Digital Technologies and Behavioral Dimensions in Financial Research: A Bibliometric Mapping of the Past Decade

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ABSTRACT

The convergence of digital technologies and behavioral research has become a defining feature of contemporary financial innovation, bringing together advances in artificial intelligence, machine learning and blockchain with evolving work on decision-making, risk perception and investor behavior. Yet the literature at this convergence remains fragmented, with few studies offering an integrated view of its intellectual structure. This paper responds to that gap through a bibliometric analysis of 4975 articles retrieved from the Web of Science Core Collection between 2015 and 2024, combining Bibliometrix R and VOSviewer for performance analysis and science mapping. The findings show a marked acceleration of research output following the Covid-19 pandemic, with China, the United States and India emerging as the leading contributors, and with technologically oriented journals such as IEEE Access, Scientific Reports and Sensors serving as the core publication outlets. Keyword co-occurrence yields five coherent thematic clusters that span the technological backbone of digital finance (machine learning, deep learning, blockchain, Internet of Things) and its behavioral dimensions (risk management, uncertainty, investor response to external shocks), with notable hotspots emerging around explainable and trustworthy artificial intelligence. By offering a large-scale mapping of this broader technological and behavioral landscape, the study provides scholars, practitioners and policymakers with a structured overview of how FinTech and behavioral research intersect and where future inquiry may concentrate.

Keywords: Financial technology; investor behavior; decision-making; bibliometric analysis; network visualization.

INTRODUCTION

The proliferation of new technologies over the past few decades has drastically changed the financial landscape. Technological advancements such as Big Data, Artificial Intelligence and mobile computing drove financial technologies (Fintech) to be one of the fast-evolving innovations in the financial sector (Lee & Shin, 2018). FinTech can be described as a new financial industry that applies technology to improve financial services (Schueffel, 2016), its emergence has disrupted traditional finance by cutting costs, enhancing efficiency and increasing financial services accessibility (FinTech Revolution, 2015).

FinTech has evolved through different phases following the global financial crisis. After 2008, public trust in traditional financial institutions has eroded, and the increased desire for a more technologically advanced, inclusive and efficient services has created favorable conditions for FinTech innovations to grow (Arner et al., 2015). This evolution was later reinforced by the Covid 19 pandemic, which, starting in 2020, created financial and psychological distress on sectors and economies. As a result, the adoption of digital technologies increased dramatically to overcome the challenges caused by lockdowns and other regulatory restrictions (Kou et al., 2021).

Beyond technological innovations, financial markets continue to face inefficiencies and irrational behaviors from market participants that challenge traditional economic theories. Cognitive biases such as anchoring, overconfidence and loss aversion fundamentally influence financial decision-making, leading to market anomalies (Mahmood et al., 2024). Behavioral finance as a distinct field of study traces its roots to the pioneering work of Daniel Kahneman and Amos Tversky, whose groundbreaking research undermined the classical theory of perfectly rational investors. The prospect theory in 1977 assumed that investors' initial decisions are more influenced by cognitive and emotional drivers than rationality (Kahneman & Tversky, 1979). This view is confirmed by recent studies. Mahmood et al. (2024) find that emotional factors such as anxiety and regret significantly affect investors' financial decisions. Also, overconfidence, being one of the most recognized biases leads to excessive trading and overestimation of knowledge, which can also decrease the investors' ability to make selection choices and performance (Ahmad & Shah, 2020).

Although Behavioral Finance and FinTech have evolved as distinct fields of study, their intersection offers valuable insights into how financial innovations are adopted and used. Technological innovations alone do not ensure the effectiveness of FinTech solutions, their success depends on how individuals perceive and engage with them, a process that is influenced by emotional factors and cognitive biases. In practice, this intersection is evident in countless areas such as robo-advisory platforms, that provides financial advice using algorithms to suggest a mix of assets build upon investors' characteristics, preferences and risk perceptions ("Ask the Algorithm," 2015).

Bibliometrics is a field of study in library and information science that applies quantitative techniques to examine bibliographic data (Rai et al., 2021); Bibliometric analysis facilitates the exploration of the intellectual structure of a research domain, by examining the relationships between research constituents like authors, institutions, journals and topics. It enables a detailed analysis into the historical development of a specific field, while highlighting emerging areas within that field (Donthu et al., 2021). The present study aims to employ bibliometric analysis with the use of tools such as Bibliometrix R Package and VOSviewer to examine the literature combining FinTech and Behavioral Finance. This paper aims to examine 4975 articles gathered from the Web of Science (WOS) database to address key research questions that require examination:

RQ1. How has research at the intersection of FinTech and Behavioral Finance evolved over the past decade?

RQ2. Who are the most productive and influential authors, institutions and countries in this intersection?

RQ3. Which journals constitute the core publication sources for this field?

RQ4. What are the most influential publications shaping this research field?

RQ5. What are the key research hotspots and emerging trends that direct future research?

The remainder of this paper is structured as follows. Section II reviews existing literature. Section III outlines the materials and methodology of this study. Section IV presents the research findings and finally Section V concludes the paper by summarizing the main implications of this study as well as its limitations and future research directions.

RELATED WORK

Over the past decade, a significant number of literature reviews have examined the evolution of Financial Technology and related areas, these studies offer valuable insights into key themes and emerging trends. In the following section we synthesize some of them to provide a concise overview of their objectives and key outcomes. While these reviews have advanced understanding of the field, they also present several limitations that this paper seeks to address.

Campos-Teixeira & Tello-Gamarra (2022) conducted a bibliometric analysis of FinTech research over a 30-year period using Scopus database, the authors mapped key research trends such as consumer behavior emphasizing its growing role in Fintech adoption alongside emerging technologies like blockchain and Artificial Intelligence, their analysis offers a critical and diachronic perspective on how FinTech research has evolved overtime additionally proposing directions for future investigations. Similarly, Ameknassi et al. (2025) offered a comprehensive analysis of research at the intersection of FinTech and Financial Inclusion through his recent bibliometric study, based on 349 articles extracted from Scopus database. The study highlighted key themes such as digital financial inclusion, financial literacy, sustainability and mobile payments. Reporting a surge in research after 2019 caused by the Covid-19 pandemic. The authors accentuated FinTech's role in improving financial services accessibility and influencing behavioral changes among users and institutions. Pandey (2025) conducted a hybrid literature review employing the TCCM (Theory, Context, Characteristics, Methodology) framework on 68 Financial Technology literature reviews from top-ranked ABDC listed journals, revealing a rapid growth since 2018 while identifying five key thematic clusters, which are blockchain, sustainability, innovation, regulation and AI/Machine learning to descern the most research trends in this domain.

