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Industry 4.0 Transformation: Analysing the Impact of Artificial Intelligence on the Banking Sector through Bibliometric Trends

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Abstract: The importance of artificial intelligence in the banking industry is reflected in the speed at which financial institutions are adopting and implementing AI solutions to improve their services and adapt to new market demands. The aim of this research is to conduct a bibliometric analysis of the involvement of artificial intelligence in the banking sector to provide a comprehensive overview of the current state of research to guide future directions and support the sustainable development of this rapidly expanding field. Another important objective is to identify research gaps and underexplored areas in the field of artificial intelligence in banking. The methodology used is a bibliometric analysis using VOSviewer, analysing 1089 papers from the Web of Science database. The results of the study provide relevant information for banking professionals but also for policy makers. Thus, the study highlights key areas where banks are using artificial intelligence to gain competitive advantage, thereby guiding practitioners in strategic decision making. Moreover, by identifying emerging trends and patterns in AI adoption, the study helps banking practitioners with foresight, enabling them to anticipate and prepare for future developments in the field. In terms of governmental implications, the study can contribute to the development of more nuanced regulatory frameworks that effectively balance the promotion of AI innovation with the protection of ethical standards and consumer protection.

Keywords: artificial intelligence applications; banking industry; bibliometric analysis

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1. Introduction

Artificial intelligence (AI) is a highly topical and dynamic field in the banking sector, bringing significant changes to the way financial institutions conduct their business. Thus, the recent development of various AI technologies, such as machine learning, deep learning, neural networks, natural language processing, reinforcement learning, and robotic process automation, have significantly amplified the capabilities of AI decision-making algorithms. Algorithms can now autonomously learn from data and reveal hidden insights [1]. Therefore, such capability gives algorithms the ability to become more rational and make more efficient decisions [2,3].

Financial technology continues to advance rapidly. In the age of artificial intelligence, central banks are both adopters and overseers of the new landscape. According to Fintech Benchmarks 2024 [4], more than half (56.8%) of these institutions report using machine learning (ML) and artificial intelligence (AI) tools, up slightly from 51.4% the previous year. Monetary policy is one of the most important areas where AI is applied [4]. This advanced change indicates a progressive adaptation to new financial technologies and a shift towards efficiency and innovation among central banks, including an upper middle-income central bank.

According to statistical data [5], there are estimates that, by 2027, global spending on artificial intelligence could reach about USD 450 billion, with the banking sector projected to contribute about 13% of that amount. This investment could generate between

USD 200 billion and USD 340 billion annually, representing a 9% to 15% increase in bank operating profits [5].

The accelerating impact of the digitization of banking, already accentuated by the COVID-19 pandemic, has caused a significant change in the financial landscape [6]. The considerable increase in the use of digital services brings into question existing gaps in the skills and knowledge of the general population and those providing these services [7].

However, the COVID-19 pandemic has emphasised that innovation in digital banking is no longer an option at the discretion of the financial institution and is unanimously accepted as an essential necessity for achieving distinctive and refined customer experiences [8]. The claim that AI features such as timeliness, attractiveness, and problem solving have made banking more engaging and innovative is supported by research and trends observed in the industry [9–11]. Thus, the preference of customers to use trendy services instead of conventional ones is supported by research such as that mentioned in [9]. Modern customers are attracted to innovative technological solutions and services that offer them an advanced and personalised experience.

According to a survey [12], 77% of banking professionals believe that the ability to harness the potential of artificial intelligence will be the defining factor between the success and failure of banking institutions. In another survey [13], it was found that 80% of retail banking executives believe that generative artificial intelligence represents a significant advance in AI technologies. However, only 6% of retail banks have implemented a strategy for enterprise-wide AI-enabled transformation. This discrepancy between perception and action may indicate either a misunderstanding of the technology's true potential or challenges in implementing it in practice.

In one study [14], it was pointed out that banks increasingly see that to remain competitive, they need to address artificial intelligence while fulfilling their risk management responsibilities. This statement suggests that the adoption of artificial intelligence is not just an option for financial institutions but is becoming increasingly necessary to adapt to market demands and remain relevant in an ever-changing competitive environment. Despite the benefits, challenges, and risks abound, banks face a dilemma in leveraging AI capabilities—from data governance risks to emerging operational risks, model management, and associated liability. According to another survey [15], eighty-seven percent of banking executives anticipate a higher level of change in 2024 than in the previous year, and 53% are not fully prepared to deal with this expected change. This finding underscores the complexity and rapid pace of change in the banking industry and the urgent need to effectively address and manage these challenges to ensure long-term success and resilience.

The use and implementation of artificial intelligence technologies have brought multiple benefits to the banking industry, helping to improve their operations and services. Firstly, according to the study by Zolkepli and Kamarulzaman [16] and research by Silva [17] and Roseline et al. [18], the most important advantage is fraud prevention using AI technologies, as they have made it easier for banks to implement advanced fraud detection and prevention systems. AI's ability to analyse behavioural patterns and identify anomalies helps protect banks and customers from fraudulent activities. Secondly, Maja and Letaba [19] found that AI technologies have made a significant impact on banking operations, providing increased reliability and accuracy. Artificial intelligence algorithms can perform complex analysis, helping to make decisions efficiently and accurately. And thirdly, Garg et al. [20] highlighted that AI technologies have contributed to increased speed in data processing and banking transactions. This increased speed is essential in a dynamic financial environment, allowing banks to provide fast and efficient services to their customers.

While previous studies have provided a fundamental understanding of how artificial intelligence has driven significant change in the banking sector, these studies have failed to provide a comprehensive and in-depth perspective on the current state of research in the field. Therefore, this study represents a pioneering bibliometric analysis of the use of artificial intelligence in banking. Although there is a pre-existing discourse on this subject, the introduction of current elements related to statistics from 2024, including the bibliometric analysis of documents and articles published up to 2023 concerning artificial intelligence in the banking sector, brings forth a new perspective and relevance to our research in this continuously evolving field. By scrutinizing the most cited works and identifying emerging trends, our study underscores the recent evolution and impact of AI in the banking sector, providing a deeper understanding of the progress and challenges encountered. The novelty of this study consists of the necessity and importance of further exploration into recent trends and innovations in AI utilization, thereby solidifying our contribution to the knowledge and future directions of research and recommendations for banking practitioners and policy makers in this rapidly advancing domain. Thus, we aim to explore how financial institutions have responded to the changes brought about by the pandemic by adopting and expanding their use of AI technologies to streamline their operations, improve their services, and better serve the needs of their customers. We also discuss the challenges and opportunities brought about by this accelerating digitisation and how this may influence future directions of AI research and development in the banking sector. The present study, through the bibliometric analysis, aims to provide a detailed and comprehensive understanding of recent progress and developments in the field of artificial intelligence applied within banking institutions. Bibliometric analysis often focuses on quantitative data, such as the number of citations or frequency of keywords, but we also aim to provide a detailed understanding of the quality and relevance of publications by analysing the most cited papers. It is important that this analysis complements the research with a qualitative assessment of the publications in order to obtain a more complete and balanced picture of the literature in the field. Thus, the methodology of this study involves the use of bibliometric methods, a rigorous approach aimed at analysing and evaluating scientific papers published in this specific field. This includes identifying major trends, mapping influential authors and key institutions, assessing the impact of papers, and detecting collaborative networks.

The structure of this paper comprises an introduction, to set out the theoretical basis; a detailed methodology, to outline the approach and tools used in the bibliometric analysis; a rigorous analysis of the data collected; a presentation of the results obtained and a discussion of them; a description of our contributions to the field of research; and finally, conclusions, which summarise the findings, suggest recommendations for policy makers, and identify research limitations and future research directions.

