AI-driven Financial Decision-Making: A Bibliometric Review

Aradhana Sorout*[1], Anil Anand Pathak[2], NP Singh[3]
[1]School of Business Management and Commerce, MVN University, Haryana, India
[2]Management Development Institute (MDI), Gurgaon, Haryana, India
[3]School of Business Management and Commerce, MVN University, Haryana, India
aradhana.sorout@mvn.edu.in, Aradhanasorout01@gmail.com

Abstract

Artificial Intelligence (AI) has emerged to be a significant contributor in the field of finance. From algorithmic trading and robo-advisory services to fraud detection, AI-driven technologies are changing how people make financial decisions. It leads to a paradigm shift in the financial decision making. The main objective of this study is to highlight the increased focus on AI-driven financial decision-making. A bibliometric analysis of published research over the last decade (2016-2025) was conducted. By using a systematic framework PRISMA, 1276 research articles were retrieved from the Scopus database. To identify the key trends, influential themes and evolving areas, various bibliometric techniques were used. Over the recent years, the role of AI in the domain of finance has drastically increased. Network mapping and co-citation analyses also revealed strong collaborations between technology and finance fields. Generative AI and sustainable finance were the emerging themes of research. While highlighting the growing importance of AI in finance, the study also provides future aspects of research.

Keywords: Artificial Intelligence (AI), Finance, Bibliometric

1. Introduction

Artificial intelligence (AI) has had a substantial impact on various industries, among which the finance industry has been the most impacted. It has transformed from a future promise into a present reality in finance. AI is defined as “the imitation of human intelligence processes by machines, particularly computer systems” (Russell & Norvig, 2016). The convergence of AI and finance, sometimes known as Fintech (financial technology), has resulted in unique tools and models (Roy et al., 2025). Over the last decade, AI applications have reshaped the ways firms, markets, and investors make financial decisions. From machine-learning models for forecasting to automated investment platforms, AI adoption has evolved in the domain of investor behavior (Sorout et al., 2025). For financial prediction and reducing biases while decision making, AI is used as a supporting tool. Since the role of AI in the field of finance in increasing, it becomes essential to uncover the trends in artificial intelligence. For academicians, practitioners, policymakers and other concerned parties also, it is important to study the dimensions of AI. Increased reliance of financial industry on AI may result into both benefits as well as difficulty. Therefore, understanding its impact becomes crucial.

The academic focus on AI in the field of finance has increased over the past years. And it is still anticipated to continue, as the technology develops. The use of artificial intelligence in the domain of finance is widespread. AI is used in automating wealth management, fraud detection and

K. Sharma et al. (eds.), *Proceedings of the 12th AIM-AMA Sheth Foundation Doctoral Consortium & International Marketing Conference 2025 (IMCDC 2025)*, Advances in Economics, Business and Management Research 370,
https://doi.org/10.2991/978-94-6239-608-1_3

predicting market behavior while investing (Brynjolfsson & McAfee, 2014; Sorout et al., 2025). Beyond the role in financial decision making, its integration into KMS has further transformed businesses (Sorout & Singh, 2025). Despite of widespread discussions on AI adoption, there are still few systematic studies on the development and research trends in the literature on AI in finance. Previous research has often focused on specific AI technologies or their applications in particular areas only (Cao, 2022; Dixon et al., 2020). There is dearth of a thorough overview which highlights the increased focus on the role of AI in the domain of finance. To overcome this gap in the existing literature, a thorough literature review is required. Therefore, to highlight the major research trends, significant contributions and to provide future research directions, a bibliometric analysis is thought to be conducted. The main objective of this article is to bridge the gap by providing a comprehensive summary of AI and research in finance. The study attempts to determine the most referenced papers, significant authors and important research issues in the field. It also focusses on identifying emerging patterns that could affect future use of AI in finance. To bridge the gap in the literature, the following research questions were framed:

i. What are the latest trends in the field of Artificial Intelligence (AI) and Finance?
ii. Which sources and contributors in the extant literature are the most important, significant and impactful that have contributed to the field of AI and Finance?
iii. What is the potential for future study or possible future research directions in this field?

To answer the above-mentioned research questions, a bibliometric analysis of the publications in the field of Artificial Intelligence (AI) and Finance is conducted. 'Citation analysis' is used to identify the most prominent authors, journals, papers, institutions, and countries (Donthu et al., 2021). Similarly, a 'bibliographic coupling analysis' is performed to identify commonly cited papers (Mukherjee et al., 2022). Conceptual and Intellectual structure which includes citation analysis and author influences were also analysed. A 'co-citations analysis' will establish whether the two articles are cited in the same publication. Additionally, 'co-authorship analysis' and 'co-occurrence analyses' will be used to identify thematic patterns in the research within the domain of Artificial Intelligence (AI) and Finance. The findings from this study could aid researchers in gaining a better view of the role of AI in finance.

This research paper is divided into six sections. The first section includes the introduction containing the research objectives of the study. The second section details the background/context of bibliometric analysis, followed by the third section which states the methodology used in the research study. The fourth section contains the review of some of the selected papers from the literature based on citations and relevance. The fifth section presents findings of the bibliometric analysis. Finally, section six details the conclusion of the study.

2. Bibliometric analysis

Bibliometrics is one of the most reliable research methods, effectively eliminating subjectivity bias in synthesizing qualitative literature (Nerur et al., 2008). Using quantitative methodologies, bibliometric studies generate comprehensive summaries of extensive bibliographic data (Pritchard, 1969; Ragazou et al., 2022; Chen & Xiao, 2016; Zupic & Cater, 2015; Broadus, 1987). It is an attempt to manage huge information through conceptualization, trend analysis and analysing structural composition of a domain in scientific research (Passas, 2024). Extensive use of bibliometrics has been made to evaluate themes (Blanco-Mesa et al., 2017), journals (Donthu et al., 2020), institutions (Merigio et al., 2019), and countries (Mas-Tur et al., 2019) in the existing body of literature. To uncover publication trends, influential works and key contributors to the domain of AI in finance, this analysis was used in the study. The main stages of bibliometric analysis are shown in fig. 1 (Passas, 2024).

