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# The evolution and impact of artificial intelligence in market analysis: A quantitative bibliometric exploration of the past thirty-five (35) years

**Abstract**

*Artificial Intelligence (AI) is now involved in almost every field of activity, with its expansion driven by the significant benefits it brings to our daily activities. This research paper examines the evolution and impact of AI applications in market analysis through a comprehensive bibliometric study. To the best of our knowledge, this paper is unique by considering various papers related to market analysis, including market trend analysis, market segmentation, consumer behavior, and competitive analysis in this bibliometric study. It also identifies global regions where AI techniques are most extensively developed for these purposes. This research is based on 4,051 relevant documents related to AI and market analysis, published in the Scopus database over the last thirty-five years. The findings indicate a significant exponential increase in scientific output related to AI applications in market analysis, particularly started from 2010. The countries leading in AI-driven market analysis research include India, China, and the USA.*

## 1. INTRODUCTION

Nowadays, technology-driven tools powered by artificial intelligence are profoundly transforming how we approach daily challenges. First introduced by John McCarthy at the Dartmouth College conference in 1955 (McCarthy et al., 1955; Solomonoff, 1985), the concept of artificial intelligence (AI) has undergone significant evolution. For decades, with technological advancements and the work of numerous researchers such as (Goodfellow et al., 2014; LeCun et al., 1989; McCulloch & Pitts, 1943; Rosenblatt, 1957; Samuel, 2000), and others, particularly in machine learning, deep learning, and other branches of AI, there has been a growing application of AI in almost every field of activity. This expansion is driven by the many advantages and significant results that this technology brings to our daily lives.

Among the many sectors benefiting from AI, the economic field, particularly market study and analysis, has gained substantial advantages. Traditional market analysis techniques have numerous limitations, especially in dynamically exploiting hidden information within data. In this context, the combination of AI technologies with theoretical and empirical market analysis techniques transforms and optimizes how companies gather information, analyze data consistently, make informed decisions, and thereby maintain a competitive edge.

Thus, in this exploratory article, we aim to study and quantitatively explore the evolution and impact of artificial intelligence in market analysis by examining the scientific works published over the past thirty-five years.

## 2. LITERATURE REVIEW

The advancement of technology and digitalization has revolutionized the way we approach various aspects of the market. Digital marketing has made it significantly easier to collect and analyze data about the market and its key players. However, one of the greatest challenges remains understanding the market's evolution over time and determining how companies can leverage this information to enhance their products or services and maintain a competitive edge.

In this context, artificial intelligence (AI) has increasingly demonstrated its potential to address these challenges. A pivotal article published by Davenport and his collaborators (2020) highlights the transformative power of AI in marketing. The authors discuss how AI offers substantial benefits to both marketers and consumers. Whether the areas such as market analysis, forecasting, research, trends, segmentation or competitive analysis, AI is now integral to almost those aspects of market dynamic.

To fully grasp the evolution and impact of AI in market analysis, a rigorous bibliometric analysis of the research literature is essential. This approach allows us to systematically review the contributions of scholars who have diligently advanced this field, providing insights into the trends, key areas of focus, and future directions of AI in marketing.

### 2.1. Bibliometric approach

Bibliometric analysis is a quantitative method that employs mathematical and statistical methods to examine patterns within published literature (Saibaba, 2023). It applies statistical techniques to scientific bibliographic data, using quantitative tools for analysis and interpretation. Unlike systematic literature reviews, which rely on qualitative methods, bibliometric analysis quantifies the characteristics of a body of research (Boukhlif et al., 2023).

Today, bibliometric analysis is increasingly used in scientific research to understand the evolution of specific fields. A recent article on AI in e-commerce written by Ikhlass and Azmani (2024) provides a historical overview of this method. This approach enables researchers to draw conclusions from aggregated bibliographic data generated by other scientists in the field (Zupic & Čater, 2015). It aims to examine the connections between disciplines, expertise fields, keywords, documents, and authors (Ribeiro et al., 2022). This method of quantitative analysis provides significant insights into research trends and dynamics.

As with other domains where bibliometric analysis is used to examine their evolution, this method is also applied to examine the growth of AI in marketing. The table below presents some recent bibliometric analyses on the application of various AI techniques in different aspects of market analysis.

**Tab. 1. Bibliometric analysis papers related to AI and market analysis**

| Authors | Source Title | Database Source | Number of documents included in the analysis | Period of time |
|---|---|---|---|---|
| (Sharma et al., 2024) | Studies in Computational Intelligence | Scopus & Web of Science | 85 | 2005-2023 |
| (Inani et al., 2023) | 2023 4th International Conference on Computation, Automation and Knowledge Management, ICCAKM 2023 | Scopus | 392 | Until 2023 |
| (Aoujil et al., 2023) | IEEE Access | Web of Science | 637 | 2012-2022 |
| (Manosso et al., 2021) | Journal of Tourism, Heritage and Services Marketing | Scopus | 111 | 2012-2021 |
| (Ziakis & Vlachopoulou, 2023) | Information (Switzerland) | Scopus | 221 | 2015-2023 |
| (Sanchez-Nunez et al., 2020) | IEEE Access | Scopus | 919 | 2010-2019 |

## 3. METHODOLOGY

The objective of this research paper is to analyze the application of artificial intelligence (AI) in market analysis. The methodology used in this research involves gathering both qualitative and quantitative data and analyzing them to uncover significant insights that can contribute to advancements in the AI scientific community. This research will enable us to examine not only the progression of AI utilization in various aspects of market analysis such as market trend analysis, market segmentation, and competitive analysis but also to identify the regions of the world where AI is most extensively developed for these purposes.