Another strand of literature draws on systematic reviews, which reveals recurring themes and emerging gaps across FinTech and Behavioral Finance research. For instance, Jafri et al. (2024) performed a systematic literature review on 26 empirical studies to examine the important role of trust and security in influencing FinTech adoption in the banking sector. The authors identified key predictors which are performance expectancy, perceived security, trust and attitude as critical to user adoption. They highlighted as well significant gaps related to FinTech integration. Likewise Mohammeda and Hassan (2024) conducted a systematic literature review combined with expert verification to identify factors influencing customer's adoption of FinTech services. Analyzing 25 primary studies from 2012 to 2022, they identified 12 factors which encompass technical aspects, economic benefits, perceived risk, trust and government regulation. On the other hand, expert feedback drew attention to the need for user-friendly and secure services.

Despite the valuable contributions of existing reviews, several limitations continue to exist. Many Systematic Literature Reviews are hindered by narrow research focus or fragmented conceptual framework, posing challenges to capture the proliferation of FinTech research. In contrast bibliometric analysis often rely on relatively small datasets or adopt different bibliometric techniques resulting in inconsistent clustering outcomes and varying insights. Crucially, no existing studies offer a decade-long comprehensive bibliometric mapping of the intersection between FinTech and Behavioral Finance. To address these limitations, the present study represents an important step toward understanding how these two fields converge. Table 1 outlines the extent, methodological approach and distinctive contribution of this review compared with prior studies.

Table 1: Comparative overview of existing literature reviews in the research field.

Ref.	**Scope**	**Review Type**	**Database**	**Dataset**	**Time span**	**Key Findings**
(Campos-Teixeira & Tello-Gamarra, 2022)	Investigating global FinTech Bibliometric trends	Bibliometric Review	Scopus	1920	1991-2020	Outlined three research phases: discovery, development and expansion. While also identifying leading countries and core research themes.
(Ameknassi et al., 2025)	Examine F inTech research focusing on financial inclusion	Bibliometric Review	Scopus	349	2015-2024	Key themes identified such as mobile payment and financial literacy, alongside the rapid growth of Fintech research post Covid-19 pandemic.
(Pandey, 2025)	Mapping FinTech literature reviews using TCCM	Hybrid Bibliometric Review	Scopus	68	2018-2024	Technology Acceptance Model (TAM) adopted widespread, also five main clusters were identified such as regulation and blockchain.

(Wassim Abdessalam et al., 2025)	Mapping governance with AI	Bibliometric Review	Web of Science (WoS)	500	2003-2025	The integration of AI into governance is transforming decision-making, service delivery and public administration.
(Jafri et al., 2024)	Examine how security and trust affect the adoption of FinTech in banking	Systematic Literature Review (SLR)	Scopus, Web of Science (WoS)	26	2009-2022	Key predictors identified, including trust and security, while underscoring gaps on cognitive resistance and cybersecurity.
(Mohammeda & Hassan, 2024)	Determine the elements that affect continuous FinTech use	Systematic Literature Review (SLR)	Scopus, Web of Science (WoS)	25	2012-2022	Twelve key factors were determined across technological, economic, risk, trust and regulatory dimensions, while drawing on Technological Acceptance Model (TAM), Theory of Reasoned Action (TRA) and Institutional Theory (IT), enriched by expert insights in regulation and usability.
This study	Mapping research at the intersection of Financial Technology and Behavioral Finance	Biblimetric Review	Web of Science (WoS)	4975	2015-2024	Uncovered key trends, collaboration networks and thematic clusters showing the complementary relationship between FinTech and Behavioral Finance.

Source: Developed by the authors

MATERIALS AND METHODS

Bibliometric analysis is utilized by scholars for multiple reasons, including detecting of emerging trends in article and journal performance, analyzing collaboration patterns and research constituents, and investigating intellectual structure in a given field in the existing literature Donthu et al. (2021). This analysis has seen remarkable growth since the last two decades, offering a comprehensive view of the state of the art as well as detecting influential works and emerging themes (Mukherjee et al., 2022). The present research employs bibliometric analysis to synthesize existing studies by identifying the most influential work in the field, thus determining topical areas of research and revealing new perspectives.

Following a structured methodology recommended by Donthu et al. (2021) and Lim et al. (2024), and adopted in prior studies such as Akrami et al. (2023) this research proceeds through five key stages: (1) Search design, (2) Data collection and processing, (3) Software selection, (4) Data analysis and visualization, (5) Discussion of findings. (see Fig.1 for an overview)

Search Design

Establishing a sound research protocol begins with formulating the research question clearly and identifying appropriate keywords. The scope of the research needs to be defined broadly enough to warrant the use of bibliometric analysis (Donthu et al., 2021). As the current study aims to map and evaluate the thematic and intellectual development of research at the intersection of FinTech and Behavioral Finance, the search themes “Financial Technology” and “Behavioral Finance” were selected to ensure the correct representation of the literature.

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Data collection and processing

Database

This study was based on the Web of Science (WoS) database, a widely recognized and authoritative citation indexing platform. It was selected due to its global recognition as a leading database for scientific citation and research evaluation, while also providing extensive bibliographic records with billions of citation linkages, continuously updated daily, across leading journals in various fields (Li et al., 2018). Web of Science's multidisciplinary scope, together with its established reliability in academic and scientometric research made it a reliable and robust data source for this study.

Search strategy and selection criteria

To ensure an accurate representation of the field, the search strategy was developed around two blocks of keywords. The first block included terms related to Financial Technology, including “FinTech”, “Financial Technology”, “Blockchain”, “Cryptocurrency”, “Artificial Intelligence”, “Machine Learning”, “Digital Payments”. The second block included terms related to Behavioral Finance, including “Behavioral Finance”, “Investor Behavior”, “Investor Sentiment”, “Decision Making”, “Cognitive Psychology”, “Behavioral Biases”, “Risk Management”. These blocks were combined using Boolean operators to refine the query. Operator “OR” was used for the purpose of finding articles containing at least one of the search terms in their title, abstract, author keywords and keywords plus. The operator “AND” was used to combine FinTech block with Behavioral Finance one to ensure that the retrieved publications covered both dimensions. In addition, the proximity operator “NEAR/50” was applied to capture data in which terms from both blocks occur within 50 words of each other to increase the relevance of the retrieved documents.