By integrating the expectation–confirmation model with bibliometric analysis, this study makes a significant contribution to the banking information system literature, providing a comprehensive and in-depth perspective on the impact of artificial intelligence in the evolution of the banking sector.

2. Materials and Methods

Donthu et al. [21] showed that bibliometric analysis is an increasingly used and sufficiently rigorous method for exploring and analysing large volumes of scientific data. Although it was not initially used for business research, in recent years, it has gained popularity in this field, as evidenced by the multitude of articles that have appeared [22–26]. The increased interest in such analyses is driven by the fact that the use of such a method allows for mapping of the intellectual architecture of a literature stream [27] but also by the possibility of using bibliometric software such as VOSviewer and Gephi and the existence of scientific databases such as Scopus and Web of Science. Bibliometric analysis is useful because it allows for the use of publications and citations to analyse the performance of authors, institutions, countries, and journals [28]. A key advantage of VOSviewer is its ability to provide detailed views that allow in-depth exploration of the bibliometric maps. It offers the possibility to present the maps in different ways, highlighting different aspects of the bibliometric network. Zooming, scrolling, and searching features make it easy to explore the maps carefully, allowing one to identify significant details. VOSviewer's advanced visualisation capabilities are particularly useful for maps containing at least a moderate number of articles, e.g., at least 100 articles. A significant aspect of VOSviewer is its differentiation from most bibliometric mapping programs, which are described as failing to display such maps in a satisfactory way. Such methodologies are beneficial for illustrating the bibliometric and intellectual structure of a research area when combined with network analysis [29,30].

In this article, we have used bibliometric analysis with the VOSviewer software, which can meet the analysis needs of countries, institutions, journals, and authors and can reveal the evolution of AI's influence in banking. Keyword analysis was used to assess research trends and topics of interest. Co-word analysis is the most important analysis method in bibliometrics and scientometrics, primarily performed by identifying two keywords in the same paper, generating clusters, and analysing the density relationship between common keywords to explore keywords that reflect popular research topics and trends, among other factors. Bibliometric maps are a product of innovations in scientometrics that help to analyse and understand the relationships and interconnections between different elements in scientific research, such as articles, authors, key terms, or research areas.

The data used in this analysis were extracted from the Web of Science database. The Web of Science database was used because it is one of the most comprehensive academic databases, covering a wide range of scientific fields and publications worldwide. This extensive coverage can provide access to a variety of relevant papers in the field of artificial intelligence in the banking sector. Publications included in Web of Science undergo a rigorous review and selection process, which ensures the quality and reliability of the information and results in articles that are highly rated in terms of score. Considering two concepts from the Web of Science thematic area, artificial intelligence and banks, we chose to search for articles, papers, and book chapters. The articles in this study were selected based on specific criteria to ensure relevance to the fields of artificial intelligence (AI) and banking. The selection process involved multiple steps. Firstly, the search was conducted using the keywords "artificial intelligence and banks" in the Web of Science database. This ensured that the retrieved articles were directly related to both AI and the banking sector. After entering the keywords, a subject filter was applied to narrow down the search results. This filter allowed us to select only those articles that explicitly addressed both concepts in their titles or keywords. Articles that did not meet this criterion were excluded from the study. Another step aimed at ensuring the selection of relevant articles was the consistency of sampling. The sampling process was consistently applied across all articles to avoid bias. Each article that met the inclusion criteria was included in the analysis, ensuring that the sample represented a comprehensive overview of the intersection between artificial intelligence and the banking sector. Following these selection criteria and ensuring a rigorous review process, we aimed to minimise bias and ensure the credibility of the results. As a result, the Web of Science database returned 1089 academic papers on these topics. The data (records and references) were collected via a .txt file that was uploaded to the VOSviewer software for analysis.

3. Results

This paper aims to present data from the literature, including the year of publication of most of the research, in addition to highlighting authors who have analysed the relationship between AI and banking, identifying collaborations by country of the co-authors analysed, as well as research trends in this area based on keyword analysis, and, finally, highlighting the most cited papers and ranking the most prolific journals.

Thus, starting from the research questions, "How much has the relationship between AI and banks been studied over the years?" and "Who are the relevant contributors in the study of the relationship between AI and banks?", the following is an analysis of the articles based on the information provided by Web of Science and the results of the bibliometric analysis, structured using the following:

- Description of data from the literature.
- Publication activity by author.

- Publication activity by country.
- Co-occurrence of keywords.
- Analysis of the most cited papers.
- Analysis of specialised journals.

3.1. Description of Data from the Literature

3.1.1. Publication Type

The selected set of publications is diverse, comprising a variety of formats and types of papers in the fields of artificial intelligence and banking. Table 1 illustrates the types of publications out of the total of 1089 papers published in the fields included in the research. According to the table, most publications are articles (681 in total), representing 62.53%, followed by 260 conference papers (18.36%). Also included are 65 review articles, 60 early access, 12 book chapters, 5 editorial materials, 5 meeting abstracts, and 1 data paper. This diversity underscores that the field of artificial intelligence in the banking sector is explored and investigated from a variety of perspectives and approaches, reflecting a broad concern for the various aspects of technology application in this domain. By including a wide range of publication types, from research articles and conference papers to journals, book chapters, and other editorial materials, the scientific community demonstrates a deep and ongoing commitment to studying and developing artificial intelligence in the banking context. This diversity enhances not only the depth and breadth of knowledge but also the accessibility and relevance of research to a wide range of interested audiences, including researchers, practitioners, and decision makers. Therefore, the diversity of publication types is a source of richness and innovation in the exploration and application of artificial intelligence in banking.

Table 1. Typology of the 1089 documents.

Type	Number
Articles	681
Conference papers	260
Review articles	65
Early access	60
Book chapters	12
Editorial material	5
Meeting abstract	5
Data paper	1

Source: Own processing, using data provided by WOS.

3.1.2. Publications and Annual Citations

Although interest in research in the field of AI and banking emerged early, with an upward trend in publications year by year, most publications and citations have been made in the last 4 years. Banks have had to adapt quickly to changing consumer behaviour and rely more on digital solutions to keep their services and operations active. Implementing AI-based solutions can provide automation and efficiency in banking processes, reducing reliance on human resources, and thus reducing human error. AI technologies can also play a key role in banks' cybersecurity, helping to detect and prevent fraud and suspicious activity.

The upward trend in the number of publications and citations is also shown in Table 2, which shows an increase in the number of publications from 29 in 2017 to 232 in 2022, with the number falling to 213 in 2023. The number of citations in the researched field was relatively constant until 2010, following an upward trend, becoming much more significant from 2018. As a result, of the total number of 1089 papers, over 65% were published between 2020 and 2023, and 7895 (over 80.60%) citations were made between 2020 and 2023.

Table 2. Annual publications and citations.

Year	Number of Publications	Number of Citations
2000	3	0
2001	3	2
2002	2	0
2003	3	2
2004	4	7
2005	4	7
2006	1	14
2007	2	22
2008	6	28
2009	9	23
2010	8	40
2011	9	44
2012	12	59
2013	13	62
2014	17	128
2015	20	172
2016	13	186
2017	29	201
2018	44	312
2019	76	520
2020	122	799
2021	168	1525
2022	232	2462
2023	213	3381

Source: Own processing, using data provided by WOS.

The increase in the number of publications and citations in the field of artificial intelligence applied to the banking sector is the result of technological advancement, the impact of digitization, research investments, and the heightened interest in the industry and investors.

These statistics highlight that research into the relationship between artificial intelligence and banking has gained momentum and interest since the COVID-19 health crisis, when most sectors went digital, and the banking system experienced a true digital revolution.