### 3.1. Database selection

When it comes to bibliometric analysis, researchers often rely on various databases to collect bibliographic data. These databases share a common objective: to make research papers and references accessible to the scientific community. Some of the most frequently used databases include Google Scholar, Scopus (launched by Elsevier in 2004), Web of Science (developed by Eugene Garfield in 1997 and now managed by Clarivate Analytics since 2016), PubMed, Lens, and others. These platforms index a wide range of academic publications, such as journal articles, book chapters, and conference papers.

Scopus and Web of Science are particularly popular across multiple disciplines for locating scientific research papers, as they cover diverse fields and areas of studies (Chițimiea et al., 2021). Some researchers, like (Fernández et al., 2010) have suggested that Scopus and Web of Science can be both used as complementary databases for bibliometric analysis. (Mongeon & Paul-Hus, 2016) also recommend using both, especially to make comparisons between various fields, institutions, countries, or languages.

However, in their research paper, the authors chosen to use only the Scopus database. This decision was made to avoid the risk of duplicating data that are presented in different forms across multiple databases, as some journals are indexed in both Scopus and Web of Science. Such duplication could accordingly lead to biased results in our study. The authors opted for Scopus over Web of Science due to its broader coverage, with a higher number of indexed articles, as we have noticed according to (AlRyalat et al., 2019).

### 3.2. Data collection process overview

To identify relevant papers published in the past years, the authors used the PRISMA method (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). This evidence-based method offers a minimal set of items designed to help scientific authors rigorously report a wide range of systematic reviews and meta-analyses. Introduced by Moher et al. (2009), the PRISMA method emphasizes transparency and completeness in reporting this type of research. It facilitates the identification of relevant studies through a concise four-step process (as elaborated in Fig. 1 below): study identification, screening, eligibility assessment, and inclusion in the analysis (Echchakoui, 2020).

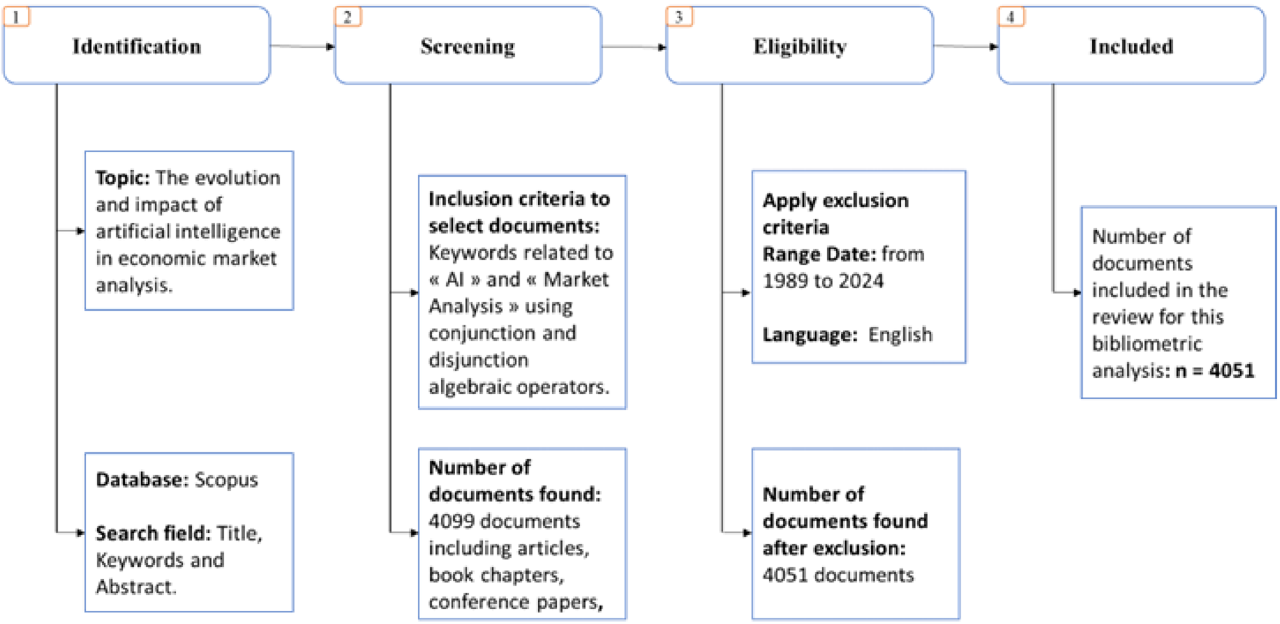


**Fig. 1. PRISMA framework flow chart**

For this bibliometric analysis, the data collection process was conducted on August 16, 2024. The goal was to gather a dataset that captured the maximum number of keywords related to AI and market analysis found within the titles, keywords, or abstracts of scientific papers over the past 35 years. This research included all types of scientific papers related to AI and market analysis, including, book chapters, articles and conference papers.

Initially, we used the keyword "Application of Artificial Intelligence in Market Analysis" to search the Scopus database, which yielded only 206 papers. However, this keyword did not encompass all the variations and related terms connected to AI and market analysis.

Therefore, in a second phase, we utilized conjunction and disjunction algebraic operators ("AND" and "OR") to combine word segments related to AI and market analysis as follows: "Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning" OR "Natural Language Processing" AND ("Economic Market Analysis" OR "Market Analysis" OR "Market Studies" OR "Market Forecasting" OR "Market Research" OR "Market Trends" OR "Market Segmentation" OR "Competitive Analysis" OR "Consumer Behavior" OR "Economic Forecasting"). This refined search resulted in 4,051 papers, including conference papers, book chapters, and articles, covering various aspects of the market.