To align with the interests of this study, the scope was restricted to articles published between 2015 and 2024.

To refine the search, only papers that met the following criteria were included: (i) Written in English; (ii)

Published as Journal articles or Review articles; (iii) Limited to disciplinary areas relevant to the current study.

Table 2 provides an overview of the applied screening criteria, while Source: *Developed by the authors*
Table 3: Data retrieval procedure and search query

Retrieval date	Database	Search statement
24-07-2025	Web of Science (WoS)	TS=("FinTech" OR "Financial Technology" OR "Blockchain" OR "Cryptocurrency" OR "Artificial Intelligence" OR "Machine Learning" OR "Digital Payments") AND TS=("Behavioral Finance" OR "Investor Behavior" OR "Investor Sentiment" OR "Decision-Making" OR "Cognitive Psychology" OR "Behavioral Biases" OR "Risk Management") Result: 32,379
		TS=(("FinTech" OR "Financial Technology" OR "Blockchain" OR "Cryptocurrency" OR "Artificial Intelligence" OR "Machine Learning" OR "Digital Payments") NEAR/50 ("Behavioral Finance" OR "Investor Behavior" OR "Investor Sentiment" OR "Decision-Making" OR "Cognitive Psychology" OR "Behavioral Biases" OR "Risk Management")) Result: 14,804

summarizes the data retrieving procedure.

Table 2: Inclusion and exclusion criteria

Inclusion Criteria	Exclusion Criteria

Publications written in English	Publications not written in English
Papers written from 2015 to 2024	Duplicated Papers
Articles or review articles	Book, book chapters, book review, conference proceedings paper, editorial material, letter and meeting abstract
Keywords included in the article's title, abstract, authors keywords, or keywords plus	Titles and abstract that did not align with the research scope
Papers mainly focused on the intersection of FinTech and Behavioral Finance	Papers outside the research scope of this study were those addressing only one domain

Source: Developed by the authors

Table 3: Data retrieval procedure and search query

Retrieval date	Database	Search statement
24-07-2025	Web of Science (WoS)	TS=("FinTech" OR "Financial Technology" OR "Blockchain" OR "Cryptocurrency" OR "Artificial Intelligence" OR "Machine Learning" OR "Digital Payments") AND TS=("Behavioral Finance" OR "Investor Behavior" OR "Investor Sentiment" OR "Decision-Making" OR "Cognitive Psychology" OR "Behavioral Biases" OR "Risk Management") Result: 32,379
		TS=(("FinTech" OR "Financial Technology" OR "Blockchain" OR "Cryptocurrency" OR "Artificial Intelligence" OR "Machine Learning" OR "Digital Payments") NEAR/50 ("Behavioral Finance" OR "Investor Behavior" OR "Investor Sentiment" OR "Decision-Making" OR "Cognitive Psychology" OR "Behavioral Biases" OR "Risk Management")) Result: 14,804

Source: Developed by the authors

Data screening

The initial records were obtained considering the period between 2015 and 2024, through the simple application of a search string that resulted in 32,379 articles. The raw dataset contained irrelevant information which is common due to the large number of publications having "FinTech" and "Behavioral Finance" in their topic. Thus, the use of the "NEAR/50" proximity operator refined the results by ensuring that terms from both blocks appeared in close context in titles, abstract, author keywords and keyword plus, which significantly reduced the dataset to 14,804.

Once this refined dataset was obtained, a multi-stage filtering procedure was applied. The dataset was restricted to only English language publications and to only journal articles and reviews as they represent original contributions in the field. Then a subject area filter was applied to retain only articles related to the scope of the study, such as, computer science interdisciplinary applications, business finance, economics, psychology and behavioral sciences, while excluding works in biomedical sciences and other unrelated fields. As a result, 9,395 articles were disregarded, reducing the dataset to 4,975 articles. Through this process, the dataset was refined from a large pool of records to a coherent set of studies that will enhance the reliability of the bibliometric mapping. The data was later extracted in "plain text" format, which contained the "Full Record and Cite References". It had several information, including author's names, article's title, year of publication, research field and citation count.

Software Selection

For this study, two complementary software tools were utilized, Bibliometrix and VOSviewer. Bibliometrix is an open-source R package, developed by Aria and Cuccurullo (2017), proposed for performing comprehensive science mapping analyses. This package provides a suite of tools for quantitative research evaluation, it has the ability to perform science mapping and performance analysis while offering flexible statistical and visualization functions, thereby making it highly suitable for this study.

In parallel, VOSviewer developed by van Eck and Waltman (2010), is a computer program designed for constructing and viewing bibliometric maps. It is well suited for this study due to its capacity in handling large datasets and producing high quality visual maps that illustrate clusters, link strength and relationships between items.

Data analysis and visualization

To address the previously outlined research questions, the bibliometric dataset was examined through a combination of two techniques: performance analysis and science mapping. In essence, performance analysis evaluates research constituents contributions, whereas science mapping focuses on the relationships among them (Donthu et al., 2021). In this study, performance analysis was first conducted to describe publication trends, authorship patterns, journal productivity, and institutions and countries contributions. Thereafter, science mapping techniques were applied to explore the intellectual and conceptual structures of the field, including co-authorship analysis, citation analysis, co-citation analysis and keywords co-occurrence analysis, which investigates structural collaborations and intellectual foundations of the research studies. For the analysis, Biblioshiny was employed to perform data cleaning, generate descriptive statistics and performance indicators, while VOSviewer was used to map and construct scientific networks.

RESEARCH FINDINGS

Overview of retrieved data

Using the biblioshiny tool, a descriptive analysis was performed to get an overview of the retrieved dataset. The search yielded a total of 4,975 documents from the period between 2015 and 2024 from 1191 sources. These documents were authored by 16,853 scholars, with an average of 4.09 co-authors per document. On average these articles had a citation rate of 27.57 reflecting the academic influence of this field. Although single authored papers are present with a number of 436, the dataset is dominated by co-authored work. The analysis also reflected the strong international orientation of the field, as evidenced by the relatively high percentage of publications resulting from international collaborations (36.42%).