3.1.3. Research Areas

Research in the field of artificial intelligence and banking covers diverse directions, as evidenced by the literature from multiple fields. This diversity reflects the complexity of the interaction between artificial intelligence and the banking industry and paves the way for significant innovations and improvements. Figure 1 illustrates the top 10 thematic areas, identified through publications, that address the above relationship for research. Computer Science Artificial Intelligence is the area with the most publications (169), accounting for 15.51%, and includes research focusing on algorithms, machine learning models, and AI technologies to improve banking services, data analytics, security, and other areas.

The ranking is followed by Computer Science Information Systems (149), covering 13.66% of the total publications and including articles focusing on the use of information systems in financial institutions for information management, operational efficiency, and decision support systems. The next field in the ranking is Electrical Electronic Engineering (133), accounting for 12.21%, and the last fields in the ranking are Management (69), Economics (67), Telecommunications (66), and Business and Finance (62). These cover the financial aspects of AI applications in banking, such as financial modelling, risk analysis, investment management, and financial performance evaluation, as well as communication technologies used in banking, such as communications security and data networks.

Figure 1. Research areas. Source: Web of Science Core Collection Database 2023, available at: https://0c10qjxkk-y-https-www-webofscience-com.z.e-nformation.ro/wos/woscc/basic-search (accessed on 3 December 2023).

The distribution of research areas observed in the field of artificial intelligence and banking may not be unique to this specific domain. Similar distributions could potentially occur in other interdisciplinary fields where different disciplines intersect, when researchers often draw from a variety of disciplines to address complex challenges, resulting in diverse thematic areas and research directions.

However, the significance of the distribution lies in its reflection of the multifaceted nature of the interaction between artificial intelligence and the banking industry. This diversity underscores the broad impact of artificial intelligence on banking, encompassing not only technological aspects but also economic, managerial, and financial dimensions. Therefore, while similar distributions may occur in other interdisciplinary domains, the findings of this study remain valuable as they shed light on the complexity and breadth of research in the intersection of AI and banking.

The diversified distribution in these research areas suggests that despite the many thematic areas addressed, the fundamental research directions can be placed in two main categories: computer science and economics. This distribution shows that studies on AI and banking are conducted in a broad spectrum of areas, covering technological, economic, management, and financial aspects. This diversity reflects the complexity and wide-ranging impact that artificial intelligence has on the banking industry and how researchers and practitioners explore and investigate this relationship from different perspectives.

3.2. Publication Activity by Author (Co-Authorship)

Bibliometric analysis, using the VOSviewer application, provides the opportunity to identify the most cited authors in the field of interest, both through author citations and author co-citation in publications.

Thus, the graphical representations obtained through this type of analysis allow us to highlight the most influential authors in the field, which can serve as support in the documentation. Figure 2 represents the map of co-citation, with the unit analysed being authors, and by setting the minimum number of citations per author at 20, 59 authors were identified as meeting this condition out of a total of 31,246. The larger the node (circle), the more cited the author. It should also be noted that the thicker the link between nodes, the stronger the link, and the more frequent the co-citation of these authors. These authors have been grouped into five clusters: (red, green, blue, yellow, and purple).

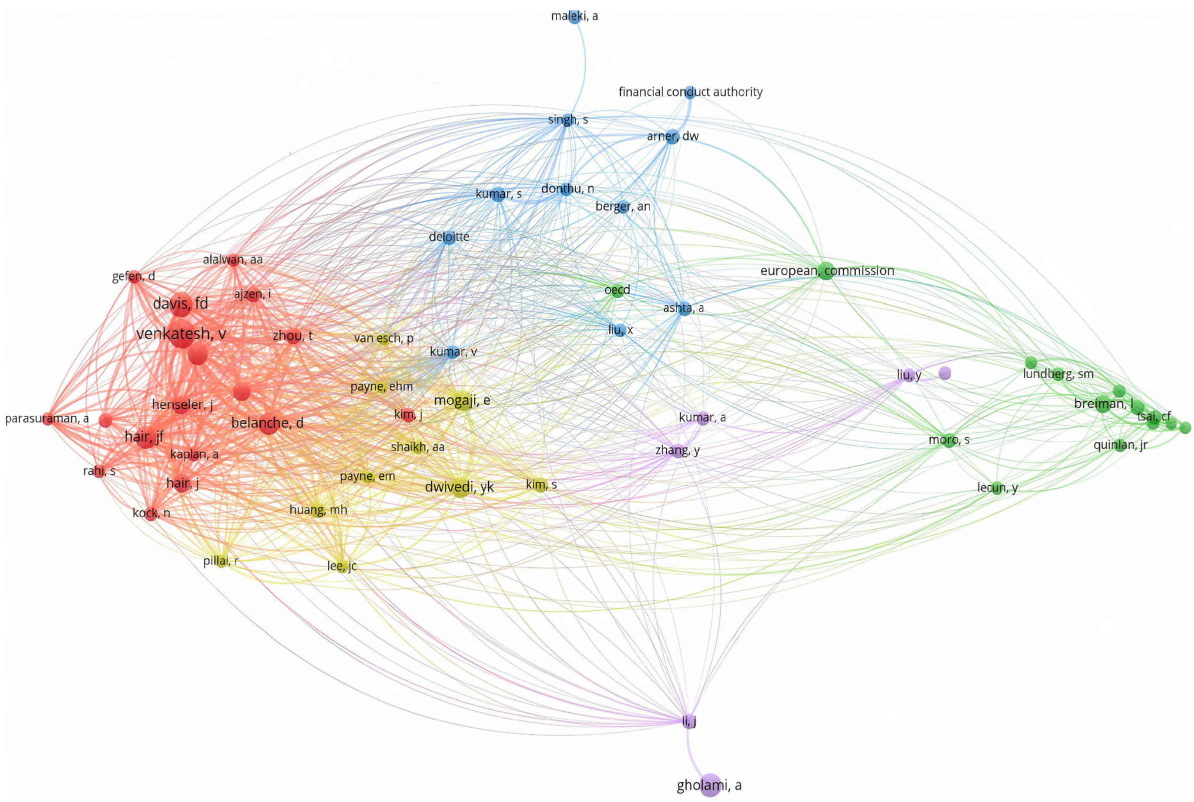

Figure 2. Co-citation of authors. Source: Own processing using VOSviewer, 2023.

The first cluster (red) contains 18 authors, and the most cited authors in this cluster are Venkatesh, V (97 citations); Davis, FD (75 citations); Belanche, D (63 citations), and Hair, JF (61 citations). The second cluster (green) comprises 14 authors, the most representative authors being Breiman, L (43 citations) and the European Commission (41 citations). Clusters three (blue) and four (yellow) have 11 and 10 authors, respectively, and the most influential authors in these clusters are Arner, DW (31 citations) for the blue cluster and Dwivedi, YK (53) and Mogaji, E (53 citations) for the yellow cluster. The last cluster contains six items, and the most cited author in this cluster is Gholami, A (66 citations), who is one of the top 10 cited authors in this domain.

Therefore, according to this analysis, we can answer one of the research questions (Who are the relevant contributors in the study of the relationship between AI and banks?) by identifying the authors with the highest impact in this field based on the number of citations. Their ranking includes names such as Venkatesh, V; Davis, FD; Gholami, A; Belanche, D; Hair, JF; Fornell, C; Mogaji, E; Dwivedi, YK; Hair, J; Breiman, J; Henseler, J; and the European Commission.

3.3. Publishing Activity by Country

Using the Web of Science database, the study reveals that research into the interaction between artificial intelligence and banking is taking place on a global scale, demonstrated by the significant contributions of authors from 98 separate countries. Below, we analyse the countries with the most publications as well as co-author collaboration between these countries.