### 3.3. Data analysis tools

For the analysis in this research paper, the authors utilized R software, a widely recognized open-source statistical tool commonly employed by scientists. After extracting data from the Scopus database, they chose to use a dataset exclusively from this source. To ensure data integrity and avoid accidental duplicates, they cross-checked the dataset using Zotero software.

The analysis began in R, specifically using the Biblioshiny library which has been created and developed by Massimo A. and Corrado C. (Aria & Cuccurullo, 2017; Rashid, 2023). It is a web-based application that provides a user-friendly interface for performing bibliometric analysis using the R package bibliometrix. This library is particularly used when conducting systematic reviews, meta-analyses, or anyone interested in understanding the bibliometric characteristics of a particular research field.

## 4. ANALYSIS AND INTERPRETATIONS

This section presents the results of the bibliometric analysis. Various metrics were used to analyse the information gathered from the publications, including the number of document citations, co-authorship networks, annual scientific output, author productivity, and institutional affiliations. These metrics allowed the authors to capture critical insights that deepened their understanding of the evolution of artificial intelligence in market analysis.

### 4.1. Main statistical information

#### 4.1.1. Overview of the key retrieved information

The following table summarizes the key information extracted from the dataset using Biblioshiny. Between 1989 and 2024, a total of 4,051 scientific documents related to the application of artificial intelligence in various aspects of market analysis were published in the Scopus, reflecting an annual growth rate of 17.32%. These publications involved approximately 10,935 authors, including 350 who authored single-authored documents, with an average of 3.35 co-authors per document. As shown in the table, 1,704 of these publications are articles, and 1,815 are conference papers. Additionally, the rate of international co-authorship among these publications stands at 20.02%.

**Tab. 2. Key retrieved information**

| Description | Results | | Description | Results |
|---|---|---|---|---|
| Timespan | 1989:2024 | | DOCUMENT TYPES | |
| Sources (Journals, Books, etc) | 2010 | | Article | 1704 |
| Documents | 4051 | | Book | 51 |
| Annual Growth Rate % | 17.32 | | Book Chapter | 242 |
| Document Average Age | 3.71 | | Conference Paper | 1815 |
| Average citations per doc | 11.83 | | Conference Review | 102 |
| References | 135824 | | Data Paper | 4 |
| Keywords Plus (ID) | 14837 | | Erratum | 4 |
| Author's Keywords (DE) | 8918 | | Letter | 2 |
| Authors | 10585 | | Retracted | 12 |
| Authors of single-authored docs | 350 | | Review | 91 |
| AUTHORS COLLABORATION | | | Short Survey | 6 |
| Single-authored docs | 374 | | Editorial | 10 |
| Co-Authors per Doc | 3.35 | | Note | 8 |
| International co-authorships % | 20.02 | | | |

### 4.1.2. Annual scientific production and average citation trends

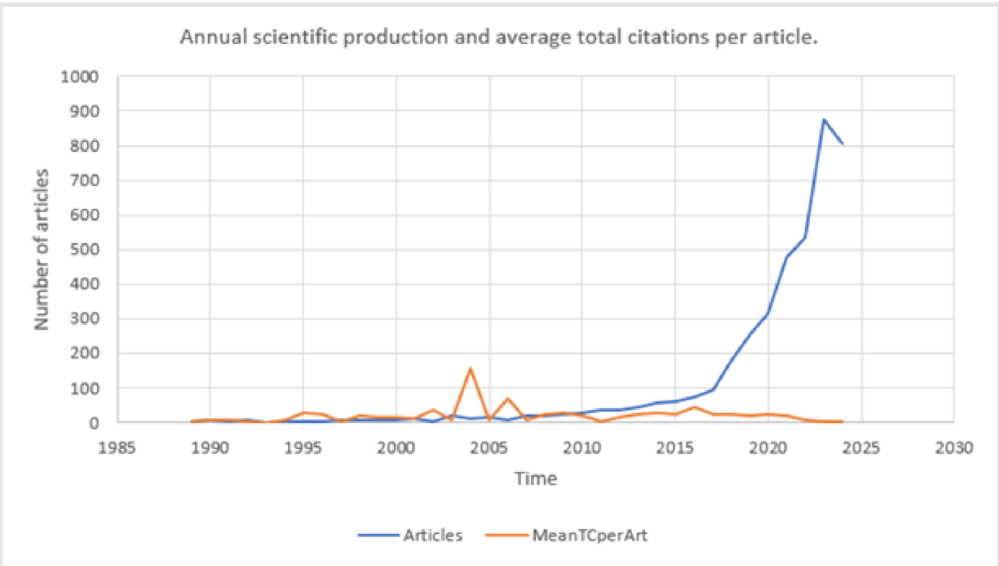


**Fig. 2. Annual scientific production and average citation trends. note(s): MeanTCperArt = average total citations per article**

The figure above illustrates the annual scientific production and the average total citation trends per article over the past thirty-five years, beginning in 1989. Scientific production, a key metric for assessing the evolution of research on AI applications in market analysis, has increased exponentially from 2010 to 2023. However, since the research was conducted in August 2024, data for the remaining months of 2024 are not yet available, leaving us unable to confirm whether this exponential growth will continue throughout the year.

### 4.1.3. Most relevant sources

According to the main statistics in Tab. 2 previously, 4,051 documents have been published over the past thirty-five years, drawn from 2,010 different sources. The Fig. 3 below highlights the ten most relevant sources, which account for 35.27% of the total. Among these, “Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)” is the leading the most relevant sources with 169 documents, followed by “IEEE ACCESS” with 120 documents.

