce research has been described as lacking [16]. A structured synthesis is therefore needed.

B. Keyword Co-occurrence and Cluster Structure

The literature base for this section is the Scopus export described in Section III, analysed in Bibliometrix. Of the 1,496 English-language records, 1,374 are articles and 122 are reviews. Output is led by IEEE Access and the Journal of Theoretical and Applied Electronic Commerce Research (47 documents each; Fig. 6). Reviews and recent 2026 papers were screened by title and abstract, and 35 papers directly related to e-commerce were retained; only these are cited in this section. Author keywords were harmonised, and a co-occurrence analysis with a minimum of 10 occurrences left 53 keywords (Table 1). Following the VOSviewer approach [21], links were normalised by association strength and keywords were grouped by modularity-based clustering. Three clusters resulted (Fig. 1 and Table 2), and these structure the remainder of the review. Cluster labels were assigned by the research team from the keywords in each cluster.

Table 1. Most frequent technical keywords and their cluster

Keyword	Occurrences	Cluster
artificial intelligence	**551**	**1**
e-commerce	**333**	**1**
machine learning	**154**	**1**
deep learning	**72**	**1**
recommender systems	**64**	**1**
chatbots	**55**	**1**
generative artificial intelligence	**41**	**1**
big data	**34**	**2**
systematic literature review	**33**	**3**
supply chain management	**28**	**2**
digital transformation	**27**	**2**
bibliometric analysis	**21**	**3**

Note. Author keywords, harmonised; minimum of 10 occurrences. Source: Authors' analysis of the Scopus export in Bibliometrix and VOSviewer.

Fig. 1 displays the resulting keyword co-occurrence network. Node size reflects keyword frequency, and colours mark the three clusters, which are summarised in Table 2.

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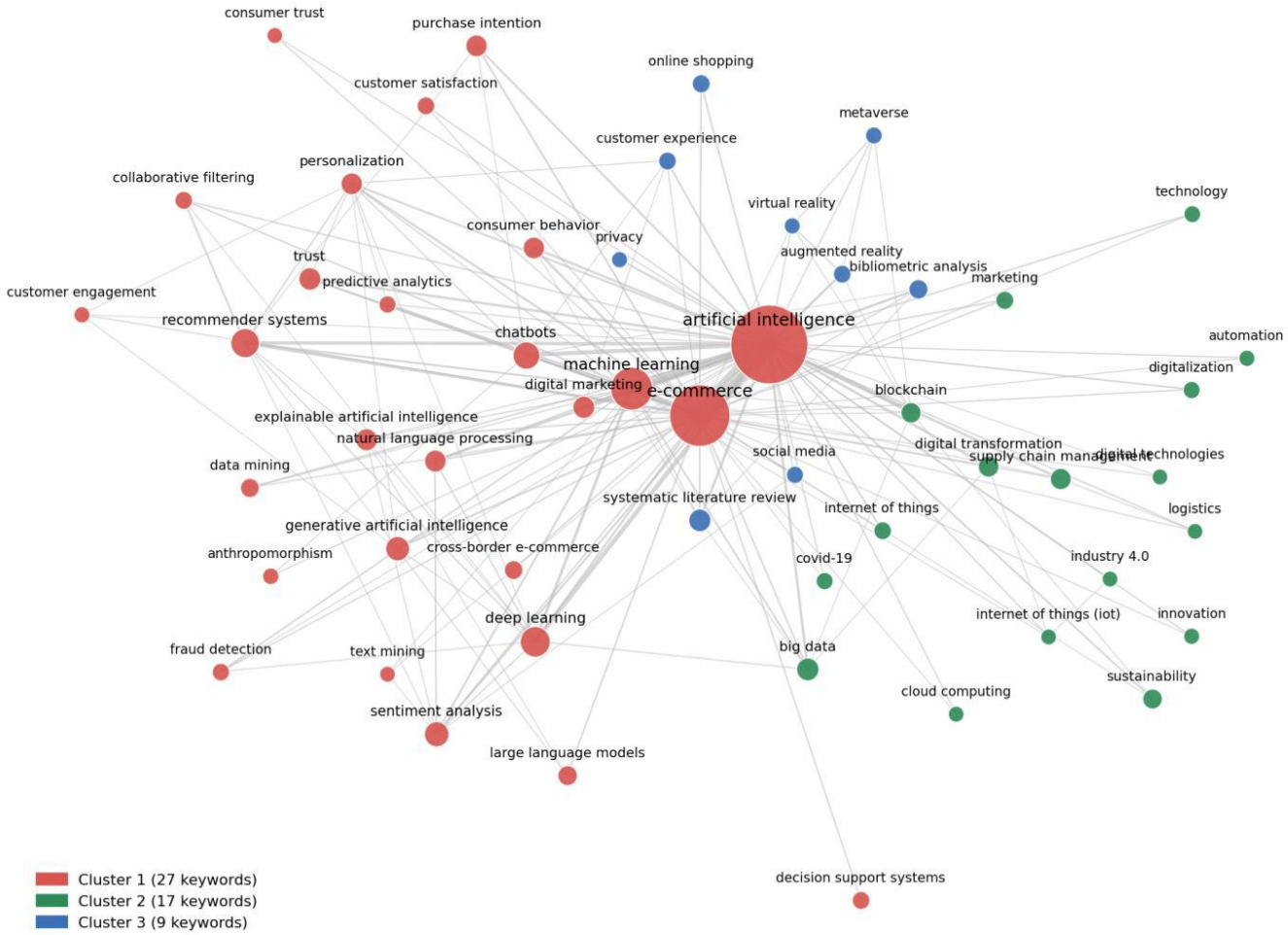


Fig. 1. Keyword co-occurrence network (53 keywords, minimum 10 occurrences). Node size reflects frequency; colours mark the three clusters.
Source: Authors' analysis of the Scopus export (16 September 2026) using VOSviewer [21].

Table 2. Summary of the three keyword clusters

Cluster	Theme	Keywords (total occurrences)	Representative keywords	Selected papers
1 (red)	**AI methods, personalisation and consumer trust**	**27 (1,713)**	**artificial intelligence, machine learning, deep learning, recommender systems, chatbots, generative AI, trust, fraud detection**	**20**
2 (green)	**Digital transformation, supply chains and decision-making**	**17 (283)**	**big data, supply chain management, digital transformation, blockchain, sustainability, Industry 4.0, logistics**	**8**
3 (blue)	**Customer experience, immersive technologies and review-based synthesis**	**9 (152)**	**systematic literature review, bibliometric analysis, customer experience, online shopping, augmented reality, metaverse, privacy**	**7**

Note. Selected papers are those retained by the research team for this review (Section II-B) and do not measure cluster size.
Source: Authors' analysis of the Scopus export in VOSviewer.