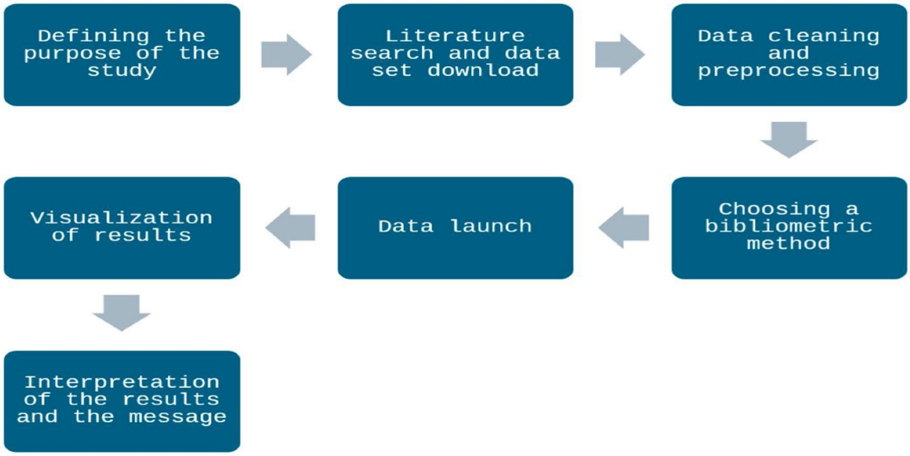

Figure 1. The main stages of bibliometric analysis

3. Research methodology

A bibliometric analysis was conducted on literature published in Scopus-indexed journals related to the domain of AI and Finance. As discussed in Section 2, Bibliometric analysis is quantitative method and facilitates literature review for big databases (Ellegaard & Wallin, 2015; Chen & Xiao, 2016). A comprehensive review with regard to co-authorship patterns and intellectual structure was conducted using Vos viewer. Key publications, authors, and journals that influenced discussion, trends over time and top contributors were identified. Bibliometric analysis provided an overview of literature on Artificial Intelligence (AI) adoption in financial decision making using both descriptive and network analyses. The overall number of publications and citations are highlighted in the descriptive analysis performed using bibliometric tools (Tsay, 2009).

As per Donthu et al., (2021), a methodical procedure was followed to conduct the review. In the first phase, scope of the review was defined followed by research analysis in the second phase. Research techniques suitable for the study were identified and a database for the study was extracted. For bibliometric analysis, research papers selected were based on certain criteria's which is detailed in the section. The data collected from database and findings were interpreted. In addition to this, selected research papers were reviewed at the end to bring out the theme of the past researchers based on citation and relevancy. Figure 1 (given below) provides an overview of the research process and the outcomes of the research.

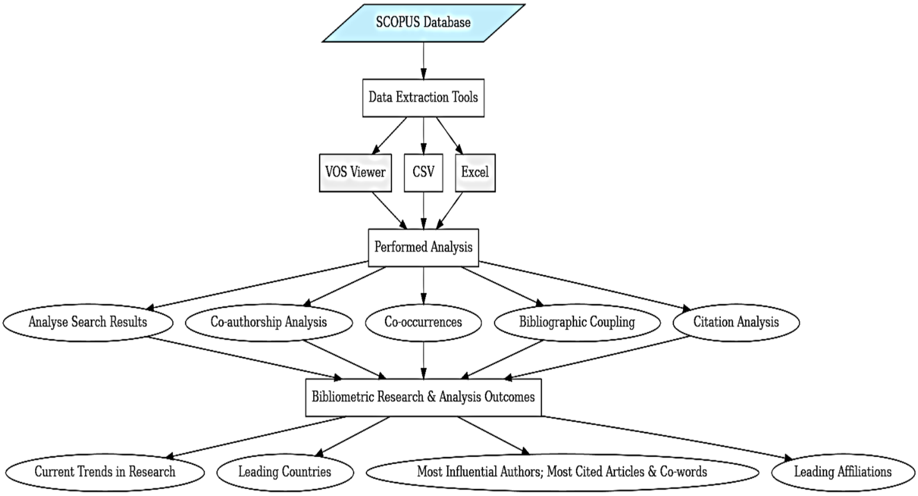

Figure 2. Analytical techniques used and the expected outcomes of the bibliometric investigation

3.1 Methodology for searching and data extraction procedure

Table 1 (given below) presents the article selection criteria for performing the bibliometric analysis. After many iterations, a thorough search term was created by choosing frequently used synonyms or related terms connected to the main theme of the research. The study concentrated on identifying significant contributions and new developments in the fields of AI adoption and financial decision-making by narrowing the search to the most relevant terms. All kinds of literature that were indexed in the Scopus database were searched using it. The time frame was restricted to last decade i.e. 2016 to 2025 as this decade represents the most dynamic phase of AI integration into financial systems. Following advancements in machine learning and the beginning of the industry 4.0 (Gomber et al., 2017), research in this area has significantly increased. Moreover, in the post-COVID period also, AI adoption in finance has accelerated. Instead of restricting the review to only high-ranking journals (A*, A, and B category or WoS journal articles), all category journal articles from the Scopus database were used to offer an unbiased perspective of the study (Khudzari et al., 2018). Research articles and conference papers were selected as document type and documents only in English language were considered for analysis.

Table 1: Filtering/ Search criteria for selecting articles

Search Criteria	Number of articles resulted
Filtering Criteria	
Search Engine: “Scopus” **Search date:** “20 October 2025” **Search term:** “AI” OR "Artificial intelligence" AND "Finance" OR "investment decision-making" OR "robo-advisors") AND TITLE-ABS-KEY	7677
Articles screened out: 118 (Based on language)	
Language: English	7559
Articles screened out: 954 (Based on time frame)	
Time Frame: 2016 to 2025 (10 years)	6605
Articles screened out: 4290 (Based on subject field)	
Subject Field: “Business, Management and Accounting”, “Economics, Econometrics and Finance”, “Environmental Science”, “Social Sciences”	2315
Articles screened out: 1039 (Based on relevance of abstracts)	
Document Type: Article, conference paper	1276
Articles included in bibliometric analysis	

3.1.1 Establishing the proper search terms

The terminology used was based on a combination of “Artificial Intelligence”, "Investment decision-making" and “Finance”. These terms have been derived from established literature, which are repeatedly used in the current paper. The title-abstract-keywords (TIT-ABS-KEY) search query was used using the search string “AI” OR "Artificial intelligence" AND "Finance" OR "investment decision-making" OR "robo-advisors". This resulted into 7677 documents, the search results were confined to the language of English only (7559 documents). The time period was taken from the year 2016 to 2025 (10 years) which resulted into 6605 documents. Further the search results were confined to the areas of “Business, Management and Accounting”, “Economics, Econometrics and Finance”, “Environmental Science” and “Social Sciences” resulting into 2315 documents. Using the PRISMA framework, screening of articles was performed, some duplicates and irrelevant articles were removed using manual screening. The final analysis was conducted on 1276 documents screened using a methodical approach. Figure 3 summarises the selection strategy using PRISMA framework.