3.3.1. Prolific Countries/Regions

Research in artificial intelligence and banking is growing steadily, both year-on-year and country-by-country. The significant increase in interest in investigating AI and banking research in recent years in most countries can be attributed to several key factors: advances in technology, increased availability of data, demand for innovation in the banking sector, the impact of the COVID-19 pandemic, substantial investment in R&D, accelerating international collaborations, etc. These factors combined have helped to create an environment conducive to the expansion of AI and banking research, reflecting the need for innovation and adaptation in the face of constant change in the financial sector. Depending on the level of awareness of these factors but also on the financial resources available to a country for research, the number of publications differs from country to country.

Figure 3 is a map of countries that have investigated and published papers on artificial intelligence and banking. The number of these publications ranges from 1 publication (light blue) to 136 (dark blue).

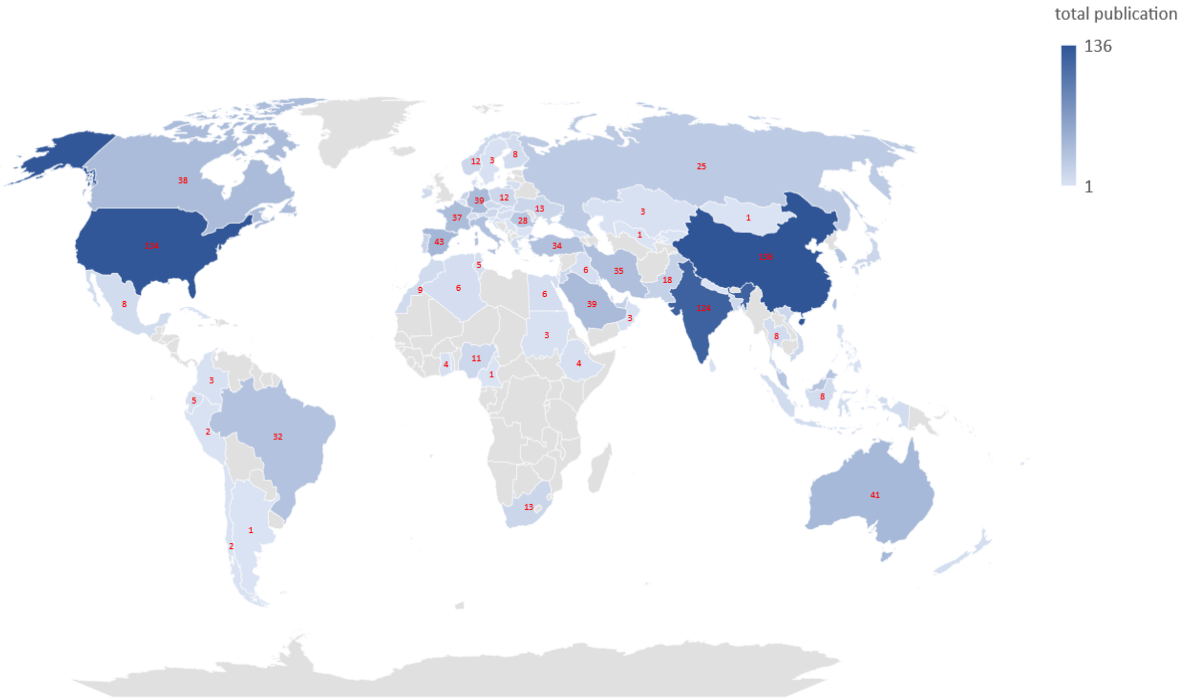

Figure 3. Prolific countries/regions. Source: Own processing using VOSviewer, 2023.

According to the map in Figure 3, most publications over time have been produced in China (136), the USA (134), and India (124), with these three major countries accounting for more than 36.1% of the publication volume. The ranking is followed by England (72), Spain (43), Australia (41), Germany (39), Saudi Arabia (39), Canada (38), and France (37), with the remaining countries publishing between 1 and 35 papers. Romania, with 28 publications, is in the top 20 most prolific countries. It is worth noting that 286 papers were published in the European Union, more than 26% of the total number of publications, highlighting the great interest in this topic in the European region.

We also see a particular interest from African and South American countries. This shows that research on artificial intelligence and banking does not depend on the level of development of a country but rather on the research interest of a country. However, although publication in this area is international, there is still a more considerable contribution from a smaller group of wealthy nations. Specifically, more than 70% of all published studies on artificial intelligence and banking come from the US, China, the UK, India, Germany, Italy, Canada, France, Romania, Ireland, Greece, Finland, and Spain. Of these, only China and India are emerging economies.

In conclusion, although the topics of artificial intelligence and banking have been predominantly addressed by developed countries, it is essential to recognise the significant contribution and interest of developing countries. These results indicate the particular importance of this area, highlighting the need for a global perspective and international collaboration to fully understand and harness the potential of the relationship between artificial intelligence and banking.

3.3.2. Country Collaboration of Co-Authors

Although research on the relationship between artificial intelligence and banking started early, collaboration between countries on the subject has intensified in recent years.

Figure 4, obtained using VOSviewer, illustrates the most intense and close collaborations of 61 countries out of the 98 by setting the minimum number of documents per country to five, as well as showing the period when the collaborations took place. The nodes in Figure 4 denote countries/regions, while the size of the nodes symbolises the number of publications, and the connecting lines between two nodes denote a collaborative relationship between the two countries. The more they collaborate, the stronger the link. The colour of the nodes and links symbolises the year (period) of collaboration between countries, with dark blue symbolising 2015 and yellow symbolising 2022–2023.

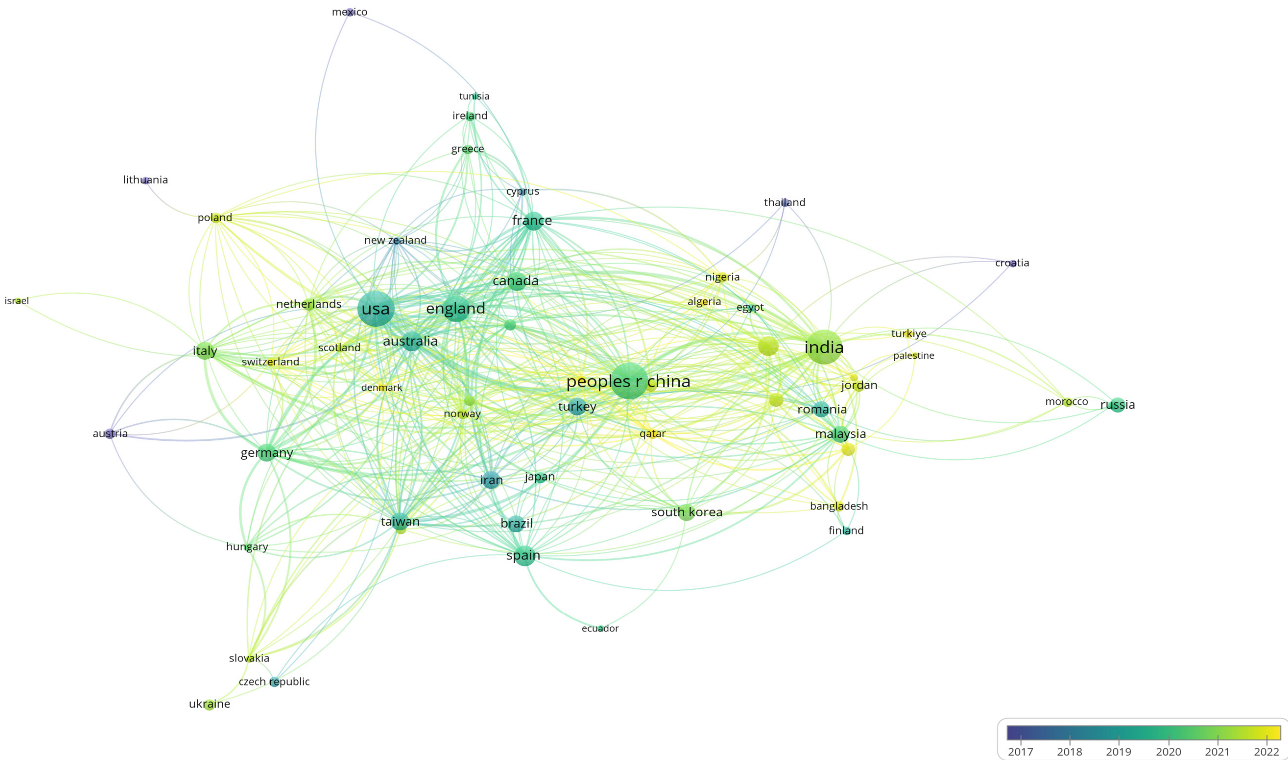

Figure 4. Collaboration by country of co-authors. Source: Own processing using VOSviewer, 2023.