Description	**Results**
Main Information	
Documents	4,975
Sources	1,191
Annual Growth rate %	50.3
Average citation per document	27.57
Refrences	245,638
Document type	
Article	4,565

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Review	410
Document content	
Keywords Plus	5,357
Author’s Keywords	13,028
Authors	
Authors	16,853
Authors of single-authored papers	420
Author’s collaboration	
Signle-authored documents	436
Average co-authors per document	4.09
International co-authorships %	36.42
Source: Developed by the authors	

Table 3 presents a summary of the main information.

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Signle-authored documents	436
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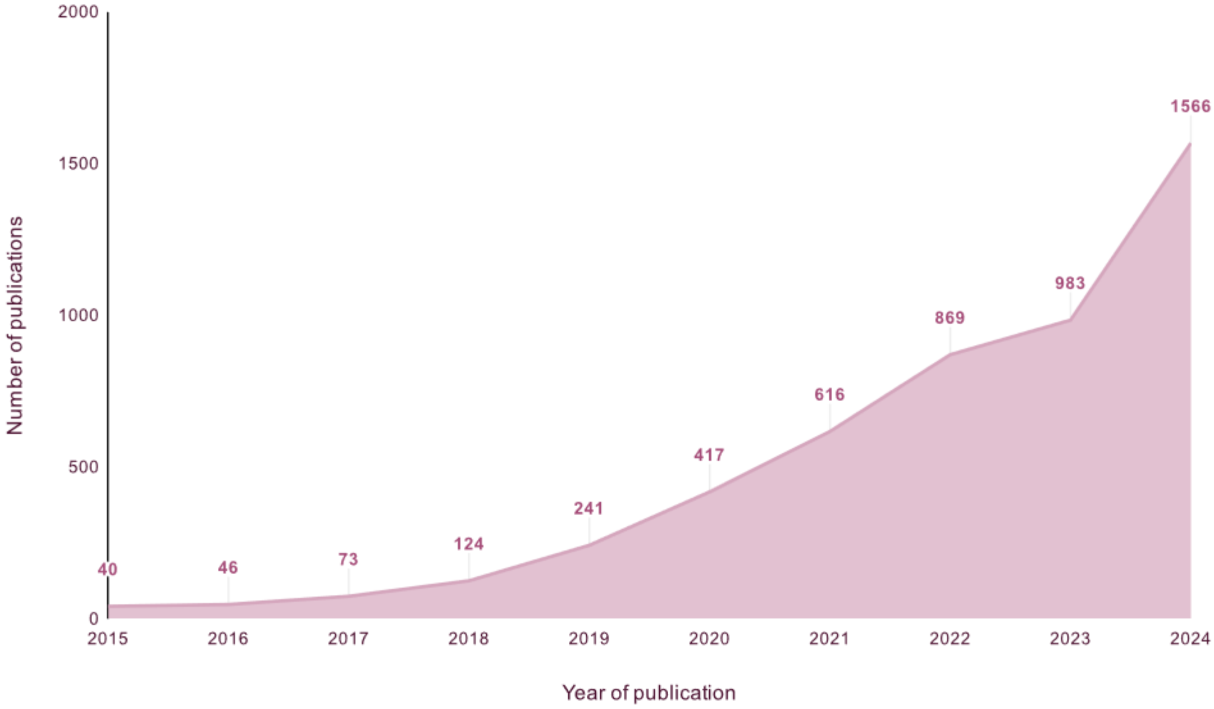
Source: Developed by the authors	

Table 3: descriptive statistics of the dataset extracted between 2015 and 2024

Performance analysis

Publication trends

Figure 1: Annual scientific productions on FinTech and Behavioral Finance (2015-2024)



Source: Developed by the authors

Figure 1 illustrates the annual distribution of 4975 papers from 2015 to 2024. The dataset revealed a remarkable growth in the number of documents, rising from only 40 articles in 2015 to 1566 articles in 2024, exhibiting an annual growth rate of 50.3%. This growth demonstrates the increased academic recognition of the intersection of FinTech and Behavioral Finance as an emerging field within scientists across the world. As shown in Figure 1, a remarkable increase in publications was observed between 2019 and 2021, coinciding with the Covid-19 pandemic, which can be linked to the proliferation of digital financial services during the lockdowns, leading to increased academic attention on how FinTech tools influence investor behavior, decision-making and risk perception.

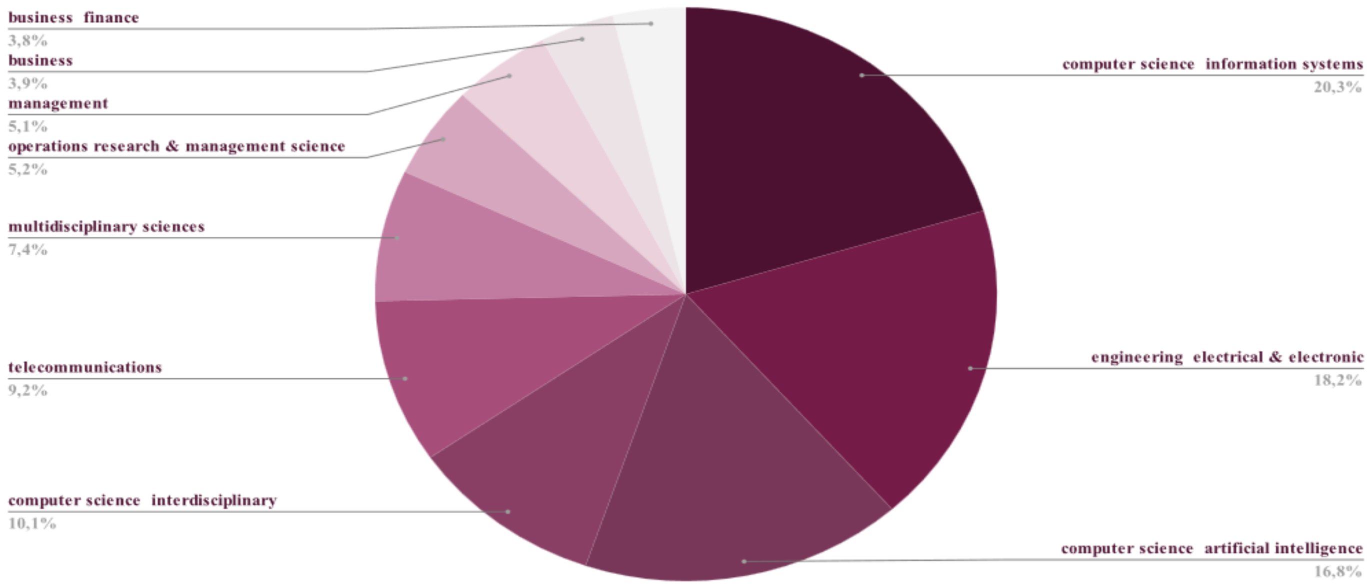
Disciplinary distribution of publications

The subject-area distribution according to Web of Science (WoS) categories is presented in Figure 2 that reports the top 10 categories in which academic papers related to the research area were published between 2015 and

2024. The largest shares are Computer Science Information Systems (20.3%), Engineering Electrical and Electronic (18.2%) and Computer Science Artificial Intelligence (16.8%). On the other hand, contributions from Multidisciplinary Sciences (7.4%), Operations Research and Management Science (5.2%), Management (5.1%), Business (3.9%) and Business Finance (3.8%) reflect the managerial, financial and behavioral perspective that enriches the field's technological foundation.