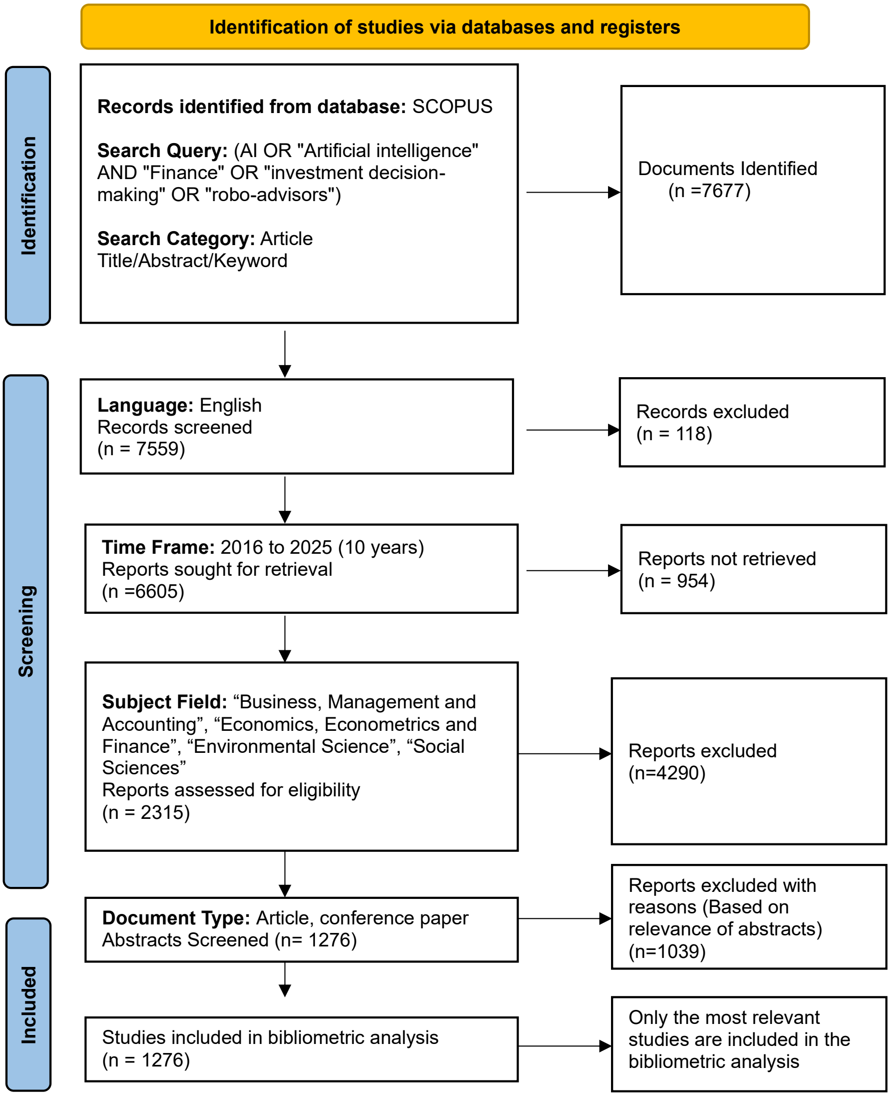

Figure 3. Article screening process for bibliometric analysis using PRISMA
(Source: Page MJ, et al. BMJ 2021;372: n71. doi: 10.1136/bmj. n71)

3.1.2 Data Collection

Initially many databases were considered for data extraction like Google Scholar, Dimensions, Web of Science & Scopus. But the database of Scopus was selected as it provided a large collection of double-blind peer-reviewed publications, most of which appear in high-impact-factor journals. (Groff et al., 2020). Using a methodical approach- PRISMA framework, the authors arrived at a count of 1276 articles (Table 1). The filtering criteria is shown in figure 3 along with the number of articles excluded from the review. Inclusion of newly published research papers in the field may lead to inaccuracies in bibliographic and bibliometric data collected from Scopus (Donthu et al., 2021). To deal with this issue and to remove the inaccurate records that could have led to an incorrect analysis, authors manually refined the articles retrieved. Therefore, articles were refined based on relevancy of the abstracts and other parameters in alignment with the recommendations of Zupic and Cater, (2015) and Donthu et al., (2021). The study conducted a search for bibliometric data along with data visualization and analysis of the findings.

3.1.3 Selected techniques for analysis

In this study, bibliometric analysis is used which is a set of quantitative tools to examine and measure both text and information (Mishra et al., 2018; Goyal & Kumar, 2021). To gain fresh perspectives from existing literature reviews, this technique is used (Suominen et al., 2016; Groff et al., 2020). Various techniques of bibliometric analysis were used to analyse the current scenario based on evaluation of past studies Donthu et al., (2021). Performance analysis which includes evaluating the impact of researchers, institutions, and countries using metrics such as total publications, author contributions, and citation-related indicators (Van Raan, 2014). To understand the emergence of research domain and identification of key trends in the field of study other techniques were also used, such as trend analysis, authorship analysis, citation analysis, bibliographic coupling and co-word analysis (Gao et al., 2021; Hossain et al., 2022).

Bibliographic coupling and co-occurrence analysis helped in identifying the research connections in the same field and emerging themes in the area. Keyword analysis, on the other hand, identified the most prominent subjects, whereas co-word analysis revealed the area's conceptual structure. The data was mostly mapped and visualized using Vos Viewer, with some bibliographic analysis performed in MS Excel.

4. Literature review (selected papers from the literature)

An extensive review of the literature was done in order to provide contextual findings to support the bibliometric analysis. To highlight the themes, methodologies, and findings from the previous studies, pertinent papers from the body of existing literature were examined. The inclusion criteria were based upon relevancy of the content and quality of the research paper. The research papers with the highest number of citations indicating impact in the field were considered. To ensure that only the most relevant and high-quality research contributions were included, a comprehensive reading of the abstract and the full paper within the domain of AI adoption in Finance or AI driven investment decision-making was done. A summarised review is presented in table 2.

Table 2: Comprehensive review of selected articles from literature

Authors & Year	Objectives	Methods Used	Key Findings	Conclusion	Relevance to the field
Dwivedi et al. (2021)	To examine multidisciplinary perspectives on AI challenges, opportunities, and research agenda.	Workshop-based qualitative synthesis + Scopus literature review.	Identified opportunities (automation, decision support) and challenges (bias, governance, transparency).	AI requires explainability, policy frameworks, and human-AI collaboration.	Provides macro-level issues affecting finance (trust, transparency, regulatory governance).
Belanche et al. (2019)	To understand factors influencing robo-advisor adoption.	Survey (n=765), SEM analysis, moderation testing.	Attitudes, usefulness, and subjective norms drive adoption while familiarity moderates effects.	Robo-advisor adoption depends on psychological and sociodemographic factors.	Explains behavioural acceptance of AI-driven investment tools.
Androutsopoulou et al. (2019)	To improve citizen–government interaction using AI chatbots.	System architecture design + validation with government case scenarios.	NLP-based chatbots handle complex queries, enable richer communication.	AI chatbots are scalable and effective if backed by integrated data systems.	Lessons apply to AI financial chatbots (customer service, KYC automation).
Dowling & Lucey (2023)	To assess ChatGPT's usefulness for finance research tasks.	Reviewer-based evaluation of AI-generated content.	Useful for idea generation but weak for literature synthesis; output quality depends on user expertise.	Generative AI complements but not replaces finance researchers.	Highlights utility & limitations of generative AI in financial analysis/research.
Ma et al. (2018)	To predict P2P loan default using LightGBM & XGBoost.	ML modelling with real Lending Club data + multidimensional data cleaning.	LightGBM outperforms XGBoost; reduces loan losses significantly.	Data cleaning + advanced ML greatly improve credit risk prediction.	Demonstrates strong ML applications for credit scoring.