C. Cluster 1: AI Methods, Personalisation and Consumer Trust

The largest cluster (27 keywords) joins machine learning, deep learning, recommender systems and explainable AI to chatbots, generative AI, trust and purchase intention. Artificial intelligence (551 occurrences), e-commerce (333) and machine learning (154) are its most frequent keywords. The existing literature is extensive and focuses particularly on these strands, which are usually studied together. Reviews explain supervised, unsupervised and reinforcement learning and their applicability to e-commerce [3], and a decision-oriented survey covers behaviour prediction, demand forecasting, fraud detection and reinforcement learning for pricing and logistics, while noting limits of scalability, robustness and interpretability [1]. In a review of 690 documents, link prediction is shown to have moved from statistical approaches to graph neural networks [11].

A considerable amount of literature has been published on recommender systems. These studies show a progression from collaborative filtering to explainable transformers [22], sequential models based on contrastive learning, graph networks and attention [23], and large language model (LLM) recommenders that address the limits of deep neural networks [24]. Traditionally, research has focused on prediction accuracy, but accuracy only partially constitutes user experience [6]. More recent attention has focused on purchase-intent detection, which directly affects conversion rates and engagement [25], on agentic AI systems [4], and on aspect-based sentiment analysis, which has evolved from early ML techniques to transformer models [26].

A number of authors have considered how consumers respond to conversational agents. A randomised online experiment showed that anthropomorphic chatbot cues raised users' compliance, with social presence as a mediator [5]. Reviews of conversational AI [27], voice assistants [28] and artificial empathy [29], which argues that embedding empathy in technology has become a critical frontier, extend this work. Generative AI is the newest theme: recent evidence suggests that it supports content creation and personalised marketing [30], and a review of 134 articles finds that it reshapes consumer decisions [15].

Opacity and fraud are recurring risks. Several lines of evidence suggest that black-box models hinder adoption [7], and that transparency builds trust only alongside uncertainty communication and trust calibration [17]. Various studies have assessed AI against fraud: ensemble models exceed 98% detection in online fraud and deep learning improves real-time anomaly detection [31], and ML supports anomaly detection and risk scoring in Nigeria's digital economy [32].

D. Cluster 2: Digital Transformation, Supply Chains and Decision-Making

The second cluster (17 keywords) covers big data, supply chain management, digital transformation, blockchain, sustainability and Industry 4.0, with supply chain management (28 occurrences), digital transformation (27) and blockchain (25) the most frequent. It is the most relevant to operations research because it treats e-commerce as a system of decisions. Interviews conducted by Modgil et al. [8] with 35 supply chain experts show that AI strengthens resilience through transparency, last-mile delivery, personalised solutions and agile procurement. AI driven by Industry 4.0 technologies has improved connectivity, yet information sharing across supply chain partners still faces barriers [33]. Platform decisions are also modelled: seller evaluation must now weigh service quality and platform contribution as well as price [34]. Across 1,301 publications from the past two decades, AI-based dynamic pricing has shifted from econometric methods towards deep and multi-agent reinforcement learning [2].

Most studies in a review of 94 documents corroborate that digital transformation improves the efficiency and market reach of small firms, despite resource constraints [9]. A scoping review of 35 studies examines how AI and automation are transforming marketing and international trade [35]. Governance is a growing concern: generative AI creates system-level risks across cross-border e-commerce supply chains [36], and AI ethics declarations universally cite fairness and privacy, yet their practical force in platform governance is questioned [18].

E. Cluster 3: Customer Experience, Immersive Technologies and Review-Based Synthesis

The smallest cluster (9 keywords) combines customer experience, online shopping, augmented reality, the metaverse and privacy with the methodological keywords systematic literature review and bibliometric analysis, which are its most frequent keywords (33 and 21 occurrences). A large volume of published studies describes the role of AI in customer experience (CX): one bibliometric analysis covers 257 works [12] and a systematic review synthesises 82 studies, reporting a shift from transactional to technology-enabled CX [14]. Much of the current literature pays particular attention to chatbots, recommendation and personalisation [12], while further reviews consider sensory marketing cues across 191 records [13] and 50 empirical articles on fashion e-commerce [37].

A number of studies have postulated a convergence between AI and extended reality, with annual growth of 91.29% across 880 articles, although the field remains in its infancy [38]. Previous findings on privacy in such settings have been inconsistent, because concerns are context-dependent and not static [39]. Bibliometric analysis co-occurs mainly with artificial intelligence (11 times) and e-commerce (6 times), and numerous bibliometric studies have mapped e-commerce in general [16], CX, fashion, pricing and link prediction. Each, however, addresses one theme at a time.

F. Theoretical Lenses, Synthesis and Research Gap

Different theories exist in the literature regarding how

consumers respond to AI (Table 3). For example, Adam et al. [5] draw on social response and commitment–consistency theory, Wu et al. [28] on the cognition–affection–conation framework, and Zhang and Liu [37] on the theme–theory–method framework. Guo and Polak [17] add the TEUT framework, which links transparency, explainability, uncertainty and trust calibration. Behavioural theories dominate the consumer-facing clusters, whereas the operational cluster relies on decision models and review protocols. Across clusters, trust, explainability and governance are cross-cutting concerns [7, 17, 18], and decision intelligence in pricing, logistics and seller selection is gaining importance [1, 2, 34].

Table 3. Theories and frameworks used in the reviewed studies

Theory or framework	Source	Use in the study
Social response theory; commitment–consistency theory	**Adam et al. [5]**	**Explains why anthropomorphic chatbot cues and consistency pressure increase user compliance**
Cognition–affection–conation framework	**Wu et al. [28]**	**Organises research themes on consumer behaviour with digital voice assistants**
Theme–theory–method (TTM) framework	**Zhang and Liu [37]**	**Guides content analysis of AI-related consumer studies in fashion e-commerce**
User-centric evaluation framework	**Knijnenburg et al. [6]**	**Links system aspects to the user experience of recommender systems**
TEUT framework (transparency, explainability, uncertainty, trust calibration)	**Guo and Polak [17]**	**Proposes conditions under which explainability supports trust in AI**

Note. Frameworks are reported as described in the abstracts of the cited studies.

Among the papers reviewed, there is a relatively small body of literature that combines a keyword co-occurrence map of the whole field with a decision-oriented reading of the clusters. Prior reviews are either general [16], consumer-side [12], or limited to one problem such as pricing [2] or recommendation [22]. The present study therefore treats trust, algorithmic performance and supply chain decisions as parts of one structure. It addresses this gap by mapping 1,496 Scopus records, explaining the three clusters in turn, and highlighting operational decision problems of direct interest to operations research. Because the dataset is a single English-language Scopus export, the findings may not cover non-indexed or non-English work.

III. RESEARCH METHODOLOGY

A. Research Design

The present study adopts a systematic, bibliometric approach to examine and synthesise existing research on AI in e-commerce. Relevant scholarly publications were identified through a structured search process and selected on the basis of predetermined criteria, in line with accepted guidelines for bibliometric analysis [10]. The literature was subsequently analysed to identify key themes, theoretical perspectives, methodological approaches and research gaps. This approach was adopted to provide a comprehensive and systematic account of existing knowledge and to facilitate the synthesis of findings across previous studies. The review therefore moves beyond a descriptive account of the literature by critically examining existing research and identifying areas that warrant further investigation.