This distribution emphasizes the multidisciplinary nature of research at the convergence of FinTech and Behavioral Finance. In Figure 2 the diagram revealed the domination of technology-oriented categories in terms of volume; however, the presence of business, finance and management areas demonstrates that behavioral and decision-making aspects remain crucial to the development of the field.

Figure 2: The top 10 WoS categories in FinTech and Behavioral Finance



Source: Developed by the authors

Most productive journals

The journal Impact Factor (JIF) is a recognized metric calculated annually and provided by WoS journal citation report to evaluate journal's influence. Thus, Identifying the journals that most actively publish articles on FinTech and Behavioral Finance is valuable for researchers to select journals that align with their research scope. The analysis shows that 4975 publications are distributed across a wide range of journals, therefore Table 5 lists the top 10 most productive journals along with their WoS categories, Journal Impact Factor (JIF), and JIF Quartile as provided by the 2024 Web of Sciences journal citation reports.

According to the results provided by Table 5, IEEE Access ranks first, outpacing the rest of the journals by publishing 311 articles on the research field, followed by Scientific Reports (157 publications) and Sensors (107 publications). The remainder of the journals are also specialized in fields related to Financial Technology and Behavioral Finance, the majority of them are ranked in the first quartile (Q1) with a high impact factor (JIF ≥ 3.4), exhibiting a strong visibility and credibility within the research community. The publications wide distribution across management and technology-oriented journals highlighted that FinTech and Behavioral Finance research has not been confined to a single discipline, instead it has evolved into an interdisciplinary domain that links technological advancements with research on investor's behavior and financial decision-making.

Table 4: Top 10 productive journals published in FinTech and Behavioral Finance research

Rank	Sources	Articles	WoS Category	JIF	Quartile
1st	IEE ACCESS	311	Computer science, Engineering, Telecommunications	3.4	Q2
2nd	Scientific Reports	157	Multidisciplinary sciences	3.8	Q1
3rd	Sensors	107	Engineering, Instruments & Instrumentation	3.4	Q2
4th	Expert Systems With Applications	93	Operations research & Management science; Computer science, Artificial Intelligence; Engineering, Electrical & Electronic	7.5	Q1
5th	Plos One	82	Multidisciplinary Sciences	2.9	Q2
6th	Electronics	73	Computer Science, Engineering, Physics	2.6	Q2
7th	Engineering Applications Of Artificial Intelligence	54	Computer Science, Engineering, Multidisciplinary	7.5	Q1
8th	IEEE Internet Of Things Journal	48	Computer science, Engineering, Telecommunications	8.2	Q1
9th	Heliyon	42	Multidisciplinary Sciences	3.4	Q1
10th	Technological Forecasting And Social Change	40	Business	12.9	Q1

Source: Developed by the authors

Contribution of leading countries and institutions

The broad international engagement of research on FinTech and Behavioral Finance is revealed by the dataset, as 99 countries contributed to research production between 2015 and 2024. China, as a leading force in scientific production dominated with 982 publications representing 19.7% of the research contribution. Followed by the USA and India, forming successively 13% and 7.4% of the world's total publications. **Error! Reference source not found.** displays the top 10 productive countries in FinTech and Behavioral Finance production, SCP refers to single-country publications and MCP refers to multiple-country publications.

According to the analysis, collaboration patterns reveal the role of international partnerships. The dataset distinguishes between single-country publications (SCP) and multiple-country publications (MCP). China and USA record the highest rates of collaborations at 33.6% and 22.8% respectively. However, across all leading countries SCP values remain higher than MCP revealing that research is predominantly conducted at the national level. However, the United Kingdom stands out, with more than half of its scientific production (51.3%) involving international co-authorships. **Error! Reference source not found.** reveals this international collaboration network. The lines connecting countries indicate cooperative relationships, with the thickness of

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the line reflecting the intensity of the collaboration. Notably, China distinguished itself as the most active participant in this network, with a high collaboration level with USA, United Kingdom, Australia and India.

Table 5: Top 10 productive countries in FinTech and Behavioral Finance research

Rank	Country	Articles	Articles %	SCP	MCP	MCP %
1st	CHINA	982	19,7	652	330	33,6
2nd	USA	649	13	501	148	22,8
3rd	INDIA	368	7,4	272	96	26,1
4th	UNITED KINGDOM	269	5,4	131	138	51,3
5th	AUSTRALIA	198	4	107	91	46
6th	GERMANY	177	3,6	125	52	29,4
7th	SPAIN	156	3,1	114	42	26,9
8th	KOREA	145	2,9	87	58	40
9th	ITALY	142	2,9	89	53	37,3
10th	CANADA	125	2,5	72	53	42,4