Mhlanga (2020)	To analyse AI's role in promoting digital financial inclusion.	Documentary & conceptual content analysis.	AI enables inclusion through fraud detection, chatbots, risk assessment.	Government/industry must scale AI for inclusion.	Shows AI's role in expanding access to financial services.
Flavián et al. (2022)	To examine technology readiness & awareness affecting AI investment services usage.	Survey (n=404) + SEM + post-hoc analyses.	Optimism ↑ adoption; discomfort unexpectedly ↑ adoption when AI reduces user effort.	Awareness, naming, and readiness shape AI service adoption.	Deep behavioural insight for AI investment products.
Luckin & Cukurova (2019)	To advocate learning-science-driven AI design in education.	Case studies + conceptual framework.	Domain expertise improves AI system design.	Interdisciplinary collaboration is essential.	Incorporate behavioural finance & regulation into AI models.
Mhlanga (2021)	To study AI's impact on SDGs in emerging economies.	Content analysis of AI-related SDG literature.	AI improves data systems, inclusion, agriculture, infrastructure.	AI accelerates SDG progress but needs governance.	Emphasizes AI-driven inclusion & infrastructure relevant for emerging financial systems.
Ahmed et al. (2022)	To map AI/ML in finance through bibliometric review.	Scopus dataset (n=348), RStudio, VOSviewer.	Growth in themes like bankruptcy prediction, AML, portfolio ML.	AI-finance research is expanding & clustering into strong themes.	Helps identify key AI finance research streams.
Palmié et al. (2020)	To study FinTech ecosystem evolution & disruptive innovations.	Conceptual synthesis of ecosystem literature.	AI & FinTech disruption emerges at ecosystem- not firm-level.	Need ecosystem-level research, not firm-level.	Explains how AI reshapes financial ecosystems & competition.
Kushwaha et al. (2021)	To identify emerging management areas powered by big data.	Systematic literature review + text mining (NLP, network analysis).	Big data drives new sub-fields including data-driven finance.	Big data creates new avenues of research.	Places AI-finance within broader data-driven management evolution.

Hajek & Henriques (2017)	To detect financial statement fraud combining text & numbers.	ML comparison study: ensemble methods, Bayesian networks, text mining.	Ensemble models best for fraud detection; hybrid features enhance accuracy.	ML + textual data strengthen fraud detection tools.	Demonstrates AI application in forensic finance & compliance.
Yigitcanlar & Cugurullo (2020)	To evaluate sustainability of AI in smart cities.	Comprehensive viewpoint literature review.	AI impacts sustainability, governance, and urban services.	Need responsible & sustainable AI adoption.	Impacts financial decision areas tied to urban data (insurance, lending).

Dwivedi et al., (2021) offered a multidisciplinary examination of AI's emerging opportunities and challenges using a workshop-based qualitative synthesis, concluding that AI's future impact in finance lies on explainability, governance, and responsible adoption. Complementing this macro-level perspective, Belanche et al., (2019) empirically analysed robo-advisor acceptance through a survey of 765 users and structural equation modelling, finding that attitudes, perceived usefulness, and subjective norms shape adoption, thereby highlighting behavioural determinants in AI-enabled financial services. Similarly, Flavián et al., (2022) examined technology readiness among potential robo-advisor users using SEM. The study revealed that optimism increases AI adoption and even technological discomfort may encourage AI use when it reduces user effort. The study highlighted consumer interactions with AI in financial decision-making.

In the domain of applied predictive modelling, Ma et al., (2018) leveraged high-dimensional data cleaning and advanced machine learning algorithms on Lending Club data. Finding suggest that these algorithms improved default prediction accuracy and reduced real losses, demonstrating AI's ability to materially enhance credit risk assessment. Likewise, Hájek and Henriques (2017) used text mining and ensemble ML to detect financial statement fraud. The research focused on highlighting the role of AI in financial forensics. Dowling and Lucey (2023) assessed ChatGPT's utility for finance research through reviewer evaluations. They observed that generative AI helps with data identification and idea generation, it is still lacking in methodological rigor and literature synthesis. The study highlighted both potential and limitations of generative AI in financial research workflows. Ahmed et al., (2022) conducted a bibliometric analysis of 348 studies using RStudio and VOSviewer. He identified key thematic clusters in AI-finance research, including bankruptcy prediction, portfolio optimization, and anti-money-laundering, mapping the intellectual structure of the field. Through a systematic review and text-mining analysis, Kushwaha et al., (2021) showed how big data and AI are driving new managerial sub-disciplines, including data-driven finance.

Mhlanga (2020) used documentary analysis to show role of AI in digital financial inclusion. He argued that AI strengthens digital financial inclusion through improved risk management and reduced information asymmetry. While in his later study, he focused on role of AI in achieving SDGs by enabling inclusive finance, infrastructure reliability, and poverty reduction (Mhlanga, 2021). Palmié et al., (2020) used a conceptual ecosystem-level analysis to demonstrate how

FinTech and AI evolve through disruptive innovation ecosystems. Yigitcanlar and Cugurullo (2020) also reviewed role of AI in smart cities and noted implications for financial systems linked to urban sustainability, data governance, and technological disruption. Androutsopoulou et al., (2019) designed and validated an AI-powered financial chatbot used in customer support, KYC processes, and service automation. Luckin and Cukurova (2019) used case studies to highlight the role of AI in enhancing educational technologies. The findings suggest integration of behavioural finance, risk psychology, and regulatory constraints into AI model design to improve relevance and trustworthiness.

5. Findings

The findings of the study show the bibliometric analysis of the articles. The research articles were selected in a methodological way, using PRISMA model. As suggested by (Zupic and Cater, 2015), various bibliometric analysis or techniques were applied on the retrieved data. The findings from the analysis are presented in the form of bibliographic figures and tables. The section is divided into various sub-sections, containing the performance analysis and bibliographic networks.

5.1 Performance analysis

The publication trend presented in Figure 4 shown an upward trend in research related to artificial intelligence (AI). Over the past decade, the role of artificial intelligence has increased within the domain of finance. From the year 2019, the interest towards integration of AI techniques in financial decision making has drastically increased. This increase continues to expand in the year 2021 and 2022 with 76 and 103 publications respectively. Over the last three years i.e. 2023, 2024 and in the current year 2025, AI has emerged as a mainstream theme of research. Many researchers have contributed in this area, specifically within the domain of finance. Due to advancements in generative AI and FinTechs, the academic attention to this field has increased. The trend not only highlights the academic relevance but also the need for interdisciplinary research. The rise in the academic publications may also be attributed to issues of risk management and financial inclusion.

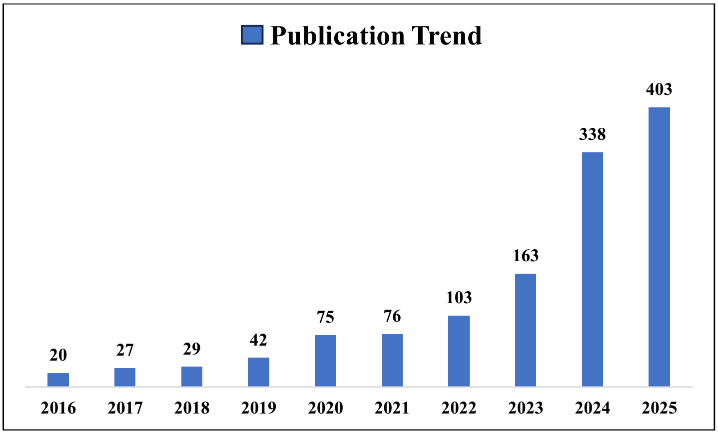

Figure 4. Publication trend of "Artificial Intelligence and finance" research

5.1.1 Contribution by subject area

The distribution of publications across subject areas reveals the multidisciplinary nature of research at the intersection of artificial intelligence (AI) and finance. As shown in Table 3, the highest research contribution is from the area of Business, Management and Accounting (20.12%). It indicates adoption of AI in investment decision-making, financial analytics, risk modelling are increasingly prioritized within the domain of management. Other disciplines also contribute meaningfully as well, reflecting the methodological backbone of AI research.