B. Article Selection, Inclusion and Exclusion Criteria

A database search was conducted on 16 September 2026 in Scopus (Elsevier), using search keywords appearing in the title, abstract and keywords of records. The PRISMA statement [19] was adopted to guide the reporting of the review. PRISMA provides a structured approach to the reporting of systematic reviews through a checklist and a flow diagram, and it was employed here to ensure that the identification, screening, eligibility and inclusion of relevant studies were reported systematically and transparently. The complete selection process is summarised in Fig. 2.

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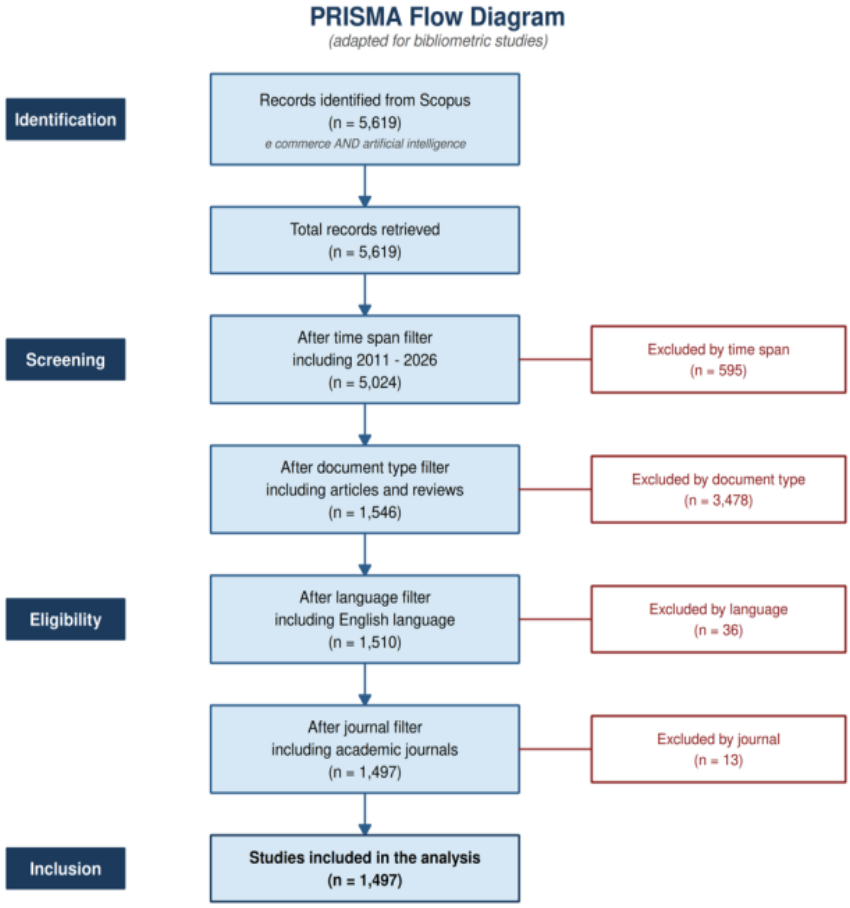


Fig. 2. PRISMA flow diagram of the identification, screening, eligibility and inclusion of records.
Source: Authors' compilation from the Scopus search of 16 September 2026, following the PRISMA reporting framework [19].

1) Identification and screening

Initially, the search returned 5,619 documents when the keywords "e commerce AND artificial intelligence" were used (Fig. 2). The results, however, contained documents dating back to 1987, which were not relevant to the present purpose and had to be filtered. The period 2011 to 2026 (the most recent 15 years) was therefore taken as the sample, which reduced the number of documents to 5,024. Only 595 documents were excluded over the preceding 24 years, which indicates that e-commerce became markedly more relevant to this research area during the selected period.

Following this first step, the search results were refined by document type, limiting the dataset to articles and reviews, since these publication types were considered the most relevant to the objectives of the study. The database initially contained various document types, including conference papers (2,594), articles (1,422), book chapters (519), conference reviews (202), reviews (124) and other publications. Selecting only articles and reviews narrowed the dataset to 1,546 publications and excluded conference papers, books, book chapters and other document types from the subsequent analysis.

The subject areas represented in the retrieved literature were also examined to understand the interdisciplinary coverage of the domain. Computer Science accounted for the largest number of subject-area classifications (3,756 records), followed by Engineering (1,644) and Business, Management and Accounting (1,137). Other substantial areas included Mathematics (894), Decision Sciences (845), Social Sciences (633) and Economics, Econometrics and Finance (582). Smaller numbers of records were classified under Energy, Physics and Astronomy, Medicine, Materials Science, Environmental Science, Arts and Humanities, Psychology, Multidisciplinary studies, Chemical Engineering, and Agricultural and Biological Sciences. These classifications indicate that the research area extends across several academic disciplines. Because individual publications may be assigned to more than one Scopus subject area, the

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subject-area figures are not mutually exclusive and do not correspond to the total number of publications in the final dataset.

2) Eligibility and inclusion

At the eligibility stage, further criteria were applied to ensure that the retrieved publications matched the scope of the study. First, a language filter retained only publications written in English. Of the publications remaining after document-type screening, 1,510 were in English, while the remaining records were published in other languages, including Chinese, Spanish, Portuguese, Japanese and Azerbaijani. The English-language criterion was applied to maintain consistency in the interpretation of titles, abstracts, keywords and other bibliographic information. A source-type filter was then applied. The records comprised journal publications, book series, conference proceedings and trade journals, and only journal publications were retained, because the study focuses on scholarly academic literature and requires consistent bibliographic information for the bibliometric analysis. This criterion excluded 13 records (6 book series, 4 conference proceedings and 3 trade journals), so that 1,497 journal publications remained.

At the inclusion stage, the 1,497 publications that satisfied all predefined criteria were retained for the final analysis. The final dataset therefore consisted of English-language journal publications classified as articles or reviews and published between 2011 and 2026. This set was exported from Scopus and prepared for bibliometric analysis in Bibliometrix through RStudio. The software reported 1,496 documents after import, a difference of one record from the PRISMA count, and the analyses in Section IV therefore refer to 1,496 documents.

C. Tools Used for Data Collection and Analysis

Several tools were used at different stages of the research process to collect, organise, analyse and manage the selected publications. Scopus, an Elsevier database, was used to search for and collect research papers on e-commerce and artificial intelligence. It supplied the title, authors, keywords, publication year, journal, citations and other information required by the study. After the filters were applied, the final set of 1,497 papers was exported from Scopus. Microsoft Excel was used to organise and check the exported data before analysis, which kept the data in a clear and structured format. The data were then analysed with the Bibliometrix package [20], run through RStudio, to study publication trends, authors, keywords, sources and other patterns in the selected papers, and to produce the thematic map [40]. Keyword co-occurrence networks were constructed with VOSviewer [21]. Mendeley Desktop was used to store the research papers and manage the references. Thus, Scopus was used for data collection, Excel for data organisation, Bibliometrix and VOSviewer for analysis, and Mendeley Desktop for reference management.