China, which has the most publications, does not have the most collaborations, with only 111 collaborations, occurring more in 2020. The most collaborations were recorded for the US, with 118 strong links, most occurring in 2019. This suggests that researchers in the United States are active in establishing international partnerships and working collaboratively with colleagues in other countries to address challenges and opportunities in artificial intelligence applied to banking. China has collaborated with countries such as Singapore, Egypt, South Korea, India, the US, England, France, and, most recently, Qatar. The US has opted for collaborations with England, Australia, Canada, Scotland, the Netherlands, Germany, and New Zealand, with the most frequent and recent collaborations being with Poland and Switzerland. In the case of India, the links between nodes are shorter and thicker (which means more intense and frequent collaboration) with Jordan, Romania, Malaysia, Germany, Turkey, and Nigeria. The ranking of collaborations is followed by England (117 collaborations, the most frequent being with France, Australia, USA, Canada, and South Africa), Germany (78), Australia (74), France (74), Saudi Arabia (69), and Thailand (61). We therefore find that the countries with the most collaborations are the US, England, China, India, Germany, Australia, and France.

3.4. Co-Appearance of Keywords

The pattern of occurrence of keywords across multiple studies can be used to determine the main direction of study for future investigations [31]. A co-occurrence network of keywords is generated by the VOSviewer visualization program as a dimensional map [32]. Using VOSviewer, we can obtain the keyword map of both automatically selected keywords depending on the number of occurrences in the text and the keywords proposed by the author [33].

Figure 5 illustrates the authors' keyword map, with the minimum threshold for the occurrence of a keyword set at five. This resulted in a network of 88 terms out of a total of 3253 keywords proposed by the authors. This suggests a wide range of keywords proposed by authors on this domain (heterogeneity of the literature), and only 2.70% of them were found in at least five papers.

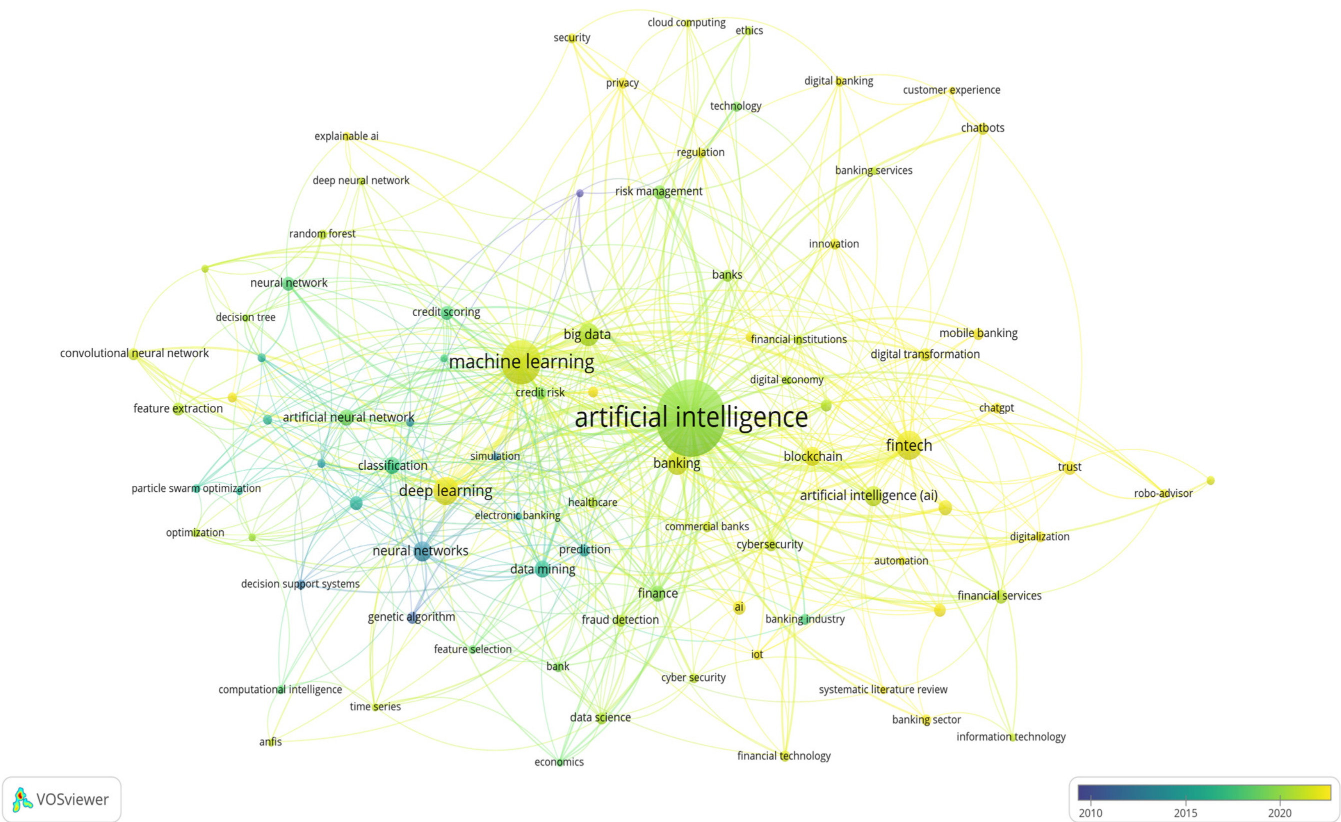

Figure 5. Co-appearance of keywords. Source: Own processing using VOSviewer, 2023.

The first, most frequently used keyword is "artificial intelligence", with 378 occurrences and 499 links to other words (banking, blockchain, machine learning, big data, fintech, etc.), being the most frequently used in 2019. It shows that artificial intelligence is associated and interconnected with a variety of other key concepts and technologies in banking and finance [34]. "Machine learning" is the second most used term in the analysed searches, with 123 occurrences and 225 links to other keywords (big data, credit risk, artificial intelligence, deep learning, etc.); this term was the most frequently used in 2021. This trend reflects the increased interest and adoption of machine learning technologies in the banking and financial industry, along with continued advances in research and development in this area. Technological innovations in artificial intelligence and machine learning, such as AI and ML, have played a significant role in the expansion of the sector and have also contributed to building consumer confidence in digital banking [35]. Fintech is the third most frequent keyword proposed by the authors, with 54 occurrences and 105 links (blockchain, banks, trust, financial institutions, digital transformation, etc.); this term was more often used in 2022. The ranking is followed by "deep learning" (49), "banking" (35), "big data" (34), "neural networks" (26), and "blockchain" (23).