Table 3. Publications by subject area

Subject Area	Articles	Percentage (%)
Business, Management and Accounting	639	20.12
Computer Science	558	17.57
Social Sciences	526	16.56
Economics, Econometrics and Finance	429	13.51
Decision Sciences	332	10.45
Engineering	221	6.96
Mathematics	131	4.12
Energy	87	2.74
Arts and Humanities	75	2.36
Environmental Science	71	2.24
Medicine	60	1.89
Psychology	47	1.48

5.1.2 Notable authors, organizations and nations in research for AI and financial decision making

The analysis of documents by authors, institutions, and countries reflects the scholarly productivity and geographic distribution of research in the field of artificial intelligence and finance. As presented in Table 4, Mhlanga (2020) emerges as the most influential contributor with 881 citations and four publications, indicating a strong research focus on AI-driven financial inclusion and Industry 4.0 transformations. This is followed by Belanche (2019), Casaló (2019), and Flavián (2022) with 847 citations. In terms of institutional contributions, the "University of Johannesburg" and "University of Zaragoza" rank among the leading institutions with 881 and 847 citations achieved out of 4 & 2 documentation publication by the institute respectively. United Kingdom is the most productive country, publishing research papers with highest number of citations (5808) in the domain of AI and Finance.

Table 4. Notable authors, organizations and nations in research for AI and Investment decision making

TC	Author	TP	TC	Institution	TP	TC	Country	TP
881	Mhlanga, D.	4	881	University of Johannesburg	4	5808	United Kingdom	106
847	Belanche, D.	2	847	University of Zaragoza	2	4994	India	193
847	Casalo, L.V.	2	634	Trinity Business School	4	3713	China	262
847	Flavion, C.	2	449	DCU Business School	3	3179	United States	186
435	Dowling, M.M.	2	430	University of Aegean	2	2953	Netherlands	28
430	Loukis, E.N.	2	384	Queensland University of Technology	2	2851	Denmark	9
384	Yigitcanlar, T.	2	372	Harbin Institute of Technology	2	1633	Australia	57
256	Wincent, J.	2	321	Rennes School of Business	4	1315	Spain	43
249	Dwivedi, Y.K.	3	264	University of St. Gallen	3	1198	United Arab Emirates	27
199	Thalmann, S.	2	261	Columbia University	5	985	Ireland	10

Note(s): TC= 'Total Citations' & TP= 'Total number of article(s) publications'

5.2 Bibliometric Maps

The co-occurrence analysis for bibliographic coupling for documents, co-citation analysis, author keywords and maps of co-authorship for authors and nations were developed in Vos viewer.

5.2.1 Co-citation analysis (Cited References)

According to Donthu et al. (2021), Co-citation analysis depicts the knowledge foundations of a field. Co-citation refers to the methodology of mapping the frequently cited publications i.e. the citations of two documents by a third document. The authors conducted the co-citation analysis of 775 articles by keeping a threshold of minimum 2 citations. The largest and most central cluster, which includes frequently cited authors such as Belanche, Barredo-Arrieta, Adadi, and Bolton, reflects the dominant research stream focusing on AI adoption, behavioural acceptance, explainable AI, sentiment analysis, and algorithmic decision-making in financial services. The visualisation also shows strong cross-linkages across disciplines, emphasizing that AI-finance research is evolving through interdisciplinary integration.

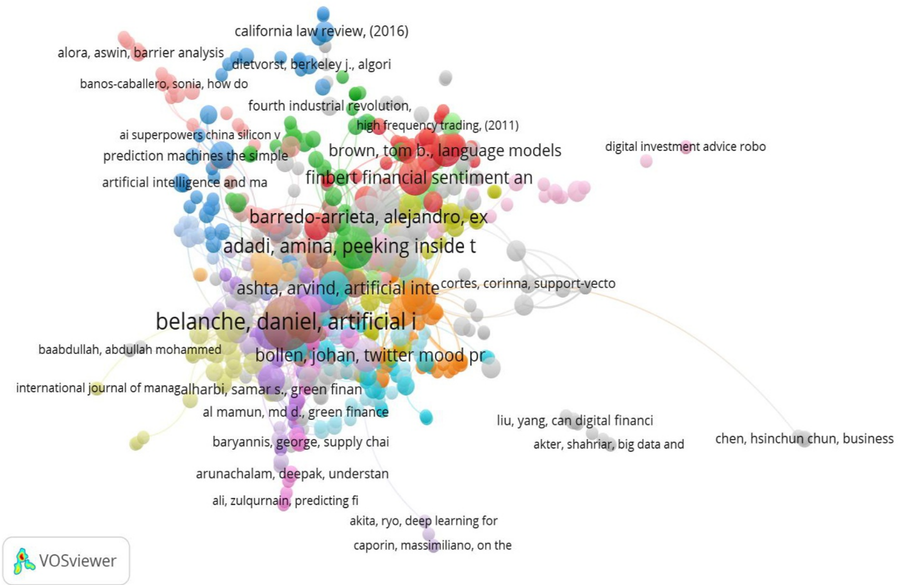

Fig. 5. Co-citation analysis as a network visualisation, based on references

From the above fig. 5, it is visible that Belanche, D., Daniel D. and Adadi, Amina is connected and all have a link strength of 127 with 2 citations each.

5.2.2 Bibliographic coupling (documents analysis)

Bibliographic coupling refers to the referencing of third document by two documents together (Van and Waltman, 2013; VanEck and Waltman, 2017). It is an enhanced form of Co-citation analysis as takes into consideration even those articles which are less co-cited. The visualisation reveals several tightly interconnected clusters, indicating that multiple research streams in the field draw upon similar foundational literature. The authors performed bibliographic coupling by keeping minimum citation of documents as 2 and thus 715 documents were included. At the centre of the network, Dwivedi (2021) stands out as the most influential and highly coupled document with 2791 citations, reflecting its broad conceptual contribution to AI's multidisciplinary challenges and future research agenda. Followed by, Belanche (2019) with total link strength (TLS) of 13 and 546 citations followed by Dowling (2023) with 2 TLS and 423 citations and Androutsopoulou (2019) with 2 TLS and 430 citations.