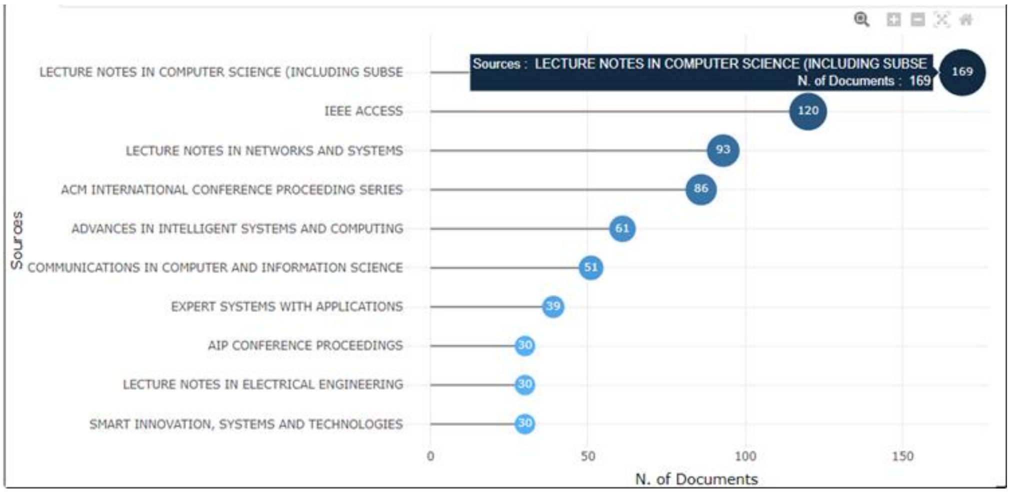


**Fig. 3. Most valuable sources**

### 4.1.4. Affiliations of authors

The table below presents an analysis of the affiliations of authors who have contributed to the evolution of AI in market analysis. The category "NotReported" has the largest number of articles, totaling 55. This is followed by the School of Computer Science and Engineering, which has contributed 39 articles.

**Tab. 3. Most relevant affiliations**

| Affiliation | Articles |
|---|---|
| Notreported | 55 |
| School Of Computer Science And Engineering | 39 |
| Chandigarh University | 35 |
| Tsinghua University | 35 |
| Nanyang Technological University | 34 |
| Beihang University | 30 |
| Huazhong University Of Science And Technology | 27 |
| National Institute Of Technology | 26 |
| Amity University | 24 |
| Islamic Azad University | 24 |

### 4.1.5. Statistics by country

Table 4 below provides statistics on the contributions of various countries to the development of this field. India leads the ranking with 3,168 documents published over the last thirty-five years, followed by China with 2,357 documents, and the USA with 1,383 documents. However, documents from the USA have received more citations than those from other countries, with a total of 6,840 citations. The results for the top ten countries show that Asia, represented by India, China, South Korea, and Japan, collectively contributed 6,049 documents, accounting for 67.04% of the total. The USA, representing the Americas, contributed 1,383 documents.

Additionally, concerning the productivity of countries over time, the publication output of India and China has increased more significantly compared to other countries, as illustrated in Fig. 4 below.

**Tab. 4. Countries' scientific production and most cited countries. Note TC: Total Citations**

| Countries' Production | | | Most Cited Countries | | |
|---|---|---|---|---|---|
| Region | Frequency | | Country | TC | Average Article Citations |
| India | 3168 | | Usa | 6840 | 30.70 |
| China | 2357 | | China | 5288 | 9.50 |
| Usa | 1383 | | India | 3643 | 7.30 |
| Uk | 431 | | United Kingdom | 2243 | 24.40 |
| Spain | 324 | | Korea | 1546 | 21.20 |
| Germany | 312 | | Singapore | 1484 | 64.50 |
| Italy | 288 | | Germany | 1180 | 18.40 |
| South Korea | 280 | | Finland | 1157 | 96.40 |
| Japan | 244 | | Spain | 995 | 14.20 |
| Australia | 235 | | Italy | 974 | 17.70 |

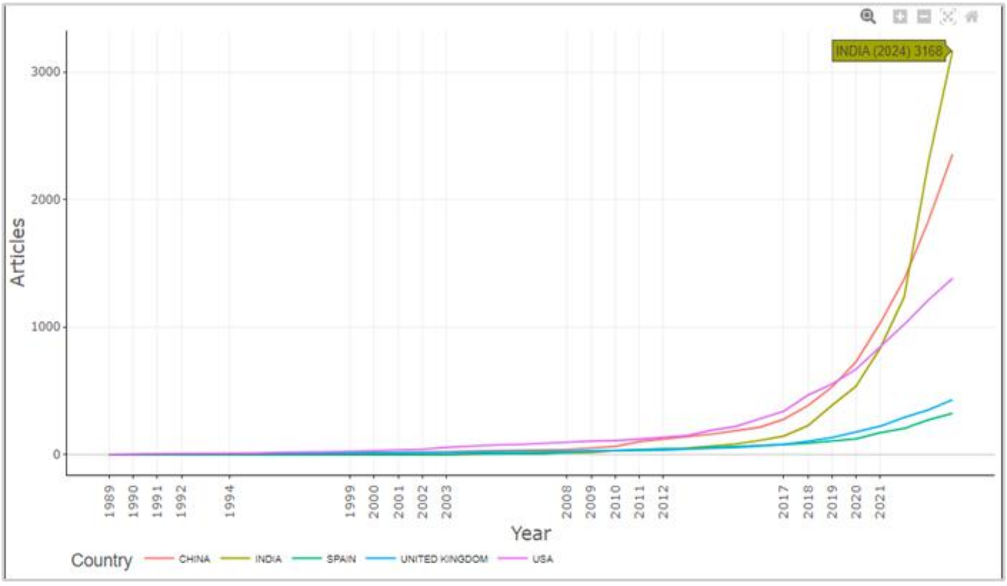


**Fig. 4. Countries' production over time**

### 4.1.6. Statistics by authors

In this subsection, we present the ten most influential authors based on total citation count as a measure of impact. The author WANG Y has published the most documents related to the application of AI in market analysis, with a total of 46 publications, followed by LIU Y with 37 publications.