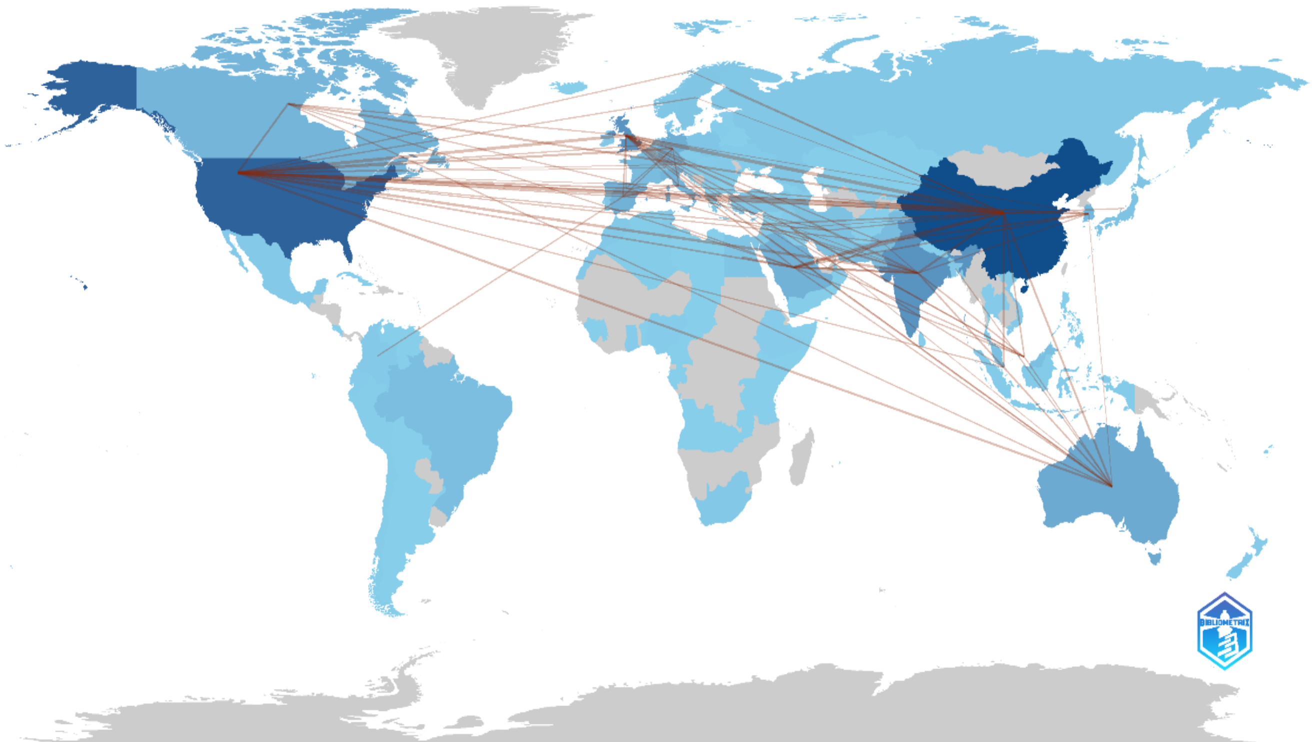

Figure 3: Countries' collaboration world map (biblioshiny)

Source: Developed by the authors using biblioshiny

Source: Developed by the authors

At the institutional level, the dataset revealed the organizations that have made the most significant contributions to the FinTech and Behavioral Finance field. The Chinese Academy of Sciences ranks first with 103 publications, followed by Egyptian Knowledge Bank and University of California System with total papers of 99 and 94 respectively. Table 6 lists the top 10 most productive affiliations within the research field.

Table 6: Top 10 most productive institutions in FinTech and Behavioral Finance field

Rank	Affiliation	Articles
1st	CHINESE ACADEMY OF SCIENCES	103
2nd	EGYPTIAN KNOWLEDGE BANK (EKB)	99
3rd	UNIVERSITY OF CALIFORNIA SYSTEM	94
4th	UNIVERSITY OF LONDON	88
5th	KING ABDULAZIZ UNIVERSITY	66
6th	INDIAN INSTITUTE OF TECHNOLOGY SYSTEM (IIT SYSTEM)	60
7th	HARVARD UNIVERSITY	56
8th	NATIONAL INSTITUTE OF TECHNOLOGY (NIT SYSTEM)	56
9th	UNIVERSITY OF TORONTO	56
10th	STATE UNIVERSITY SYSTEM OF FLORIDA	54

Source: Developed by the authors

Author's influence

Authors play an important role in shaping the evolution of scientific research across all fields, their contribution is crucial as they influence not only the volume of publications but also the direction and the pace of development of a particular field. Table 8 presents the top 10 authors involved in the research of FinTech and Behavioral finance, ranked by the number of publications, total citations and h-index. The most productive and influential ones include Zhang Y, Rudin C and Kumar A. Among these, Zhang Y has the highest number of publications, totaling 24 articles; Rudin C being the most cited author in this research field with a total of 103 citations, and Kumar A has the highest h-index (12).

Table 7: Contributions of top 10 authors in FinTech and Behavioral Finance field

Rank	Hight published authors		Hight cited authors		h-index	
	Authors	**Count**	**Authors**	**Freq.**	**Authors**	**h-inde**
1st	ZHANG Y	24	RUDIN C	103	KUMAR A	12
2nd	ZHANG C	17	MILLER T	82	ZHANG Y	11
3rd	ZHANG J	17	DAI HN	51	ALBAHRI AS	10
4th	DINÇER H	16	JARRAHI MH	50	KUMAR S	10
5th	KUMAR S	16	SARKIS J	50	ALBAHRI OS	9
6th	WANG L	16	ZHENG ZB	50	ZHANG C	9
7th	YÜKSEL S	16	JORDAN MI	49	ALAMOODI AH	8
8th	KHAN MA	15	MITCHELL TM	49	DINÇER H	8
9th	KUMAR A	15	KOUHIZADEH M	44	KHAN MA	8
10th	WANG Y	15	SHRESTHA YR	44	LI Y	8

Source: Developed by the authors

Keywords statistics

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In this section, keywords analysis reveals the intellectual core of the structure of FinTech and Behavioral Finance research. The Web of Science database distinguishes between two types of keywords: Author's keywords which are the ones provided by the authors to reflect the core of their articles, and Keywords Plus which are generated using an algorithm to identify the most frequent terms in titles and cited references to highlight broader thematic associations. To illustrate these patterns, **Error! Reference source not found.** displays the top 10 keywords identified in the dataset. On the other hand, Figure 5 and **Error! Reference source not found.** present a word cloud of the 50 author's keywords and keywords Plus, the size of each word corresponds to its frequency of occurrence. As shown in Figure 5, terms such as "Machine Learning", "Artificial Intelligence" and "Blockchain" appear most frequently. On the other hand, **Error! Reference source not found.** revealed that most frequent terms are "Model", "Management" and "Classification" reflecting broader themes than authors keywords.