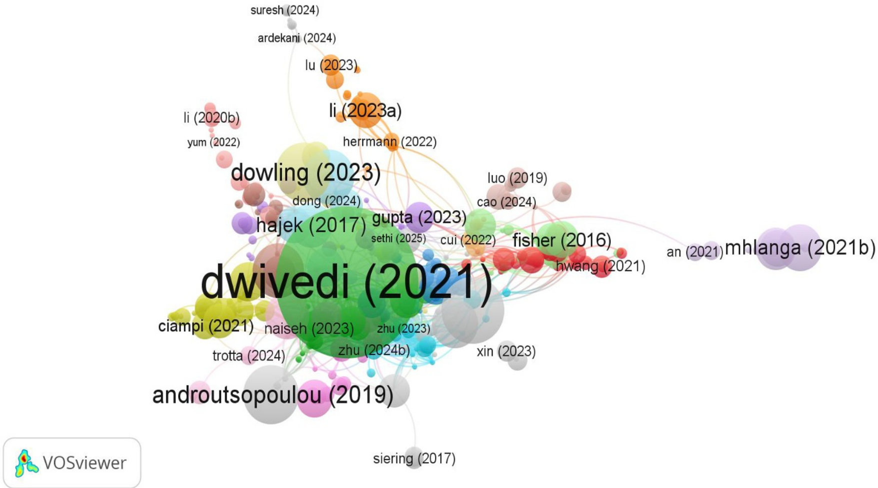

Fig. 6. Network visualization of bibliographic coupling (documents) for all based on total link strength (TLS)

5.2.3 Co-authorship Analysis (Based on Authors)

The authors who have co- authored the documents can be examined using the co-authorship option in Vos Viewer. The co-authorship analysis represents the relationships between the items (like authors) and identifies how authors collaborate in a related research area. The co-authorship network visualisation in Figure 7 highlights the collaborative structure among researchers contributing to the field of artificial intelligence and finance. The largest and most interconnected cluster centres around Zhang, W. (2025), who forms the core of a multi-author collaboration network. For the analysis, publication number per author is restricted to 2 with minimum citation of 2. A total of 179 authors were selected under the designed criterion. Three clusters were formed, keeping number of publications per author restricted to 2 with a total link strength of 20.

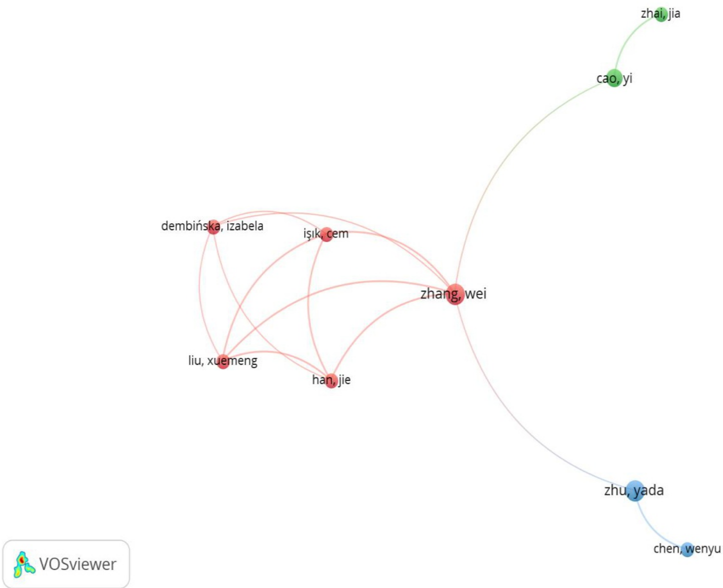

Fig. 7. Co-authorship analysis presented as a network visualisation, based on the authors

5.2.4 Co-authorship Network (Based on participation of Countries)

The retrieved database has details of researchers from 99 different countries who contributed towards the publication. Figure 8 presents co-authorship network among different countries generated with the help of Vos Viewer. A minimum threshold of 2 publications and single citation was kept as an eligibility for selection of a country. A total of 83 countries got selected under the scheduled criterion. China, India and the United Kingdom appear as the largest and most influential nodes, indicating that these nations contribute the highest number of publications. China was ranked first with a total of 262 documents followed by India (193 documents) and the United Kingdom (106 documents).

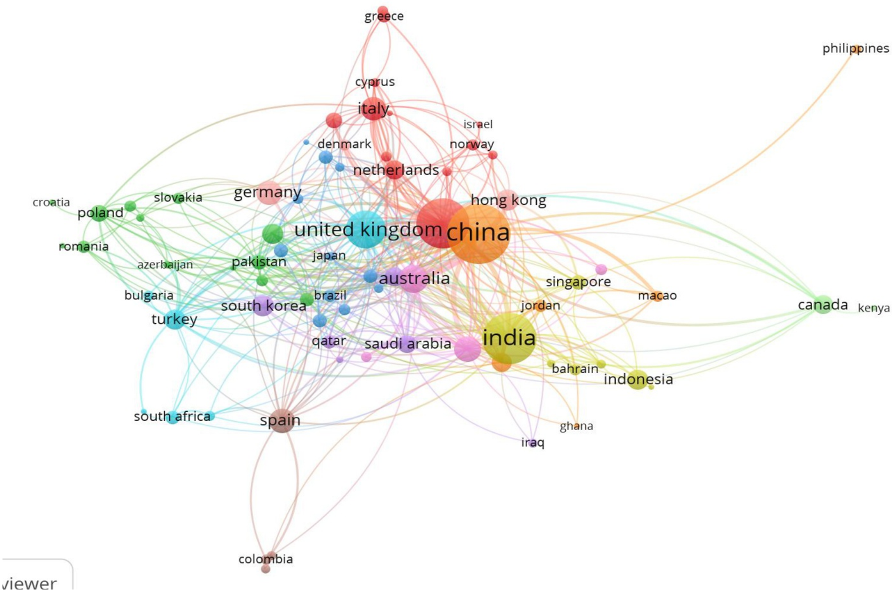

Fig. 8. Co-authorship Network based on participation of Countries

Australia, Germany, the Netherlands, Italy, and Spain also occupy important positions in the network, forming mid-sized clusters that actively collaborate with both leading and emerging research nations. The dense web of cross-country connections demonstrates that research in AI and finance is highly collaborative and internationalized.

5.2.5 Co-occurrences Network (Based on Author keywords)

Author keywords are key terms chosen by researchers to highlight the main themes of their studies. The keywords that occur frequently have a thematic association. These keywords play a crucial role in selecting relevant papers during the review process. The co-occurrence network of author keywords presented in Figure 9 provides a comprehensive overview of the conceptual structure and thematic evolution of research in the field of artificial intelligence (AI) and finance. The importance of the keyword “artificial intelligence”, which appears as the largest and most central node serves as the core conceptual theme.