IV. DATA ANALYSIS

A. Main Information on the Dataset

Fig. 3 presents the main information dashboard produced by Bibliometrix for the Scopus collection. The twelve indicators describe the size, recency and authorship pattern of the dataset, and they provide the basis for the analyses that follow.



Fig. 3. Main information dashboard for the Scopus collection (2011–2026).
Source: Authors' analysis using Bibliometrix (RStudio) on a Scopus export dated 16 September 2026.

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Scale and coverage. The collection spans 2011 to 2026 and contains 1,496 documents (1,374 articles and 122 reviews) published in 717 sources. The collection is large enough to support network and cluster analysis. The large number of sources relative to documents shows that the topic is dispersed across many outlets and not concentrated in a few core journals. The annual growth rate shown on the dashboard is 1.15%. Recalculating the compound growth rate from the yearly counts (5 documents in 2011 and 394 in 2026) gives approximately 34% per year between 2011 and 2026, and this recalculated figure is the one used in the rest of the paper because it describes the trend far more faithfully (Section IV-B).

Authorship and collaboration. The collection involves 4,113 authors, of whom 169 have written at least one document alone, so single authorship is rare (about 4% of authors). The average team size is 3.39 co-authors per document, which indicates a collaborative field. International co-authorship stands at 27.61%, so a little more than one document in four involves researchers from different countries.

Keywords and references. The documents carry 9,122 unique author keywords, a pool large enough for thematic mapping but one that contains near-duplicate terms, such as "artificial intelligence" and "artificial intelligence (ai)", which the thematic map (Section IV-E) treats as separate terms. The references indicator shows 0, which most likely means that cited references were missing from the exported file and not that the documents cite no sources. Citation-based analyses such as co-citation and bibliographic coupling therefore could not be performed, and exporting the data again from Scopus with cited references would resolve this.

Recency and impact. The average document age is 2.49 years, so the collection draws heavily on recent work, which is consistent with about 65% of documents appearing between 2024 and 2026. The average of 29.38 citations per document is high for a collection of this age. Because a small number of highly cited papers can raise a mean considerably, the median should be examined in future work.

B. Annual Scientific Production

Table 4 and Fig. 4 show the number of documents published each year. Output remained modest during the first eight years, rising from 5 documents in 2011 to 21 in 2018. It then increased to 54 in 2019, fell to 38 in 2020, and recovered to 71 in 2021 and 126 in 2022. Output remained level at 126 in 2023 and then rose sharply to 226 in 2024, 352 in 2025 and 394 in 2026. These last three years contribute 972 of the 1,496 documents, approximately 65% of the collection.

Table 4. Number of documents per year in the dataset (n = 1,496)

Year	2011	2015	2019	2021	2022	2023	2024	2025	2026
Documents	5	15	54	71	126	126	226	352	394

Note. Selected years shown. Source: Bibliometrix export of a Scopus search, 16 September 2026.

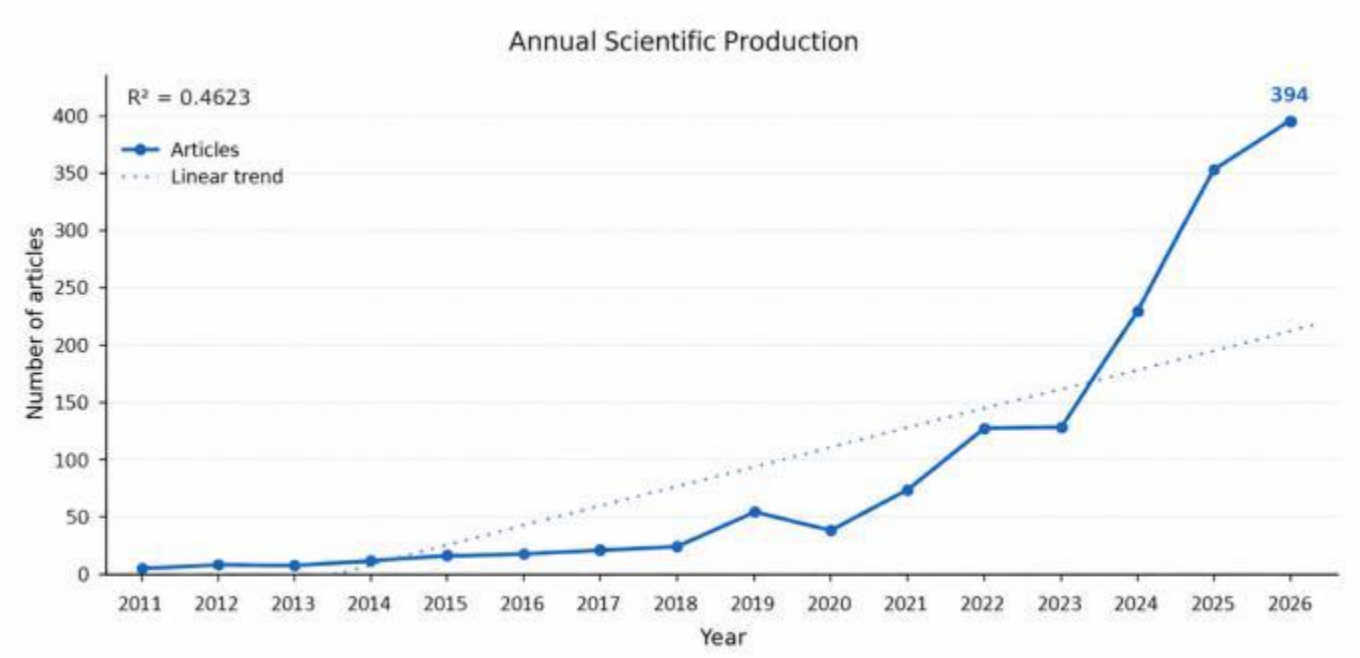


Fig. 4. Number of articles published per year, 2011–2026, with a linear trend line.
Source: Authors' analysis using Bibliometrix (RStudio) on a Scopus export dated 16 September 2026.

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Because the Scopus search was run on 16 September 2026, the count for 2026 may still be open and could end higher.
A linear trend fitted to all sixteen years (dotted line in Fig. 4) adds roughly 17 documents per year, with $R^2 = 0.4623$. About 46% of the variation in yearly output is therefore explained by a straight line, which is a moderate fit. The remaining variation reflects features that a linear model cannot capture, namely the acceleration after 2023 and the dip in 2020. Growth in this field appears closer to exponential than linear, with an average of about 34% per year between 2011 and 2026.

C. Three-Field Plot

The three-field plot in Fig. 5 links three components of the dataset in one diagram: authors (left), author keywords (centre) and the sources that published them (right). The plot shows the top 20 items in each field, and a link is drawn only when it rests on at least two documents. The thicker the band, the stronger and more frequent the connection. Bands between the left and middle columns show which themes each author writes about, and bands between the middle and right columns show where those themes are published.