Table 8: Top 10 frequent keywords in FinTech and Behavioral Finance research

Rank	Author's Keywords	No. of articles	Keyword Plus	No. of articles
1st	Machine Learning	1098	Model	431
2nd	Artificial Intelligence	745	Management	269
3rd	Blockchain	343	Classification	257
4th	Deep Learning	288	Framework	243
5th	Decision Making	211	Prediction	218
6th	Decision-Making	122	System	203
7th	Internet Of Things	122	Artificial Intelligence	185
8th	Big Data	118	Performance	179
9th	Reinforcement Learning	113	Internet	174
10th	Predictive Models	99	Impact	171

Source: Developed by the authors

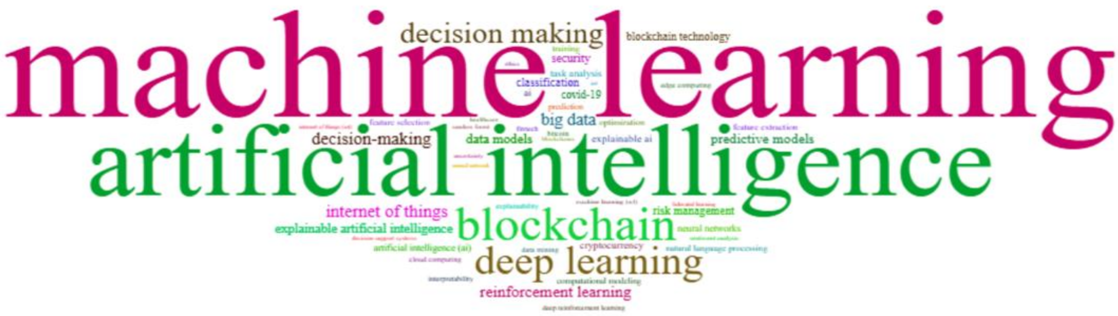

Figure 4: Word cloud of keywords. *Source: Developed by the authors*

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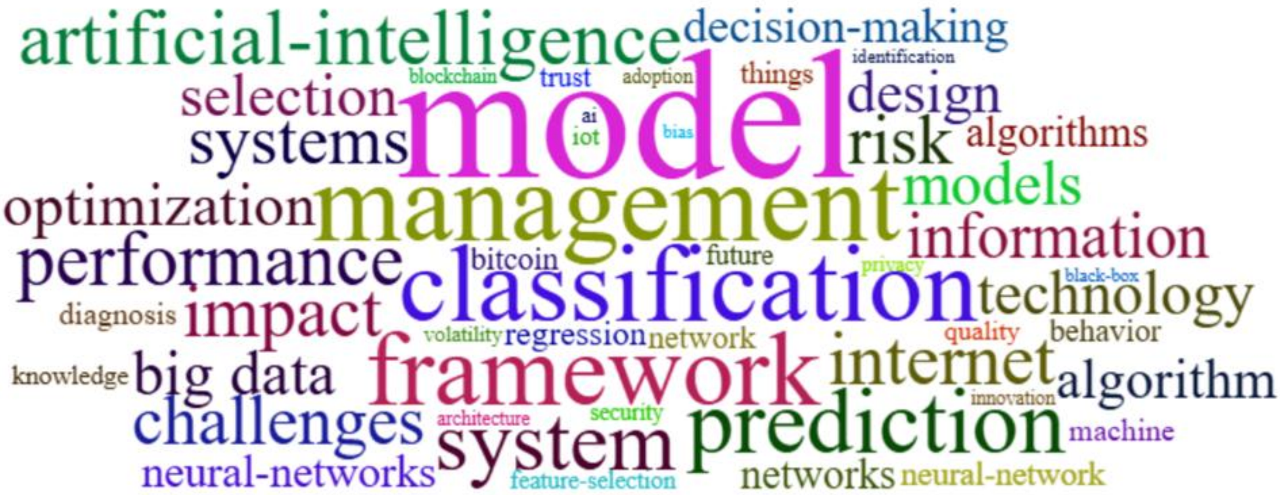

Figure 4: Word cloud of author keywords. *Source: Developed by the authors*

Science Mapping

Co-authorship analysis

Co-authorship analysis examines the interaction between scholars in a particular research field (Donthu et al., 2021). In this study, the analysis was conducted using VOSviewer, and a minimum threshold of three documents per author was applied, resulting in 416 authors. However, to ensure clarity, only 74 authors with the highest total link strength were selected. Figure 6 displays the collaborative network of co-authors in the field of FinTech and Behavioral Finance, where the size of each circle reflects the number of publications co-authored by an individual, and the thickness of the lines connecting authors represents the strength of their collaborative relationships. Based on the bibliometric analysis, nine distinct clusters were identified, revealing that authors such as Dincer and Pamucar play an important role in shaping collaborative activity.