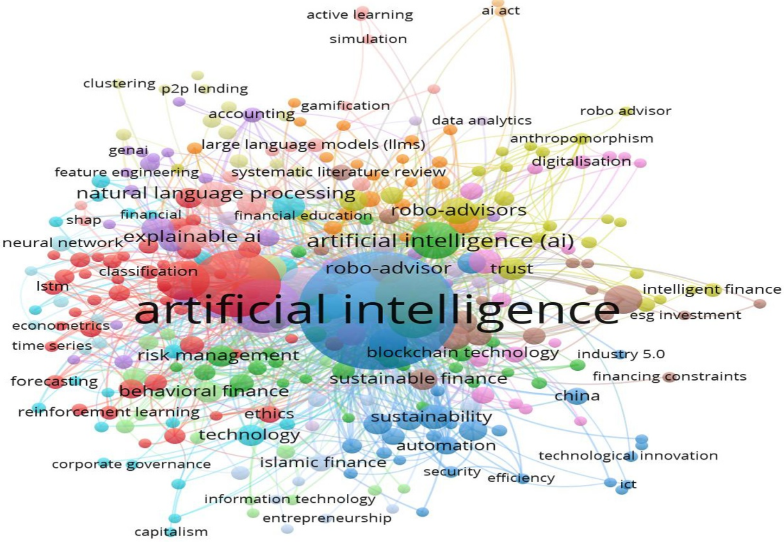

Fig. 9. Co-occurrences Network based on Author keywords

After a few permutations and combinations, minimum occurrence of the keyword was limited to 3 and from it 331 keywords were shortlisted which could meet the threshold. Few prominent keywords like “explainable AI”, “robo-advisors,” “trust,” “behavioral finance,” “Artificial intelligence”, “AI” etc. were identified. All connected objects were used to build the map as represented figure 7, which was based on network visualisation. Total link strength was used as the weighting factor and association strength served as the analysis's unit of measurement. The dominance of keywords with higher TLS relative to other keywords was depicted on the map.

5.2.6 Co-occurrences Network (Based on All keywords)

Analyzing the keywords allows researchers to identify the most frequently used terms across various studies, offering insights into current research trends and potential directions for future investigation. Fig. 10 presents the co-occurrence of keywords. The cluster indicates increasing scholarly interest in how AI-driven financial tools interact with human judgment, investor psychology, and trust-building mechanisms. Keeping the minimum occurrence of the keyword limited to 3 and from it 850 keywords were shortlisted which could meet the threshold. Prominent keywords were “Artificial intelligence”, “fintech “and “decision making” which shows increasing use of AI in finance.

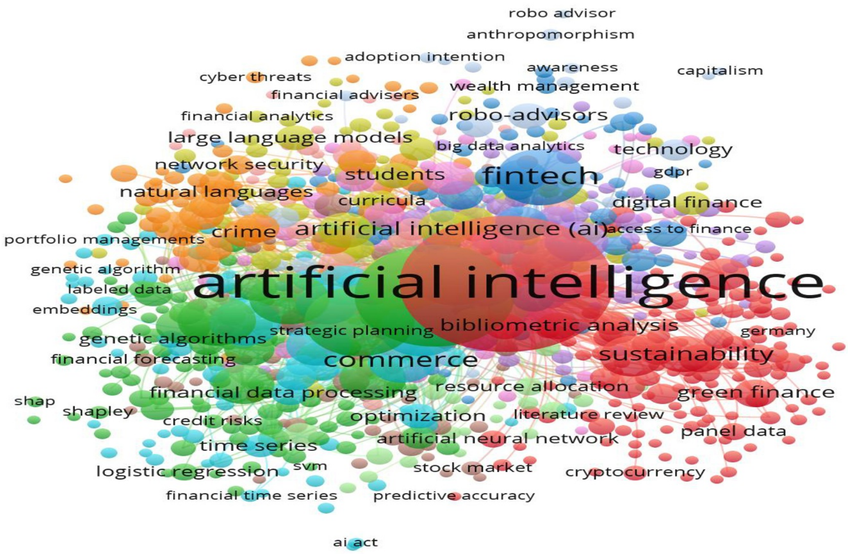

Fig. 10. Co-occurrences Network based on All keywords

6. Conclusion

This study contributes to the existing body of literature by highlighting the role of artificial intelligence (AI) in financial decision making. The network analysis provides insights on the emerging adoption of artificial intelligence (AI) in the domain of finance. The trend analysis for the publications shows a consistent rise in the number of publications. After 2020, the research has drastically expanded highlighting the global interest. This increase may be the result of digital transformation of financial services and increasing use of AI-enabled decision tools. With respect to subject area, the maximum number of research publications are in the area of business, management and accounting. This shows increased AI adoption in the field of business and finance. Some influential authors and institutions appeared to be the significant contributors within the field. A lot of interdisciplinary collaboration was seen during the analysis. United Kingdom, India, China, and Australia serve as leading countries contributing to the field of AI-finance research.

The co-citation analysis and bibliographic coupling analysis which forms intellectual structure of the field, indicates different but interconnected research streams. The researchers are integrating the use of machine learning into finance. Co-occurrence analysis revealed the core themes of the research. Applications of robo-advisory technologies, financial prediction techniques, explainable AI were the emerging themes of research along with sustainability finance, and generative AI. The results of bibliometric analysis highlight the increasing role of AI in financial decision making. AI is reshaping the field of finance with its involvement in decision making. With its relevance in the present time, the study also contributes to suggesting future avenues of research. For deeper understanding, more interdisciplinary collaboration may be done. Since there are a lot of dimensions in AI, the future studies may explore the ones which remains relatively under-explored.

References

1. Ahmed, S., Alshater, M. M., El Ammari, A., & Hammami, H. (2022). Artificial intelligence and machine learning in finance: A bibliometric review. *Research in International Business and Finance*, *61*, 101646.
2. Androutsopoulou, A., Karacapilidis, N., Loukis, E., & Charalabidis, Y. (2019). Transforming the communication between citizens and government through AI-guided chatbots. *Government information quarterly*, *36*(2), 358-367.
3. Belanche, D., Casaló, L. V., & Flavián, C. (2019). Artificial Intelligence in FinTech: understanding robo-advisors adoption among customers. *Industrial Management & Data Systems*, *119*(7), 1411-1430.
4. Blanco-Mesa, F., Merigó, J. M., & Gil-Lafuente, A. M. (2017). Fuzzy decision-making: A bibliometric-based review. *Journal of Intelligent and Fuzzy Systems, 32*(3), 2033-2050.
5. Broadus, R. N. (1987). Toward a definition of bibliometrics. *Scientometrics, 12*(5-6), 373-379.
6. Brynjolfsson, E. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies* (Vol. 236). WW Norton Company.
7. Cao, L. (2022). Ai in finance: challenges, techniques, and opportunities. *ACM Computing Surveys (CSUR)*, *55*(3), 1-38.
8. Chen, G., & Xiao, L. (2016). Selecting publication keywords for domain analysis in bibliometrics: A comparison of three methods. *Journal of Informetrics*, *10*(1), 212-223.
9. Dixon, M.F., Halperin, I., Bilokon, P. (2020). *Machine Learning in Finance: From Theory to Practice*. Springer International Publishing.
10. Donthu, N., Kumar, S., & Pattnaik, D. (2020). Forty-five years of Journal of Business Research: A bibliometric analysis. *Journal of Business Research, 109*(3), 1-14.
11. Donthu, N., Kumar, S., Mukherjee, D., Pandey, N., & Lim, W. M. (2021). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research, 133*, 285-296.
12. Dowling, M., & Lucey, B. (2023). ChatGPT for (finance) research: The Bananarama conjecture. *Finance Research Letters*, *53*, 103662.
13. Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., ... & Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International journal of information management*, *57*, 101994.
14. Ellegaard, O. and Wallin, J.A. (2015). The bibliometric analysis of scholarly production: how great is the impact? *Scientometrics, 105, (3),* 1809–1831.