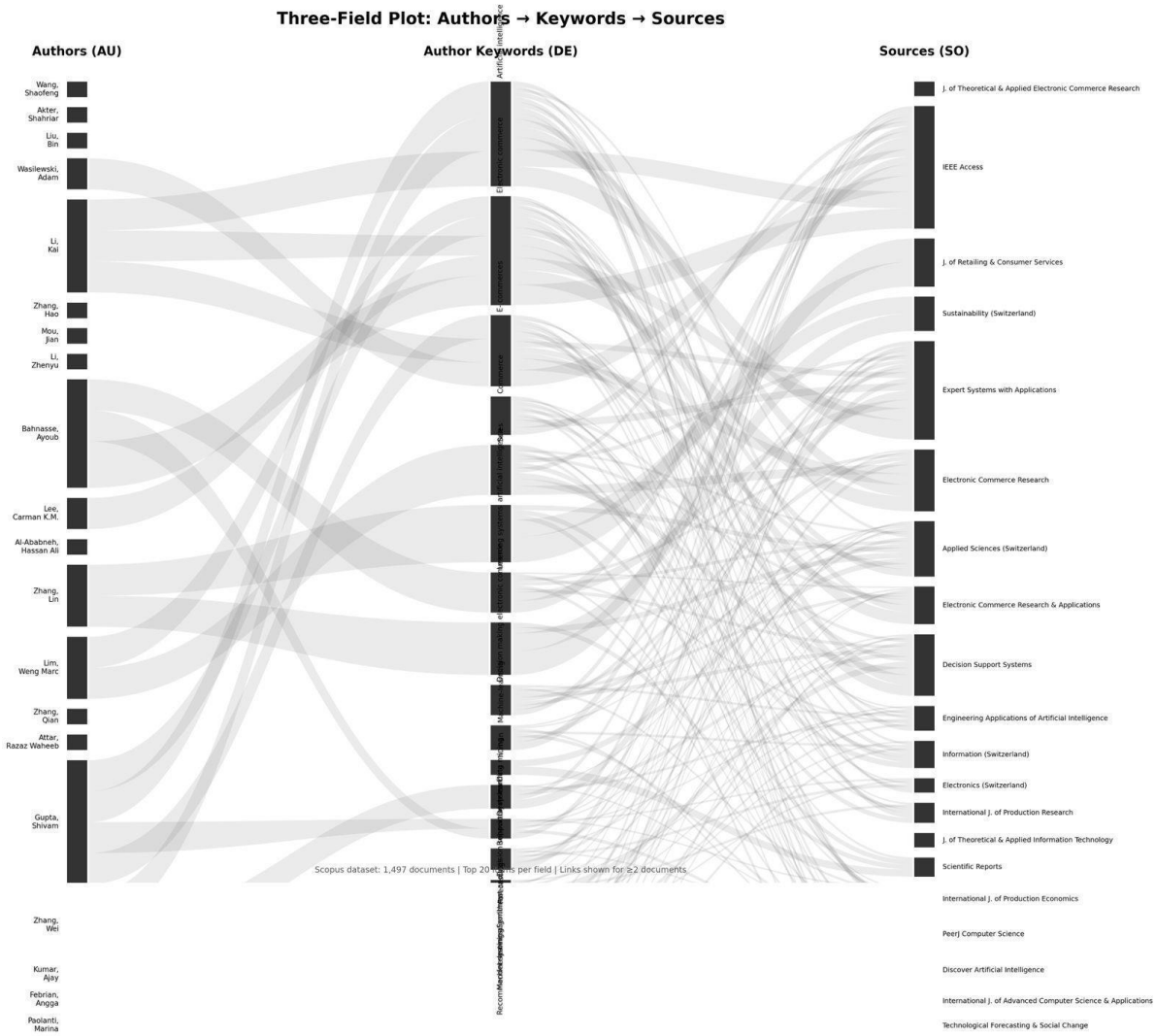


Fig. 5. Three-field plot linking authors (left), author keywords (centre) and sources (right).
Source: Authors' analysis using Bibliometrix (RStudio) on a Scopus export dated 16 September 2026.

On the author side, Gupta Shivam, Bahnasse Ayoub and Li Kai have the tallest blocks. The middle column holds the main research themes. The largest terms are electronic commerce, e-commerce, commerce, artificial intelligence, electronic commerce applications, machine learning and recommendation systems, together with a number of other technology-related keywords, and there are strong links among all of them. This shows how closely AI and e-commerce are tied, and it means that the literature rarely treats AI on its own. It keeps returning to e-commerce

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applications, digital commerce and technology-based systems.

On the right, the documents are spread over many journals. The main ones are the Journal of Theoretical and Applied Electronic Commerce Research, IEEE Access, the Journal of Retailing and Consumer Services, Sustainability and Expert Systems with Applications. Electronic Commerce Research, Applied Sciences, Decision Support Systems, Scientific Reports and the International Journal of Production Research also appear. AI in e-commerce is therefore published in outlets ranging from e-commerce and retailing journals to those for information technology, decision support and production research. The main conclusion from Fig. 5 is that a small set of keywords (electronic commerce, AI, machine learning and recommendation systems) sits at the centre of the plot and connects to most authors and most sources. The vocabulary of the field is largely shared, while its publishing is widely scattered.

D. Most Relevant Sources

Fig. 6 ranks the journals that published the most documents in the dataset. IEEE Access and the Journal of Theoretical and Applied Electronic Commerce Research share the top position with 47 documents each. The Journal of Retailing and Consumer Services follows with 37, and Expert Systems with Applications and Sustainability (Switzerland) have 30 each. The next group is smaller: Electronic Commerce Research (23 documents), Applied Sciences (Switzerland) (19), Electronic Commerce Research and Applications (18), Decision Support Systems (16) and Electronics (Switzerland) (12).