According to this analysis, in addition to highlighting the most used keywords, we can also observe their trends, which reveal the direction of future studies. Thus, in 2010, the authors found that studies on artificial intelligence and banking used terms such as "neural networks", "genetic algorithm", and "decision support systems", while from 2020 onwards, the direction was more towards terms such as "banking", "fintech", "deep learning", "digitalization", "blockchain", "mobile banking", "digital banking", and "robo-advisor". Future research is needed in these areas of study as blockchain technology and digital currency are also gaining specific interest in the literature [36].

4. Discussions

4.1. Analysis of the Most Cited Papers

In order to identify research gaps and future directions in the field of artificial intelligence in the banking sector, we reviewed and synthesised the most relevant research papers on the topic. For this purpose, we used the same article database as in the previous bibliometric analysis, covering the period of 1998–2023. To identify the most influential and relevant articles in the field, we applied a sorting filter prioritizing works based on their number of citations. We chose to select articles that exceeded a minimum threshold of 100 citations, aiming to focus the analysis on the most cited and influential articles in the field. This approach allowed us to identify and deeply analyse articles that had the greatest impact and contribution to the development and understanding of the interaction between artificial intelligence and the banking industry.

While it could be noticed that not all the papers included in the analysis specifically target the banking sector but rather a broader spectrum of industries [37], their relevance to the AI and banking sector can be inferred through several avenues. Firstly, despite their diverse focal points, these papers likely include methodologies, algorithms, and technological advancements in AI that have applicability to various domains, including banking. Therefore, even if the primary focus of a paper is not on banking, its findings, techniques, or insights may still be transferable and adaptable to the banking sector [38]. Secondly, the interdisciplinary nature of AI research often results in methodologies and advancements that have cross-industry applicability. Papers targeting different sectors may introduce novel approaches or solutions that can be adapted to address challenges specific to the banking sector. By synthesizing insights from diverse sources, researchers can identify common patterns, trends, or methodologies that are pertinent to AI applications in banking [39]. Additionally, the inclusion of papers from diverse sectors enriches the bibliometric analysis by providing a broader context and facilitating comparisons across industries. By examining how AI is utilised in various sectors, researchers can gain insights into the potential transferability of strategies, best practices, and challenges between different domains, thereby enhancing the understanding of AI's role in banking [40]. Thus, there are very few papers not directly addressing the banking sector, and their inclusion enriches the breadth and depth of the study, allowing for cross-industry insights and the identification of transferable knowledge and methodologies relevant to AI applications in banking.

The main findings of the analysis are presented in Table 3 below, with the articles arranged in descending order according to the number of citations.

The paper with the most citations, 612, is "Managerial Applications of Neural Networks: The Case of Bank Failure Predictions" by Kar Yan Tam and Melody Y. Kiang. This paper is based on the analysis of neural networks for performing discriminant analysis in the context of business research. A neural network is a nonlinear discriminant function modelled by the connections between its processing units. Empirical results show that neural networks are a promising method for evaluating bank conditions, offering high predictive accuracy, adaptability, and robustness. However, the paper also discusses the limitations of using neural networks as a general modelling tool.

Table 3. List of most cited works.

No.	Authors' Names	Title of the Paper	Year of Publication	Number of Citations	Journal Name
1	Kar Yan Tam, Melody Y. Kiang	Managerial Applications of Neural Networks: The Case of Bank Failure Predictions	1992	615	*Management Science*
2	Meryem Duygun Fethi, Fotios Pasiouras	Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey	2010	397	*European Journal of Operational Research*
3	Stjepan Oreski, Goran Oreski	Genetic algorithm-based heuristic for feature selection in credit risk assessment	2014	270	*Expert Systems with Applications*
4	Yogesh K. Dwivedi, Nir Kshetri Laurie Hughes et al.	Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy	2023	163	*International Journal of Information Management*
5	Varetto, F	Genetic algorithms applications in the analysis of insolvency risk	1998	138	*Journal of Banking & Finance*
6	Maher Ala'raj, Maysam F. Abbod	Classifiers consensus system approach for credit scoring	2016	125	*Knowledge-Based Systems*
7	Joaquín Abellán, Javier G. Castellano	A comparative study on base classifiers in ensemble methods for credit scoring	2017	123	*Expert Systems with Applications*
8	Tim Fountaine, Brian McCarthy, and Tamim Saleh	Building the AI-Powered Organization Technology isn't the biggest challenge. Culture is.	2019	107	*Harvard Business Review Home*

Source: Own processing, using data provided by WOS.

The second paper, "Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey" by Meryem Duygun Fethi and Fotios Pasiouras, provides a detailed review of 179 studies exploring operational research and artificial intelligence techniques in the process of assessing bank performance. In the first step, the broad applications of data envelopment analysis, recognised as the most widely used operational research technique in this field, are discussed. Subsequently, applications of other techniques, such as neural networks, support vector machines, and multicriteria decision aids, which have also been implemented in recent years in studies dedicated to bank failure prediction and solvency assessment, are examined, highlighting banks' sub-optimal performance.

In "Genetic algorithm-based heuristic for feature selection in credit risk assessment" by Stjepan Oreski and Goran Oreski, a paper with 270 citations, a new advanced heuristic algorithm, namely the hybrid genetic algorithm with neural networks (HGA-NN), used for identifying an optimal subset of features to improve classification accuracy and scalability in credit risk assessment, is presented. The results obtained in this research support the hypothesis that reducing the search space and using an incremental approach, together with the influence of initial population generation strategies in the genetic algorithm (GA), lead to a significant improvement in classifier performance. This improvement is of sufficient magnitude to be considered interesting from both scientific and practical perspectives.

The fourth paper, "Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy" by Yogesh K. Dwivedi, Nir Kshetri Laurie Hughes et al., summarises 43 contributions from experts in fields as varied as computer science, marketing, information systems, education, politics, hospitality and tourism, management, publishing, and healthcare. The authors recognise the productivity-enhancing capabilities of ChatGPT and suggest that it has the potential to bring significant gains in industries such as banking, hospitality and tourism, and information technology, helping to improve business activities, including management and marketing.

In "Genetic algorithms applications in the analysis of insolvency risk" by Varetto F, a comparison is revealed between a traditional statistical methodology for bankruptcy classification and prediction, namely linear discriminant analysis (LDA), and an artificial intelligence algorithm called genetic algorithm (GA). The study was carried out at Centrale dei Bilanci in Turin, Italy, and involved the analysis of 1920 Italian industrial companies between 1982 and 1995. The two types of experiments revealed that GA is a highly effective tool for diagnosing insolvency, even though the results obtained by LDA analysis could be considered superior to those obtained by GA.

The paper "Classifiers consensus system approach for credit scoring" by Maher Ala'raj and Maysam F. Abbod emphasises an innovative combination strategy based on classifier consensus for integrating multiple classification systems (MCSs) from different classification algorithms. Experimental results, analyses, and statistical tests confirm the effectiveness of the proposed combination method in improving prediction performance compared to all the baseline classifiers, including LR, MARS, and seven traditional combination methods, in terms of mean accuracy, area under the curve (AUC), H-measure, and Brier score. Model validation was performed using five credit scoring datasets from real-world environments.

In the paper "A comparative study on base classifiers in ensemble methods for credit scoring" by Joaquín Abellán and Javier G. Castellano, an experimental study is outlined in which several base classifiers are used in different ensemble schemes for credit scoring tasks. This study complements a previous one in which other more complex base classifiers were used. A simple classifier based on imprecise probabilities, the Credal Decision Tree (CDT), has been shown to show significant improvements over more complex models when used as a base classifier in an overall scheme for credit risk assessment.