15. Flavián, C., Pérez-Rueda, A., Belanche, D., & Casaló, L. V. (2022). Intention to use analytical artificial intelligence (AI) in services–the effect of technology readiness and awareness. *Journal of Service Management*, *33*(2), 293-320.
16. Gao, P., Meng, F., Mata, M. N., Martins, J. M., Iqbal, S., Correia, A. B., & Farrukh, M. (2021). Trends and future research in electronic marketing: A bibliometric analysis of twenty years. *Journal of Theoretical and Applied Electronic Commerce Research, 16*(5), 1667-1679.
17. Gomber, P., Koch, J. A., & Siering, M. (2017). Digital finance and FinTech: current research and future research directions. *Journal of Business Economics*, 87(5), 537–580.
18. Goyal, K., & Kumar, S. (2021). Financial literacy: A systematic review and bibliometric analysis. *International Journal of Consumer Studies, 45*(1), 80-105.
19. Groff, M. L., Offringa, M., Emdin, A., Mahood, Q., Parkin, P. C., & Cohen, E. (2020). Publication trends of pediatric and adult randomized controlled trials in general medical journals, 2005-2018: A citation analysis. *Children, 7*(12), 293.
20. Hajek, P., & Henriques, R. (2017). Mining corporate annual reports for intelligent detection of financial statement fraud–A comparative study of machine learning methods. *Knowledge-Based Systems*, *128*, 139-152.
21. Hossain, M. R., Akhter, F., & Sultana, M. M. (2022). SMEs in COVID-19 crisis and combating strategies: A systematic literature review (SLR) and a case from an emerging economy. *Operations Research Perspectives, 9*, 100222.
22. Khudzari, J. M., Kurian, J., Tartakovsky, B., & Raghavan, G. V. (2018). Bibliometric analysis of global research trends on microbial fuel cells using Scopus database. *Biochemical engineering journal*, *136*, 51-60.
23. Kushwaha, A. K., Kar, A. K., & Dwivedi, Y. K. (2021). Applications of big data in emerging management disciplines: A literature review using text mining. *International Journal of Information Management Data Insights*, *1*(2), 100017.
24. Luckin, R., & Cukurova, M. (2019). Designing educational technologies in the age of AI: A learning sciences-driven approach. *British Journal of Educational Technology*, *50*(6), 2824-2838.
25. Ma, X., Sha, J., Wang, D., Yu, Y., Yang, Q., & Niu, X. (2018). Study on a prediction of P2P network loan default based on the machine learning LightGBM and XGboost algorithms according to different high dimensional data cleaning. *Electronic Commerce Research and Applications*, *31*, 24-39.
26. Mas-Tur, A., Modak, N. M., Merigó, J. M., Roig-Tierno, N., Geraci, M., & Capecchi, V. (2019). Half a century of quality and quantity: A bibliometric review. *Quality & Quantity, 53*(2), 981-1020.
27. Merigó, J. M., Müller, C., Modak, N. M., & Laengle, S. (2019). Research in production and operations management: A university-based bibliometric analysis. *Global Journal of Flexible Systems Management, 20*(1), 1-29.
28. Mhlanga, D. (2020). Industry 4.0 in finance: The impact of artificial intelligence (AI) on digital financial inclusion. *International Journal of Financial Studies*, *8*(3), 45.

29. Mhlanga, D. (2021). Artificial intelligence in the industry 4.0, and its impact on poverty, innovation, infrastructure development, and the sustainable development goals: Lessons from emerging economies? *Sustainability*, *13*(11), 5788.
30. Mishra, D., Gunasekaran, A., Papadopoulos, T., & Dubey, R. (2018). Supply chain performance measures and metrics: A bibliometric study. *Benchmarking: An International Journal, 25*(3), 932-967.
31. Mukherjee, D., Lim, W. M., Kumar, S., & Donthu, N. (2022). Guidelines for advancing theory and practice through bibliometric research. *Journal of Business Research, 148*, 101–115.
32. Nerur, S. P., Rasheed, A. A., & Natarajan, V. (2008). The intellectual structure of the strategic management field: An author co-citation analysis. *Strategic Management Journal, 29*(3), 319-336.
33. Palmié, M., Wincent, J., Parida, V., & Caglar, U. (2020). The evolution of the financial technology ecosystem: An introduction and agenda for future research on disruptive innovations in ecosystems. *Technological forecasting and social change*, *151*, 119779.
34. Passas, I. (2024). Bibliometric analysis: the main steps. *Encyclopedia*, *4*(2).
35. Pritchard, A. (1969). Statistical bibliography or bibliometrics? *Journal of Documentation, 25*(4), 348-349.
36. Ragazou, K., Passas, I., Garefalakis, A., & Dimou, I. (2022). Investigating the research trends on strategic ambidexterity, agility, and open innovation in SMEs: Perceptions from bibliometric analysis. *Journal of Open Innovation: Technology, Market, and Complexity*, *8*(3), 118.
37. Roy, P., Ghose, B., Singh, P. K., Tyagi, P. K., & Vasudevan, A. (2025). Artificial intelligence and finance: A bibliometric review on the trends, influences, and research directions. *F1000Research*, *14*, 122.
38. Russell, S. J., & Norvig, P. (2021). Artificial Intelligence: A Modern Approach, Global Edition 4e.
39. Sorout, A., & Singh, N. P. (2025). Emerging Frontiers in AI and knowledge management: Visualising trends using bibliometric analysis. *Business Information Review*, 02663821251387054.
40. Sorout, A., Singh, N. P., & Pathak, A. A. (2025, May). Behavioral Finance and Sustainability: Unveiling Risk Biases in Investment Decisions. In *Sustainability in emerging economies-Integrating business excellence in management education (SEE-IBEME-2024)* (pp. 169-179). Atlantis Press.
41. Suominen, A., Li, Y., Youtie, J., & Shapira, P. (2016). A bibliometric analysis of the development of next generation active nanotechnologies. *Journal of Nanoparticle Research, 18*(9), 1-18.
42. Tsay, M.-Y. (2009). Citation analysis of Ted Nelson's works and his influence on hypertext concept. *Scientometrics, 79*(3), 451-472.
43. Van Eck, N. J., & Waltman, L. (2013). *VOSviewer manual*. Leiden University.
44. Van Raan, A. F. (2014). Advances in bibliometric analysis: research performance assessment and science mapping. *Bibliometrics Use and Abuse in the Review of Research Performance*, *87*(4), 17-28.

45. Yigitcanlar, T., & Cugurullo, F. (2020). The sustainability of artificial intelligence: An urbanistic viewpoint from the lens of smart and sustainable cities. *Sustainability*, *12*(20), 8548.
46. Zhang, W., Han, J., Işık, C., Song, J., Liu, X., Dembińska, I., & Radulesu, M. (2025). Inequality in the digital economy: The impact of artificial intelligence on income gap—an empirical analysis based on county-level data from China. *Cities*, *166*, 106280.
47. Zupic, I., & Čater, T. (2015). Bibliometric methods in management and organization. *Organizational research methods*, *18*(3), 429-472.