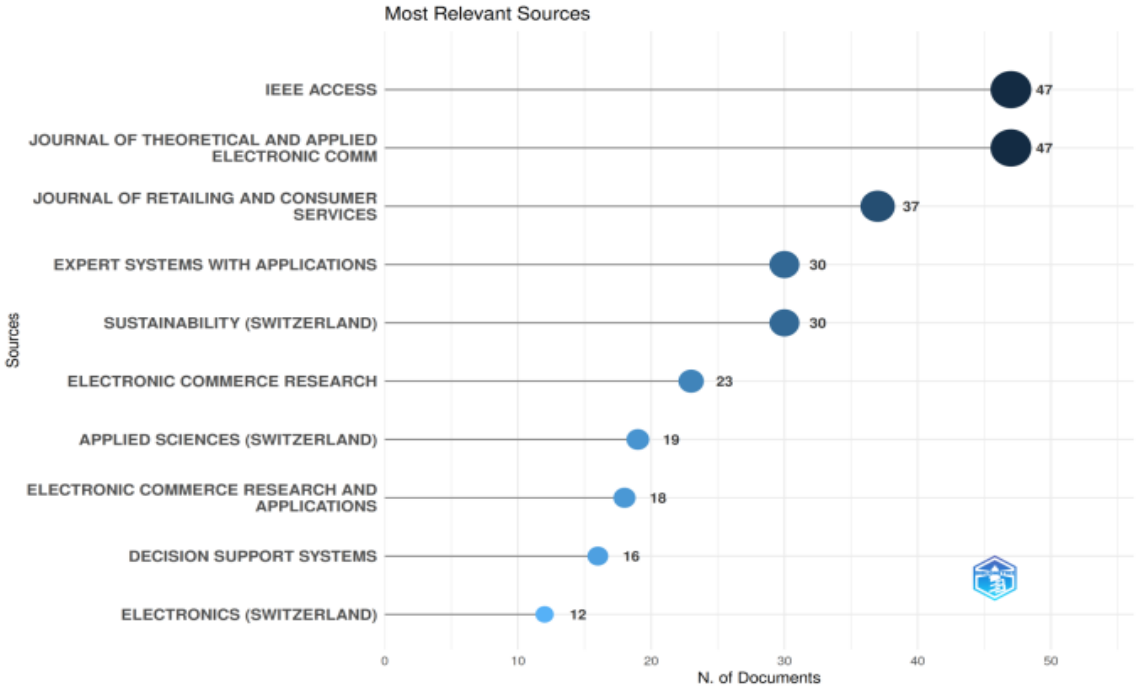


Fig. 6. Ten most relevant sources by number of documents.
Source: Authors' analysis using Bibliometrix (RStudio) on a Scopus export dated 16 September 2026.

Together, these ten sources hold 279 documents, about 19% of the collection. With 717 sources in total, the research is scattered widely and no single journal dominates. The list is also mixed: it includes dedicated e-commerce journals, a retailing journal, engineering and computing outlets such as IEEE Access and Expert Systems with Applications, and broad multidisciplinary titles such as Sustainability and Applied Sciences.

E. Thematic Map

The thematic map in Fig. 7 sorts keyword clusters using two measures [40]. Centrality (relevance degree, horizontal axis) shows how strongly a cluster is connected to the rest of the field. Density (development degree, vertical axis) shows how tightly developed the cluster is internally. Two dashed lines divide the map into four quadrants. Motor themes (top right) are central and well developed. Niche themes (top left) are well developed but only loosely connected to the rest of the field. Basic themes (bottom right) are central but less developed. Emerging or declining themes (bottom left) are low on both measures. Bubble size reflects how often the keywords in a cluster occur.

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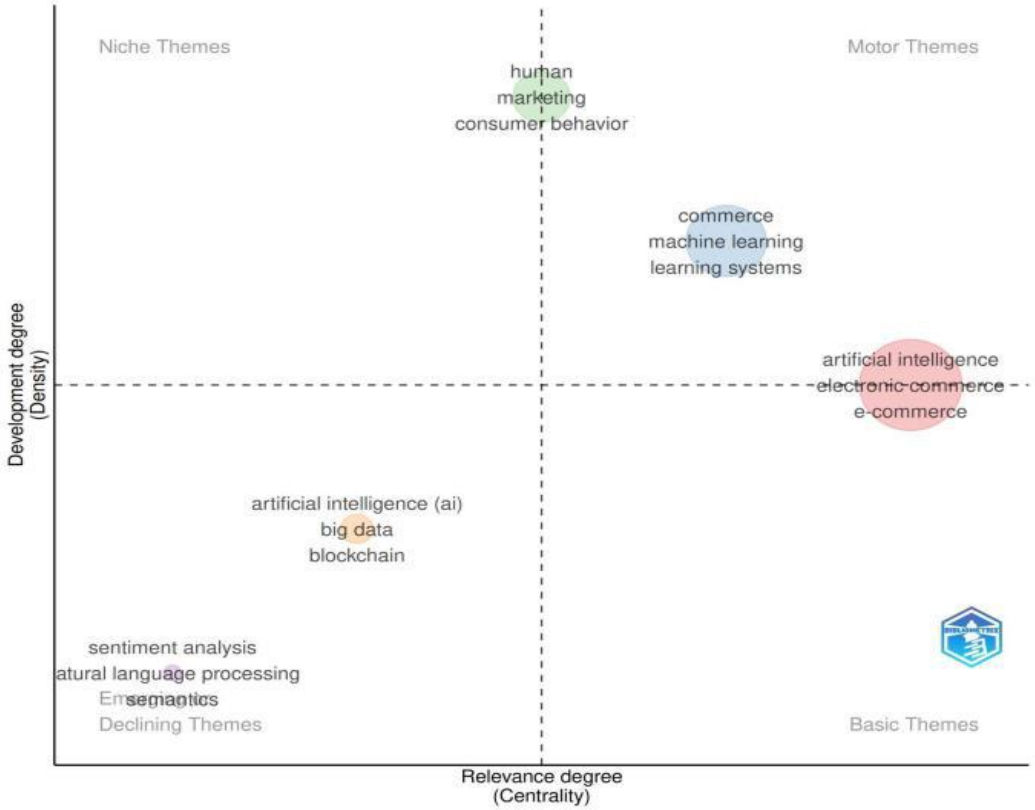


Fig. 7. Thematic map of author keywords (centrality against density).
Source: Authors' analysis using Bibliometrix (RStudio) on a Scopus export dated 16 September 2026.

The cluster of commerce, machine learning and learning systems sits in the motor quadrant, well to the right of the centre line and clearly above the density line. Machine-learning approaches are therefore both well developed and closely tied to the rest of the commerce research. The largest bubble groups artificial intelligence, electronic commerce and e-commerce, and it is the most central cluster on the map. It lies at the far right edge, on the horizontal density line, which places it on the border between motor and basic themes. This is common for the umbrella terms of a field, which define the whole dataset and connect to everything even when the cluster is not as internally specialised as the clusters above it.

Human, marketing and consumer behaviour form the most densely developed cluster at the top of the map, but its centrality is only middling, since the bubble sits on the vertical dividing line, and it is read as a niche theme. The topic is well studied in its own right and covers the people side of the subject (shoppers, marketing and consumer behaviour), yet it is less tied into the core than the AI and machine-learning clusters.

The lower-left quadrant holds two clusters. One combines artificial intelligence (ai), big data and blockchain. The other combines sentiment analysis, natural language processing and semantics, and sits in the corner of the map. Both have low centrality and low density in this dataset, and the basic themes quadrant at the bottom right is empty. The map shows only how connected and how developed these topics are at a point in time. It does not show whether they are rising or declining, which would require an examination of how they change over the years. In addition, the keyword "artificial intelligence (ai)" appears in a different cluster from "artificial intelligence" simply because authors spelled it in two ways, and merging such variants before analysis would probably give a cleaner picture. In short, the map shows a field with AI, e-commerce and machine learning at its core, consumer behaviour and marketing next to that core, and big data, blockchain, sentiment analysis and language processing further out and less developed.

V. FUTURE RESEARCH AGENDA

This section organises future research directions for AI in e-commerce into an Input–Process–Outcome (IPO) framework. It draws on the 1,496 Scopus records, the three keyword clusters (Section II-B), the thematic map (Section IV-E) and the literature review (Section II). All proposed questions, relationships and hypotheses are propositions for future testing and not established findings.