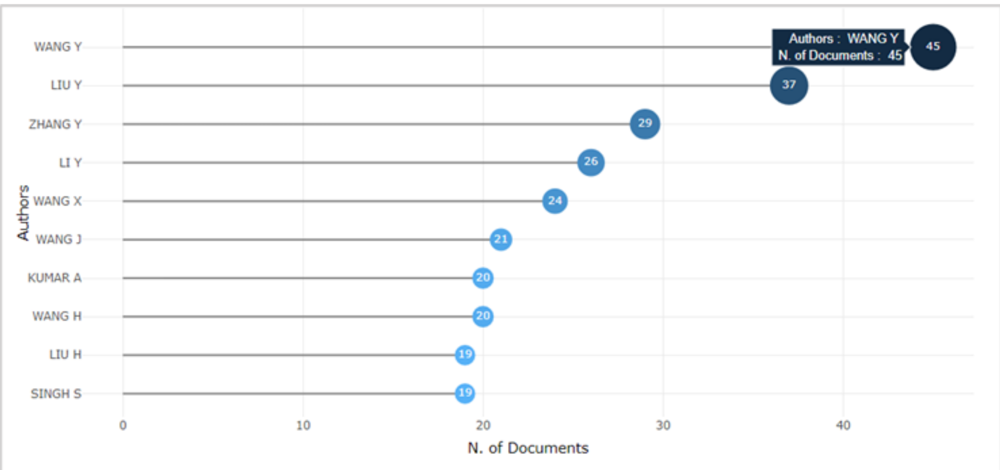


**Fig. 5. Most relevant authors. Impact measure: Total Citation (TC)**

To describe the frequency of publications by authors, we refer to Lotka's Law, a statistical principle proposed by Alfred James Lotka (1926). Lotka's Law describes the distribution of scientific productivity among authors, indicating that a small percentage of authors account for a large proportion of the total published works, while a larger percentage of authors contribute fewer articles.

The following plot has been generated by Biblioshiny based on our data for the last thirty-five years. It shows that effectively as the number of documents written increases, the percentage of authors who have written that many documents become very small.

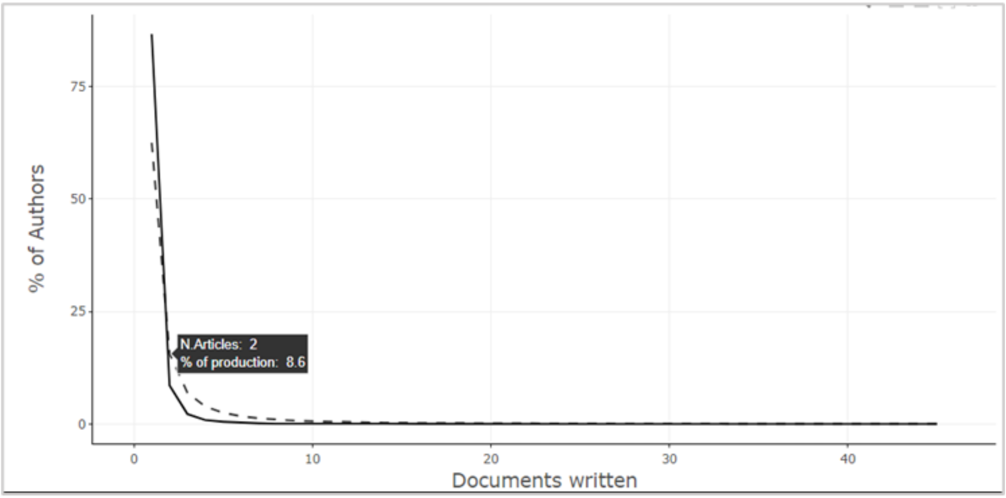


**Fig. 6. The productivity of authors according to Lotka's Law**

### 4.1.7. Statistics by documents

Among the 4,051 documents related to the application of AI in market analysis, this subsection focuses on three documents with the highest global and local citations, as shown in Tab. 5 below. (Burrell, 2016) discusses the global social implications of machine learning in analysis and has received 1,351 global citations since its publication. This is followed by (Wirtz et al., 2018), who explore consumer perceptions, beliefs, and behaviors associated with service robots and AI, earning 1,152 global citations. Locally (Chong et al., 2017) have the highest citation count with 53 local and 547 global citations. Their work specifically addresses "Deep learning networks for stock market analysis and prediction: Methodology, data representations, and case studies."