With a citation count of 107 is the paper "Building the AI-Powered Organization. Technology isn't the biggest challenge. Culture is." by Tim Fountaine, Brian McCarthy, and Tamim Saleh. This paper analyses surveys of thousands of executives and collaboration with hundreds of clients. McKinsey identifies how companies can fully exploit the opportunities offered by artificial intelligence. A crucial issue is understanding the organizational and cultural barriers faced by AI initiatives, and the proposed approach aims to reduce these barriers to facilitate the successful implementation of these innovative technologies.

Figure 6 shows a map of the most cited works, with links to other works highlighted. Thus, at a threshold of at least five citations of an article, out of 1089 articles, 344 articles exceed this threshold, and there are only links between 84 articles. The most cited paper [41] has few links (3), the explanation being the year of the paper's publication, as there were very few studies in this area at the end of the 20th century, such as those by [42–44].

Thus, these links express the situation where two or more papers are cited by one person. Another paper, appearing almost 20 years apart, is that by [45], which assesses bank efficiency and performance using operations research and artificial intelligence techniques, recording two strong links, [46,47], papers that also investigate the impact of artificial intelligence on bank efficiency. The ranking is followed by [48], which records six strong links to other papers.

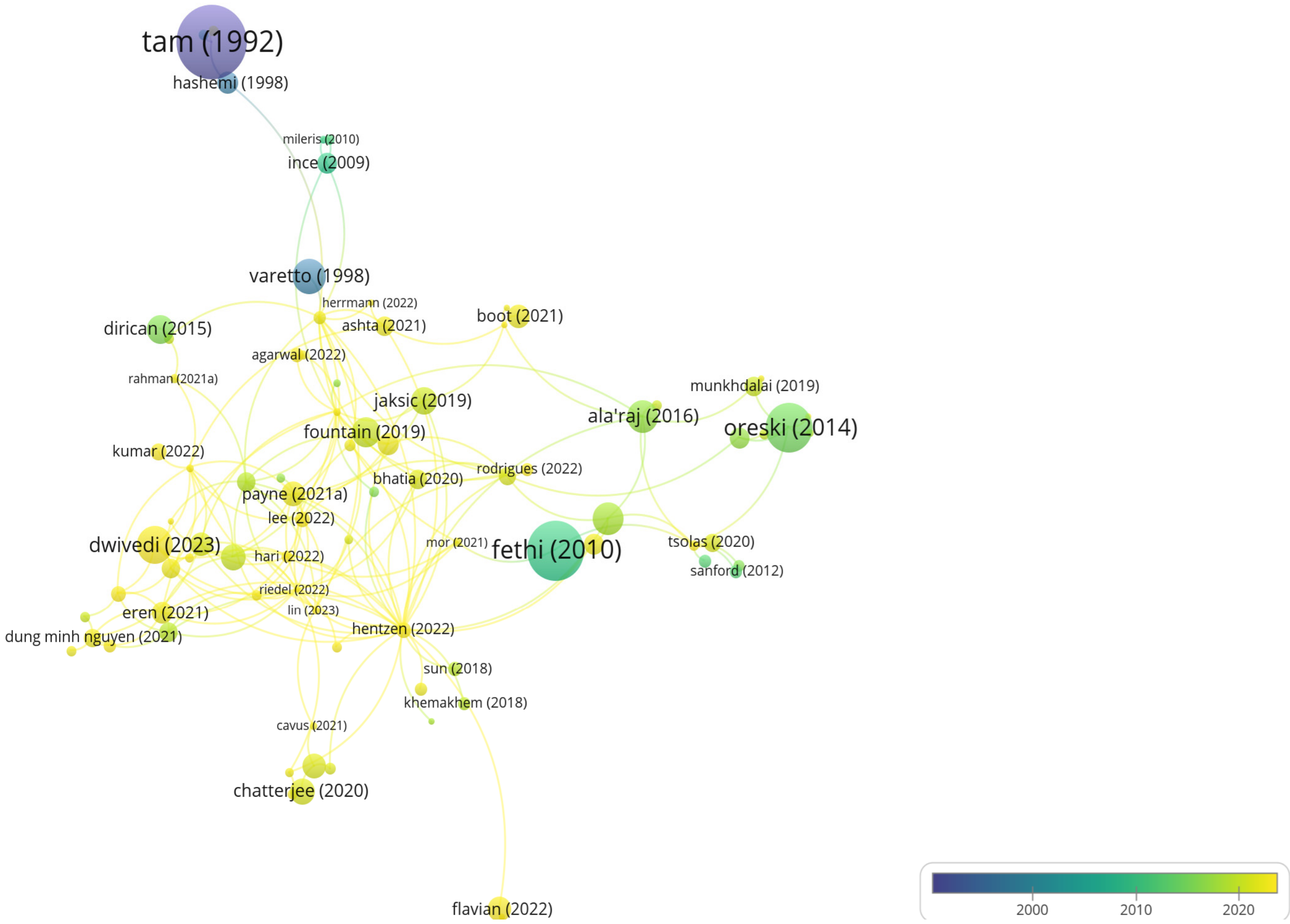

Figure 6. Co-appearance of the most cited works. Source: Own processing using VOSviewer, 2023.

4.2. Analysis of Journals

A total of 1089 papers were published/presented in 762 journals/conferences and a total of 806 articles were published in 157 journals. Figure 7 illustrates the total number of journals, with the minimum threshold of articles published in a journal being one. The number of publications varies, and based on the map, we can make a top list of journals where articles on artificial intelligence and banking have been published.

Thus, most articles (15) were published both in *The International Journal of Bank Marketing* (*IJBM*), which had an impact factor in 2022 of 5.3, and in *IEEE Access* with an impact factor in 2022 of 3.9. The top ranking is followed by the journal *Sustainability*, which had an impact factor in 2022 of 3.9, having published 13 articles on the subject over the years. Another journal where more than the sample average was published was *Expert Systems with Applications*, which had an impact factor in 2022 of 8.5, with 11 articles published here. The journals *Strategic Change: Briefings in Entrepreneurial Finance* and *Applied Sciences—Basel* published nine articles each, with an impact factor in 2022 of 2.8 and 2.7, respectively. The ranking of journals is followed by *Mathematics* with eight publications and an impact factor in 2022 of 2.4. The remaining journals have fewer than six articles.

If we analyse the ranking of these journals with the most articles in quartiles in the Web of Science (see Table 4), we find that two of them (*Expert Systems with Applications* and *Mathematics*) are classified in Q1 and the rest in Q2, which we consider to be a validation of the quality of the research papers published on the topic analysed in this study.