A. Findings and Research Gaps

Output has grown rapidly (Section IV-B), and three clusters emerged from 53 keywords: Cluster 1, AI methods, personalisation and consumer trust (27 keywords, 1,713 occurrences); Cluster 2, digital transformation, supply chains and decision-making (17 keywords, 283 occurrences); and Cluster 3, customer experience, immersive technologies and review-based synthesis (9 keywords, 152 occurrences). The literature review supports seven research gaps, labelled G1 to G7.

G1. Recommender systems are judged mainly on accuracy, which only partly captures the user experience [6].

G2. Transparency builds trust only when accompanied by uncertainty communication and trust calibration [17].

G3. Consumer, technical and operational streams are reviewed separately, one theme at a time.

G4. Information-sharing barriers persist in supply chains [33], and small-firm evidence concerns digital transformation in general [9].

G5. Privacy concerns are context-dependent [39].

G6.AI combined with extended reality is in its infancy [38], and generative AI is the newest theme.

G7.A longitudinal map is lacking [16], and generalisability is limited.

The theoretical lenses are mostly behavioural in the consumer-facing clusters: social response and commitment–consistency theory [5], the cognition–affection–conation framework [28], the user-centric evaluation framework [6] and the TEUT framework [17]. The operational cluster relies mainly on decision models and review protocols. This split helps to explain why the streams remain unconnected (G3).

B. The Input–Process–Outcome Framework

Table 5 sets out the IPO framework. The variables listed are candidate constructs and not established effects.

Table 5. Input–Process–Outcome framework and research agenda

IPO component	Key variables and themes identified	Research gap	Proposed future research question
Input	**Machine learning, deep learning, recommender systems, chatbots, generative and agentic AI; big data and customer information; digital infrastructure; blockchain; privacy; firm size**	**Capability reviews outnumber tests of consumer or business effect (G1, G6); big data and blockchain are weakly connected on the thematic map (G4)**	**Which AI capabilities add value once accuracy is held constant, and how do data, infrastructure and firm size shape small firms' gains?**
Process	**Personalisation and purchase-intent detection; explainability and trust calibration; chatbots, sentiment analysis, language processing; pricing, forecasting, fraud detection; supply chain and seller selection**	**Accuracy-focused evaluation (G1); unclear conditions for transparency (G2); pricing, seller selection and fraud reviewed separately (G3)**	**Under what conditions does explainable AI improve calibrated trust, and how can sentiment and operational decisions be integrated in one design?**
Outcome	**Experience, satisfaction, trust, purchase intention, engagement; conversion and sales; efficiency, resilience, fraud reduction; privacy and fairness**	**Consumer outcomes rarely linked to conversion data; Cluster 2 is far smaller than Cluster 1 (17 against 27 keywords; 283 against 1,713 occurrences) (G3–G5)**	**Do AI-driven changes in experience and trust translate into purchases, sales and operational performance, and when do privacy concerns offset them?**
Integrated IPO relationships	**AI capability → personalisation and decision quality → trust and performance, moderated by explainability, privacy, firm size, market and time**	**Technical, behavioural and operational literatures are unconnected; no longitudinal or cross-market view (G3, G7)**	**Does explainability moderate the effect of personalisation on trust and conversion, and does this vary across markets and over time?**

Note. Variables are candidate constructs, not established effects. Source: Authors' synthesis of the bibliometric results and the literature review.

C. Proposed Relationships and Hypotheses

Inputs are proposed to affect outcomes mainly through processes. In the consumer chain, AI capability and customer data shape personalisation quality and transparency, which in turn affect trust, experience and purchase intention. In the operational chain, data, infrastructure and AI adoption shape pricing, forecasting and logistics decisions, which affect efficiency, resilience and performance. Privacy, fairness, firm size, market and time moderate both chains, and conversion data feeds demand forecasting, which links the two. These relationships are hypotheses and not tested findings. Three hypotheses follow.

H1: Explanation and uncertainty communication moderate the effect of personalisation quality on trust.

H2: Trust and perceived experience mediate the effect of AI features on purchase intention and conversion.

H3: Digital infrastructure and information sharing moderate the effect of AI-supported decisions on supply chain performance, and the effect may differ for small firms.

D. Directions by Cluster

Cluster 1. Future studies should test recommendation quality beyond accuracy, the effect of generative and agentic AI on engagement and decisions, and the conditions under which transparency helps (explanation type, uncertainty display and product risk). Experiments on chatbot cues and compliance [5] could be extended to generative chatbots, using observed purchases as the outcome.

Cluster 2. Research should link AI adoption to measured outcomes such as forecast error, stock-outs, delivery time and margin, evaluate pricing and seller selection together with their consumer effects, and test whether AI-supported visibility reduces information-sharing barriers, especially in small firms.

Cluster 3. Studies should test how personalisation, privacy risk and immersive features (augmented reality and the metaverse) jointly shape purchase decisions, pairing experience measures with sales and retention data. Varying the shopping context, the data requested and the level of transparency would show when the benefits of personalisation outweigh privacy concerns, since concerns appear to be context-dependent.

E. Implications of the Thematic Map

On the thematic map (Fig. 7), commerce, machine learning and learning systems are motor themes, while artificial intelligence and e-commerce are central and lie on the border between motor and basic themes. Human, marketing and consumer behaviour are niche themes: well developed but moderately connected. Big data, blockchain, sentiment analysis, natural language processing and semantics sit in the lower-left quadrant with low centrality and density, and the map does not show whether they are rising or declining.

Future work should integrate the streams through designs that measure a technical property and a behavioural response together. Lower-left themes can be tied to central applications: big data to personalisation and forecasting, blockchain to supply chain visibility, and language processing to the measurement of experience. To test the direction of change, thematic maps could be drawn for sub-periods (2011–2018, 2019–2023 and 2024–2026) after merging keyword variants such as “artificial intelligence (ai)”. Co-citation and bibliographic-coupling analyses would also strengthen this work, but the current export contains no reference data and would need to be repeated with cited references.

F. Research Priorities

Five priorities that bridge the existing streams are summarised in Table 6. Priorities 1 and 2 matter because trust and explainability cut across clusters, while consumer behaviour is only moderately connected to the technical core. Priority 3 matters because Cluster 2 is small yet holds the decision problems closest to operations research. Priority 4 links themes that the thematic map places at the periphery, and Priority 5 responds to the snapshot nature of the map and the context-dependence of privacy findings. Together, the priorities test the full chain from AI inputs, through personalisation and decision processes, to consumer, operational and organisational outcomes.