**Tab. 5. Most global cited documents and local cited documents. Notes: TC: Total Citations, LC: Local Citations**

| **Global cited documents** | | | **Local cited documents** | |
|---|---|---|---|---|
| Papers | TC | | Papers | LC |
| (Burrell, 2016) | 1351 | | (Chong et al., 2017) | 53 |
| (Wirtz et al., 2018) | 1152 | | (Nti et al., 2020) | 33 |
| (Dwivedi et al., 2021) | 847 | | (Wirtz et al., 2018) | 29 |
| (Huang et al., 2004) | 758 | | (Wen et al., 2019) | 24 |
| (Bengler et al., 2014) | 682 | | (Singh & Srivastava, 2017) | 22 |
| (Ferrucci & Lally, 2004) | 654 | | (Li et al., 2019) | 19 |
| (Dargan et al., 2020) | 612 | | (Nayak et al., 2016) | 19 |
| (Chong et al., 2017) | 547 | | (Li & You, 2021) | 18 |
| (Mostafa, 2013) | 456 | | (Thakkar & Chaudhari, 2021) | 18 |
| (Huang & Rust, 2021) | 449 | | (Picasso et al., 2019) | 18 |


**Fig. 7. Tree Map of the most pertinent author keywords used in AI and market analysis**

Figure 7 above highlight the most frequently used keywords in documents related to the application of AI in market analysis. "Commerce" is the most commonly used keyword, with a total of 1,055 occurrences. This is followed by "Consumer behavior" and "Forecasting," which appear 1,013 and 890 times, respectively.

### 4.2. Intellectual structure

In this section, we use co-citation networks, betweenness centrality, and closeness centrality as metrics to examine the relationships between authors, documents, and sources. In 1973, Henry Small introduced the concept of co-citation analysis as an indicator of subject similarity (Small, 1973). Co-citation analysis evaluates the relationships between cited documents and those that cite them (Saibaba, S, 2023). As illustrated on the right of the figure below, documents A and B are associated because they are co-cited by documents C, D, and E. The underlying idea is that if two papers are frequently cited together, they likely cover related or complementary topics, indicating a conceptual or thematic similarity.

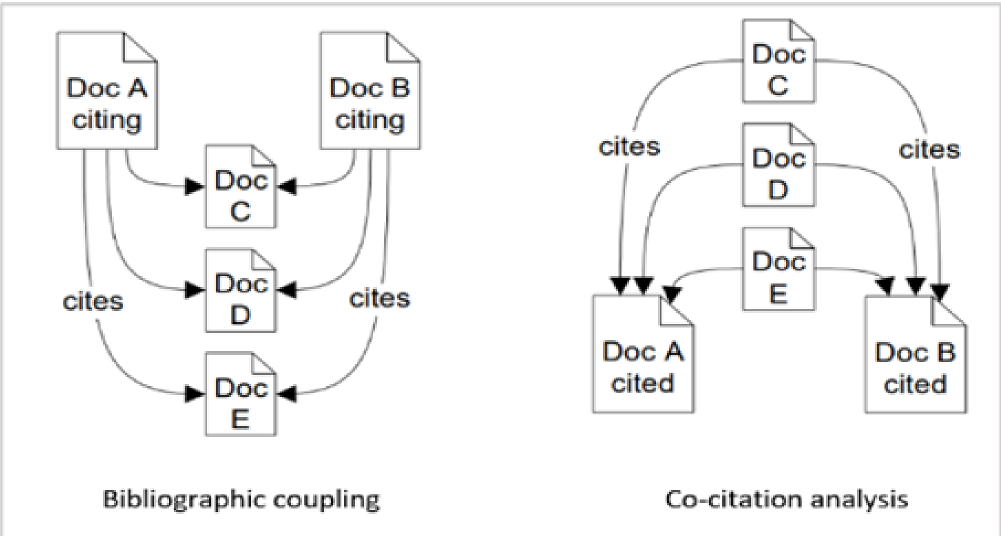


**Fig. 8. Co-citation analysis in the right (Gipp & Beel, 2009)**

As a result, we have built distinct clusters of documents, authors, and sources using Biblioshiny. In this context, centrality is used to calculate the co-authorship network. This metric indicates the level of collaboration an author has with others in creating a document (Ribeiro et al., 2022). Centrality is divided into two categories: closeness centrality, which refers to entities that have extensive connections within the network, and betweenness centrality, which refers to an entity's role as a connecting link between different research areas.

### 4.2.1. Author network based on co-citations

Figure 9 illustrates three different clusters in the authors' co-citation network. Authors sharing similar co-citation patterns are clustered together. In Tab. 6. below, we present the top ten authors with the highest betweenness and closeness centrality scores. Author Hochreiter S. has the largest betweenness centrality in this ranking, with a score of 232.70, indicating his extensive connections within the network. Meanwhile, author Vaswani A. has the highest closeness centrality, signifying his role as a key connecting link between different research areas. Both of these authors have a major impact on the progression of AI techniques in market analysis.