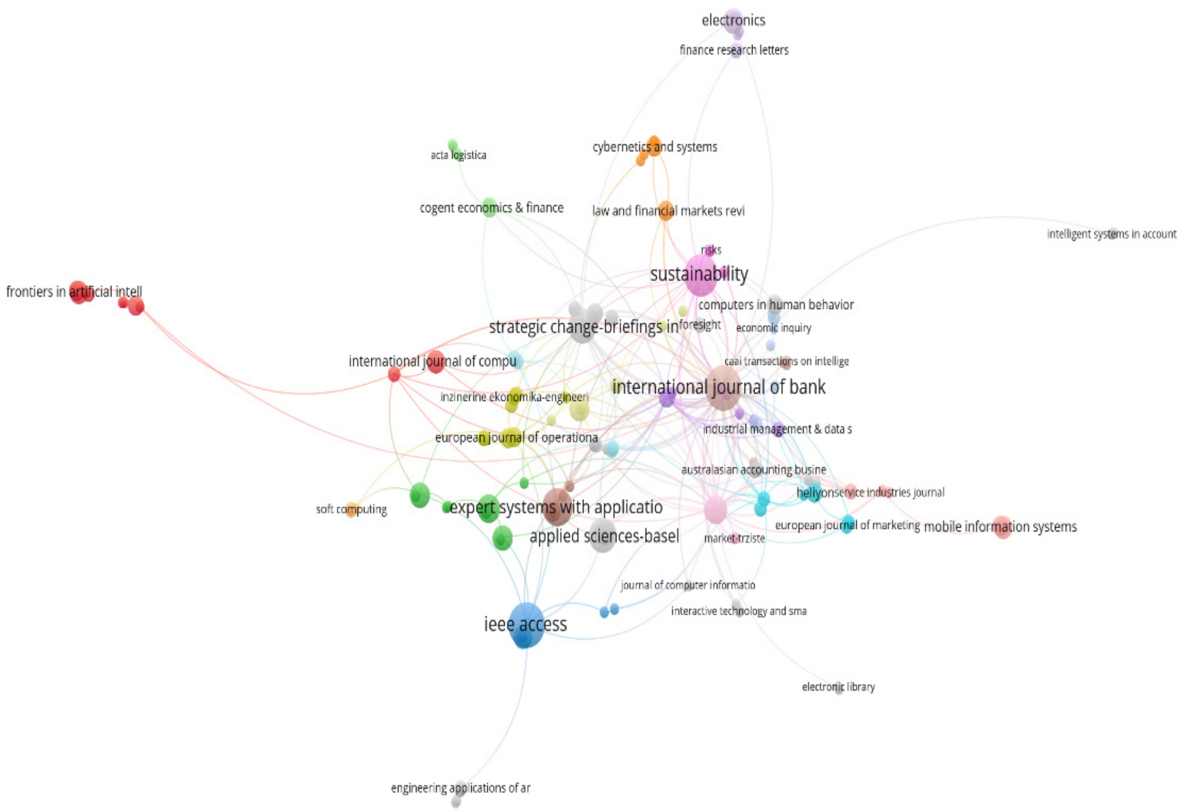

Figure 7. Journal publication activity. Source: Own processing using VOSviewer, 2023.

Table 4. Analysis of the journals.

No.	Journal	Domain	Impact Factor (2022)	Impact Factor over the Last 5 Years	Quartile	Number of Articles Published	Number of Citations
1	*International Journal of Bank Marketing*	Business	5.3	6.3	Q1	15	231
2	*IEEE Access*	Computer Science, Information Systems	3.9	4.1	Q2	15	150
3	*Sustainability*	Environmental Sciences	3.9	4	Q2	13	198
4	*Expert Systems with Applications*	Computer Science, Artificial Intelligence	8.5	8.3	Q1	11	618
5	*Strategic Change: Briefings in Entrepreneurial Finance*	Business, Finance	2.8	2.8	Q2	9	113
6	*Applied Sciences—Basel*	Engineering, Multidisciplinary	2.7	2.9	Q2	9	70
7	*Mathematics*	Mathematics	2.4	2.3	Q1	8	100

Source: Own processing, using data provided by WOS.

However, we emphasised that the journals with the most publications are not the most cited. According to the VOSviewer analysis, the most cited journals are *Expert Systems with Applications* (618 citations), *Management Science* (615 citations), *European Journal of Operational Research* (486 citations), and *The International Journal of Bank Marketing* (231 citations). The rest of the journals have less than 200 citations. These data indicate that the research published in these journals is considered by the academic community as significant and influential in the field of artificial intelligence and banking. Although journals with a high number of publications can provide a wide range of information and research, high citations indicate wider recognition and influence in the academic community.

5. Conclusions

At a time marked by rapid technological advances, this study represents a significant contribution to both theoretical understanding and practical application in banking and artificial intelligence. This research effort delves into the complexity and role of AI in redefining banking operations and strategies, presenting an analysis that is both timely and essential.

The theoretical contributions of the study are manifold. Firstly, it significantly enriches the discourse on digital transformation in the banking sector by bringing the transformative power of AI technologies to the fore. This is particularly important as the study provides a more nuanced perspective than the existing literature, which often focuses on more generalised discussions of digital technologies. The research therefore highlights the specific ways in which AI is reshaping banking practices, from improved customer service to more sophisticated risk management techniques. Secondly, the use of bibliometric analysis as a methodological tool highlights its academic novelty. This approach not only lends rigor to the review of the existing literature but also provides a structured means of identifying and classifying prevalent and emerging themes in AI in banking. The findings of this review bridge the gap between theoretical concepts and the practical realities of AI implementation in the banking sector.

From a practical point of view, the implications of this study for policy makers are particularly important. The derived insights provide a valuable guide for the development of regulatory frameworks that can nurture and support AI integration in the banking sector. This is vital as it addresses a critical need for regulatory structures that balance the imperatives of innovation with those of risk management, data privacy, and ethical considerations. In addition, the study draws attention to notable skills gaps and challenges in implementing AI in the banking workforce. This is key to highlighting the need for targeted education and training initiatives that could significantly enhance the AI capabilities of banking professionals, thereby facilitating a more efficient and effective integration of AI within the sector.

Furthermore, a more explicit delineation of the practical ramifications for industry practitioners and policy makers could enhance its utility and applicability in real-world contexts.

For banking professionals, the study's findings offer valuable insights into key areas where AI is leveraged to gain competitive advantage. Strengthening the link between the findings and practical implications could involve providing concrete examples or case studies illustrating how specific AI applications, identified through the analysis, have been successfully implemented by financial institutions to improve operational efficiency, enhance customer experiences, or mitigate risks. Additionally, highlighting emerging trends and patterns in AI adoption could inform strategic decision-making processes, enabling banking professionals to anticipate market shifts and proactively align their organizations' initiatives with evolving industry dynamics.

Similarly, for policy makers, the study's implications extend beyond the realm of industry competitiveness to encompass regulatory considerations and ethical frameworks surrounding AI integration in banking. By elucidating the current state of research and identifying underexplored areas, the study can inform the development of nuanced regulatory frameworks that balance the promotion of AI innovation with the protection of consumer interests and ethical standards. Furthermore, by highlighting potential areas of concern or risk associated with AI deployment in banking, policy makers can proactively address regulatory gaps and foster a conducive environment for responsible AI adoption.

Thus, while the study's findings provide a solid foundation for understanding the role of AI in the banking sector, strengthening the link between these findings and their implications for banking professionals and policy makers would amplify its practical relevance and facilitate informed decision making within the industry and regulatory spheres. This could be achieved through contextualizing the findings within the broader landscape of banking operations, illustrating their practical implications through relevant examples, and outlining actionable recommendations for industry stakeholders and policy makers alike.

However, the study is not without limitations. Its reliance on bibliometric data, primarily of a quantitative nature, may limit the scope to articles and journals indexed in selected databases, which may overlook important qualitative nuances and insights from non-indexed or lesser-known publications. In addition, the rapid pace of technological developments in the field of artificial intelligence suggests that the survey results may require continuous updating to remain relevant and reflect the latest trends and developments in the field.

Also, the study paves the way for several future research directions. Complementing the bibliometric approach with qualitative research methodologies, such as interviews and case studies, would provide a richer and more detailed understanding of the practical challenges and successes associated with implementing AI in the banking sector. Furthermore, future research could explore the interaction between AI and other emerging technologies such as blockchain, quantum computing, and advanced analytics, uncovering new dimensions and possibilities for digital transformation in the banking sector.

In conclusion, this study provides significant contributions to our understanding of the role of AI in banking, providing valuable insights for both academic researchers and industry practitioners. However, the dynamic nature of AI technology and the banking sector requires continued research to keep pace with emerging trends, ensuring that the discourse remains relevant and conducive to future innovation and growth in the field.

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