Table 6. Research priorities

Priority and research question	Constructs	Method	Contribution
1. How does explainable AI influence trust and purchase intention?	**Explanation type, uncertainty display, trust calibration, intention**	**Online experiments; moderated mediation**	**Boundary conditions for transparency (G2)**
2. How do recommendation and generative personalisation affect experience and sales beyond accuracy?	**Model type, diversity, perceived fit, engagement, conversion**	**Field experiments with logged data**	**Links algorithm metrics to revenue (G1, G3)**
3. How can AI improve resilience, forecasting and efficiency, including in small firms?	**Forecast error, visibility, information sharing, firm size, performance**	**Simulation, optimisation, firm surveys**	**Measurable operational value (G3, G4)**

4. How can sentiment analysis, language processing, big data and blockchain serve experience and supply chain decisions?	**Review sentiment, visibility, service quality**	**Text mining linked to sales data; case studies**	**Connects low-centrality themes to the core**
5. How do relationships vary across markets and time, and how does privacy moderate acceptance?	**Market, year, privacy concern, acceptance**	**Period-wise thematic evolution; multi-group surveys**	**Addresses G5 and G7**

Note. G1–G7 refer to the research gaps listed in Section V-A. Source: Authors' synthesis.

VI. CONCLUSION

A. Summary of Findings

This study mapped research on the use of AI in e-commerce by analysing 1,496 journal publications from Scopus for the period 2011 to 2026. The most evident result is the rapid growth of the field. Output remained modest until 2018 (21 articles) and then rose steeply, from 54 in 2019 to 394 in 2026. The last three years alone contain 972 documents, almost two thirds of all those studied. Average growth between 2011 and 2026 is approximately 34% per year, and the pattern appears closer to exponential than linear. These results address the first research objective and show that AI in e-commerce is not a niche area of research. The average document age is only 2.49 years, which means that most of the available knowledge on the subject is current and that conclusions should be updated as further documents appear.

The field is also broad in its outlets and its authorship. The documents are drawn from 717 sources, and the ten journals with the most documents account for only 279 of them, approximately 19%. IEEE Access and the Journal of Theoretical and Applied Electronic Commerce Research are tied with 47 documents each, followed by the Journal of Retailing and Consumer Services with 37. The mixture of e-commerce, retailing, engineering and general science journals shows that no single community dominates. The research is clearly collaborative: 4,113 authors contribute, with an average of 3.39 authors per document, and only 169 authors have written a document alone. About 27.61% of documents involve authors from more than one country, so there is scope for further cross-country collaboration. The documents are nevertheless well cited on average (29.38 citations) and mostly recent.

The thematic map answers the second research objective. Artificial intelligence, electronic commerce and e-commerce lie on the border between motor and basic themes and are the most central, as would be expected of the umbrella terms that define the dataset. The motor theme comprises machine learning and learning systems, which are highly developed and integrated with the rest of the research. Human, marketing and consumer behaviour is mature within its own space but less central. Big data, blockchain, sentiment analysis and natural language processing have low centrality and low density and lie in the lower-left corner. The three-field plot confirms the pattern, since a small number of keywords connects to most authors and journals. In terms of contribution to the literature, the study offers a single wide map of the field, whereas earlier reviews each focused on one industry, one method or one group of customers [2, 12]. It shows that the vocabulary of the field is shared although publication is dispersed, and that AI is studied not in isolation but in the context of e-commerce applications, digital commerce and technology-based systems.

B. Implications for Managers

Six implications follow for managers. First, ML, particularly recommendation and prediction, is the most developed area of the field and therefore the safest place for companies to invest. The research foundation for recommender systems, and the everyday use of demand forecasting and fraud detection, is strong and clear [1]. Fraud detection is notable, as ensemble models have achieved detection rates of 98% in online fraud [31]. Second, digital tools can benefit second-hand and small-scale sellers, since studies show gains in efficiency and market reach even when resources are limited [9]. A small brand does not need to develop its own models. It can begin with existing tools to suggest products to customers, respond to their feedback and plan campaigns, and then measure the changes.

Third, trust deserves managerial attention. Users are highly sensitive to the behaviour of chatbots: human cues can increase compliance [5], black-box systems limit adoption [7], and transparency fosters trust, although mainly where uncertainty is clearly communicated [17]. Firms should therefore explain what their AI engine does and avoid concealed tactics towards customers. Fourth, in supply chains, AI has been associated with improved resilience, visibility and last-mile delivery [8, 33]. Fifth, AI projects are more likely to succeed when they have a specific objective, such as conversion, service speed or reduced returns, because the strongest cases in the literature are those with a defined objective from which most benefit is derived. Sixth, managers seeking ideas should consult the principal sources identified in this study (Fig. 6) and avoid random searching.

C. Implications for Society and Policy Makers

The benefits to society include faster and better service, a wider choice for shoppers and safer payments. The risks must also be addressed. Most of these systems rely on personal data, and privacy concerns are context-specific and not governed by a single rule [39]. Customers should be

informed when they are speaking to a machine and told what their data are used for. The map presented here is also useful to students and researchers, who can select a topic, locate the relevant journals and see who is working on what, which saves considerable time for newcomers. Conversational and generative AI in particular continue to gain momentum, and new reviews of these technologies continue to appear [15, 29].

The results also suggest ideas for policy makers. Regulation is catching up with research on AI in e-commerce, which is progressing at a much faster rate. Some AI ethics declarations cite fairness and privacy, yet are regarded as having little real influence on platform governance [18], and Bostan [36] points to system-level risks of generative AI in cross-border e-commerce supply chains. Three recommendations follow. First, regulators could require large platforms to give clear information, understandable to a typical user, about automated decisions such as pricing, ranking and recommendation. Second, data protection rules must keep pace with the collection of increasingly personal data by chatbots, voice assistants and immersive technologies. Third, governments and universities can provide small businesses with training and access to digital tools at low or no cost, so that the benefits of AI are not limited to the largest firms. Funding agencies can also support research on the themes that the map identifies as less developed and encourage international collaboration, since only about 27.6% of documents have international authors. A rule that is not updated will quickly fall behind, given that the field expanded from 126 articles in 2023 to 394 in 2026.

D. Limitations

The limitations of the study should be considered. Only one database was searched, because of limited time. All records were retrieved from Scopus and are in English, so records in other languages and databases are excluded. The exported file contained no cited references, so citation-based analyses such as co-citation and bibliographic coupling could not be performed; this could be resolved by exporting the data again with references included. The PRISMA process yielded 1,497 records whereas the analysis software reported 1,496, and the most recent year may be incomplete, so the latest figures may change. Different spellings of author keywords, such as “artificial intelligence” and “artificial intelligence (ai)”, can divide a single theme into two. The analysis was carried out with default software settings, since the team was not technically specialised in the software, and the labels assigned to clusters and themes involve judgement that other teams might make differently.

E. Directions for Future Research

These limitations point to the third research objective. Subsequent studies could add databases such as Web of Science, include cited references, and follow the evolution of themes over the years to establish whether big data, blockchain, sentiment analysis and language processing are growing or declining. More work is also needed on generative and agentic AI, on trust and explainability, and on small sellers in developing economies. The propositions in Section V could be tested through surveys or case studies of actual online sellers. It is hoped that this study serves as a starting point for such work.

Declarations

Use of generative AI: During the preparation of this manuscript, the authors used Claude (Anthropic) to assist with compiling the individually written sections into a single document, formatting, language editing and checking references. The research design, data collection, analysis and interpretation, and the drafting of the original sections were carried out by the authors, who reviewed and edited all content and take full responsibility for the publication.

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