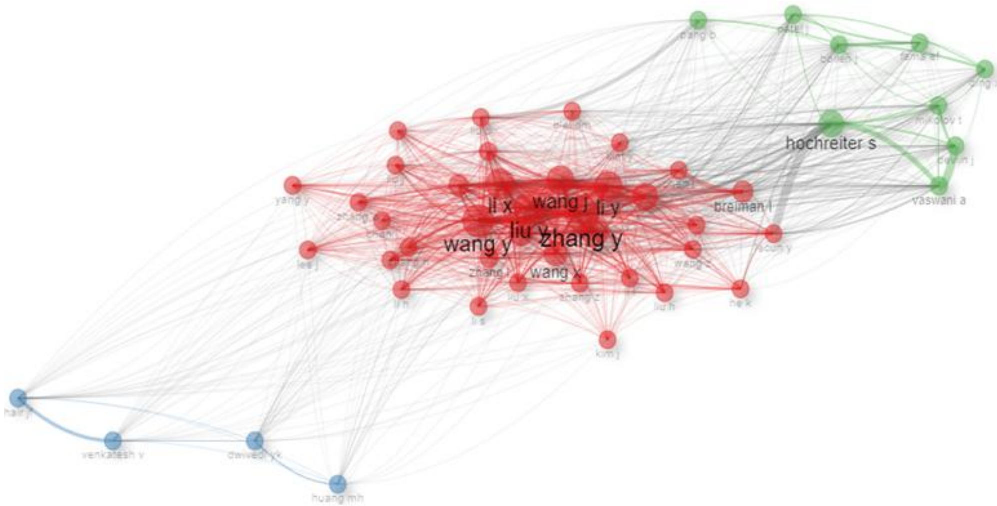


**Fig. 9. Author network based on co-citations**

**Tab. 6. Top 10 authors with high betweenness centrality and closeness centrality**

| | Authors | Betweenness | | Authors | Closeness |
|---|---|---|---|---|---|
| 1 | Hochreiter S | 232.7090863 | | Vaswani A | 0.016666667 |
| 2 | Vaswani A | 150.1945183 | | Hochreiter S | 0.016393443 |
| 3 | Devlin J | 86.85214796 | | Devlin J | 0.014925373 |
| 4 | Mikolov T | 53.11918105 | | Ding X | 0.014084507 |
| 5 | Pang B | 45.29430715 | | Dwivedi Yk | 0.014084507 |
| 6 | Fama Ef | 34.53872652 | | Pang B | 0.013888889 |
| 7 | Bollen J | 33.79331097 | | Mikolov T | 0.01369863 |
| 8 | Ding X | 31.99686353 | | Fama Ef | 0.01369863 |
| 9 | Patel J | 26.20567519 | | Hair Jf | 0.013513514 |
| 10 | Hair Jf | 21.40948899 | | Bollen J | 0.012987013 |

### 4.2.2. Co-citation network of papers

Similarly, Fig. 10 illustrates seven different clusters in the papers' co-citation network. Papers sharing similar co-citation patterns are clustered together. In Tab. 7, we present the top ten papers with the highest betweenness and closeness centrality scores.

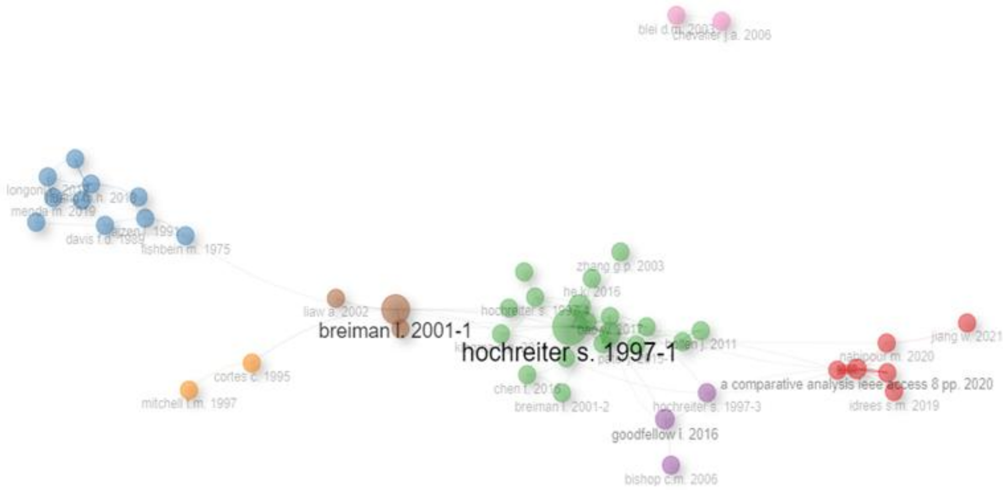


**Fig. 10. Co-citation network of papers**

**Tab. 7. Top 10 papers ranked by high betweenness and closeness centrality**

| | Papers | Betweenness | | Papers | Closeness |
|---|---|---|---|---|---|
| 1 | Breiman l. 2001-1 | 514.5619737 | | Blei d.m. 2003 | 0.2 |
| 2 | Fishbein m. 1975 | 298 | | Chevalier j.a. 2006 | 0.2 |
| 3 | Hochreiter s. 1997-1 | 218.6263084 | | Breiman l. 2001-1 | 0.00404858 |
| 4 | Fischer t. 2018 | 201.3018921 | | Hochreiter s. 1997-1 | 0.00384615 |
| 5 | Lecun y. 2015-1 | 177.1224795 | | Fischer t. 2018 | 0.00384615 |
| 6 | Hochreiter s. 1997-3 | 123.4535488 | | Lecun y. 2015-1 | 0.00380228 |
| 7 | Nabipour m. | 105.879194 | | Fishbein m. 1975 | 0.0037037 |
| 8 | Davis f.d. 1989 | 100.6333333 | | Nabipour m. | 0.00361011 |
| 9 | Ameen n. 2021 | 63 | | Hochreiter s. 1997-3 | 0.00359712 |
| 10 | A comparative analysis ieee access 8 pp. 2020 | 62.41263314 | | Patel j. 2015-2 | 0.00357143 |

### 4.3. Social structure

This section examines the social network relationships between authors, institutions, and countries that have collaborated on the application of AI in market analysis. In the three social network plots below, each node represents an author, an institution, or a country, while the edges represent the connections between them.

Figure 11 shows a clustering of co-authors who work together, with author WANG Y having the highest number of co-authors in the creation of documents. Figure 12 depicts the co-affiliation network of institutions among these authors. Institutions such as King Saud University, the University of California, Amity University, and the School of Computer Science and Engineering show strong affiliations among the authors.

Regarding the countries, Fig. 13 indicates that India and China have the largest levels of collaboration. These countries have also produced the highest number of documents, as shown by the previous statistics.

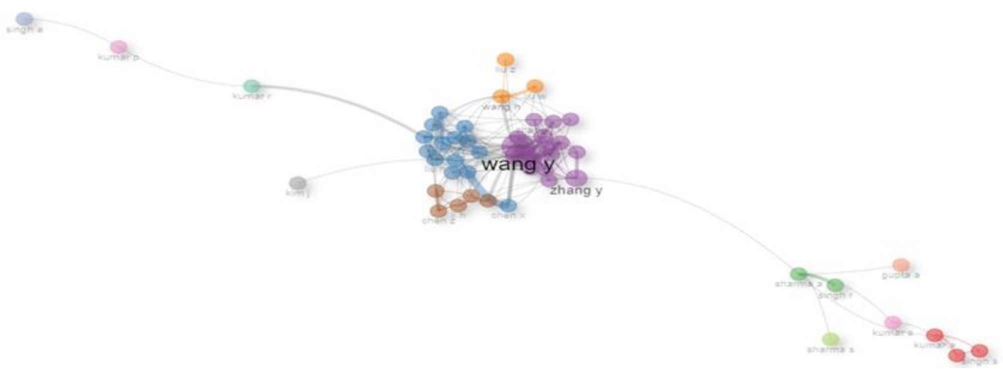


**Fig. 11. Collaboration Network of authors**

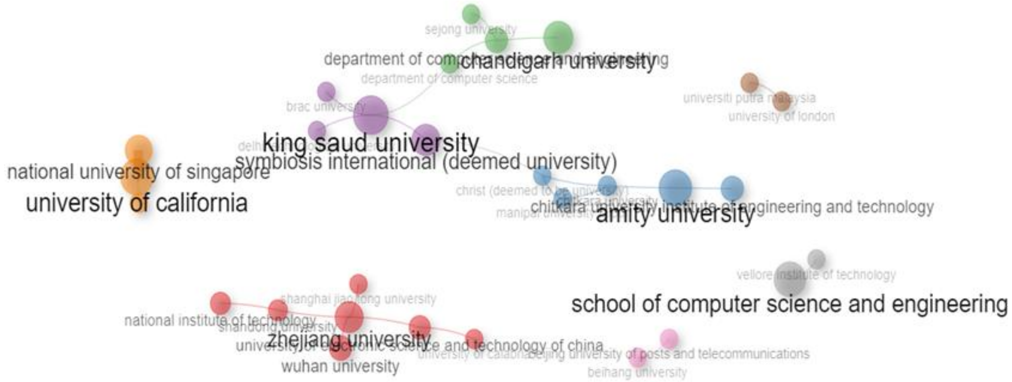


**Fig. 12. Collaboration Network of Institutions**

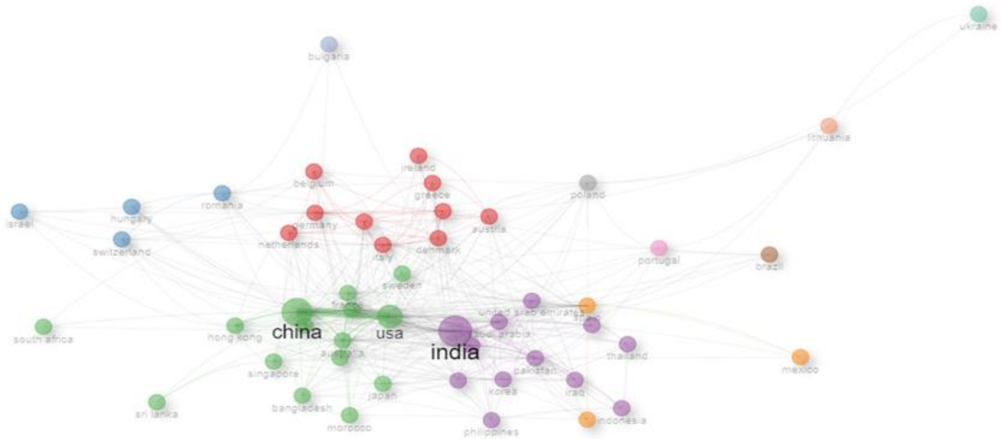


**Fig. 13. Collaboration Network of Countries**

## 5. CONCLUSIONS

This research paper has explored the evolution and impact of the application of Artificial Intelligence in market analysis through a bibliometric study. Our analysis was based on 4,015 documents published in the Scopus database over the past thirty-five (35) years. To our knowledge, this is the first bibliometric analysis that comprehensively covers various aspects of market analysis, such as market trend analysis, market segmentation, consumer behavior and competitive analysis. Additionally, it identifies the regions of the world where AI is most extensively developed for these purposes. The results of this research demonstrate that scientific production, a key metric for assessing the evolution of research on AI applications in market analysis has increased exponentially from 2010 to 2023. However, since this study was conducted in August 2024, data for the remaining months of 2024 are not yet available, making it difficult to confirm whether this exponential growth will continue throughout the year. Among the countries contributing significantly to the evolution of AI in market analysis, India, China, and the USA are at the forefront. Despite the strong findings captured in this study, it is important to note that the keywords used to collect data from the Scopus database may have influenced the results. Therefore, future research could explore the topic using different sets of keywords. Furthermore, as this study relied solely on data from the Scopus database, future studies could consider using multiple databases to provide a more comprehensive view.

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