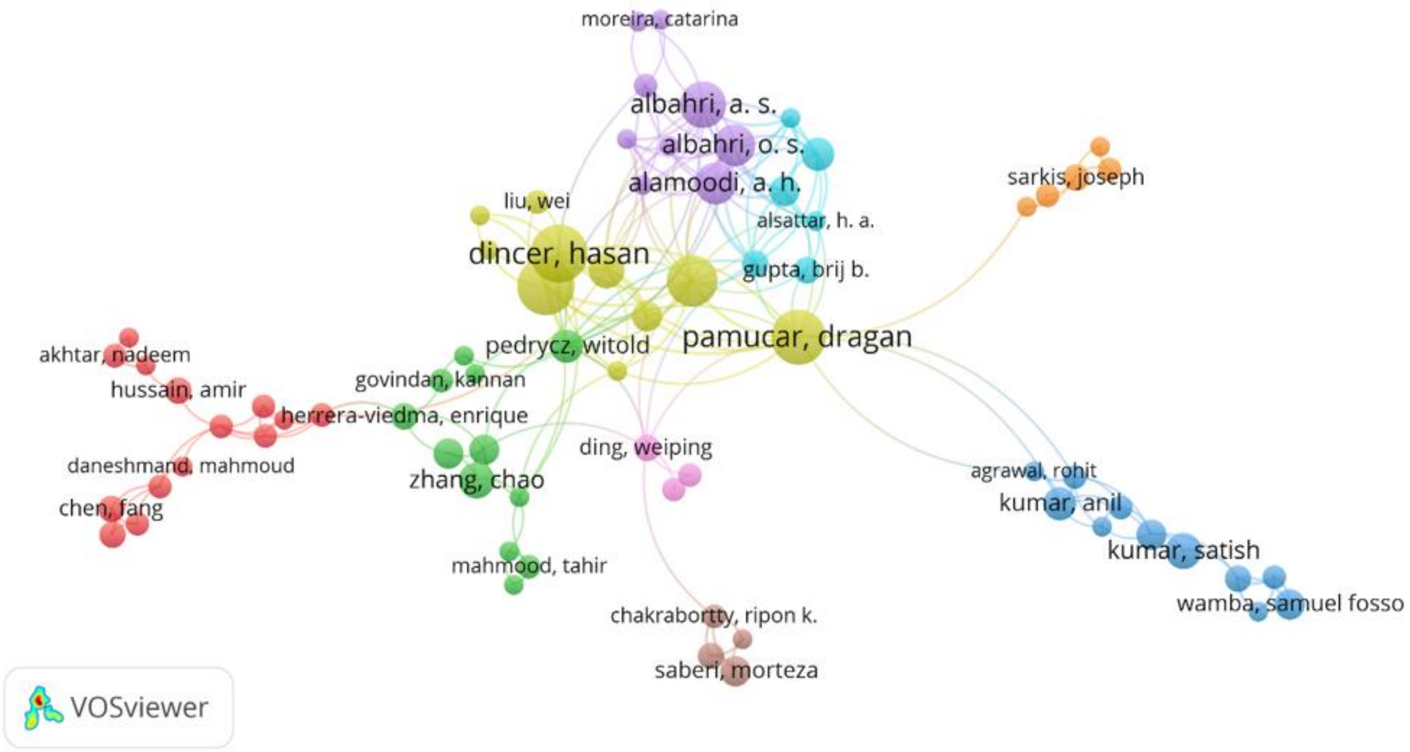

Figure 5: Collaborative network of co-authors in the field of Fintech ad Behavioral Finance

Source: Developed by the authors using VOSviewer

Collaborative countries network analysis

To complement the co-authorship analysis, it is essential to perform a collaborative countries network analysis, by shifting the focus from individual researchers to countries, to reveal the global level of the connection and distribution of FinTech and Behavioral Finance research. This analysis was performed using VOSviewer software. In Figure 7, the size of each node reflects the number of publications from a specific country, while the thickness of the lines connecting them reflects the strength of their collaborative relationships. The results reveal that China and USA are the leading contributors with strong visible links underscoring their solid academic alliance

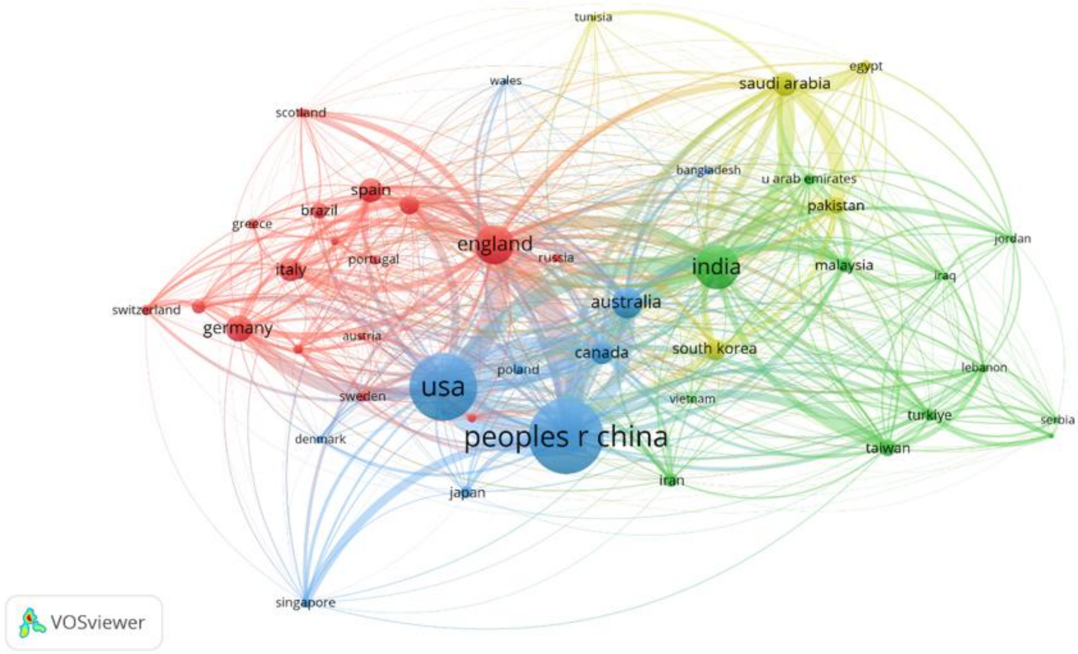

Figure 6: The countries co-authorship network of FinTech and Behavioral Finance research field

Source: Developed by the authors using VOSviewer

Citation analysis

The impact of publications is determined by the number of citations it receives (Donthu et al., 2021). Therefore, to understand the intellectual dynamics of FinTech and Behavioral finance, the most influential papers in this research field will be analyzed. **Error! Reference source not found.** lists the top 15 most cited publications in the dataset with total citations per year to measure the overall impact.

The citation network generated using VOSviewer is presented in Figure 8. Using a minimum threshold of 10 citations per document and selecting papers with the highest total link strength, a citation network of 242 documents was identified. The most frequently cited paper is Jordan & Mitchell (2015), a journal article published in SCIENCE entitled "Machine learning: Trends, perspectives and prospects" with 5388 citations in total, followed by Rudin (2019) with 4312 citations.

Table 9: Highly cited papers in FinTech and Behavioral Finance research

Rank	Publications	Total Citations (TC)	TC per year
1st	(Jordan & Mitchell, 2015)	5388	489,82
2nd	(Rudin, 2019)	4312	616,00
3rd	(Miller, 2019)	2496	356,57
4th	(Zheng et al., 2018)	1895	236,88
5th	(Haixiang et al., 2017)	1489	165,44
6th	(Goodman & Flaxman, 2017)	1040	115,56
7th	(Rasheed et al., 2020)	839	139,83
8th	(Jarrahi, 2018)	836	104,50
9th	(Chen et al., 2020)	834	139,00

10th	(Gomber et al., 2018)	826	103,25
11th	(Chlingaryan et al., 2018)	764	95,50
12th	(Jiang et al., 2017)	756	84,00
13th	(Dai et al., 2019)	738	105,43
14th	(Kouhizadeh et al., 2021)	717	143,40
15th	(Ge et al., 2017)	632	70,22
	Source: Developed by the authors		

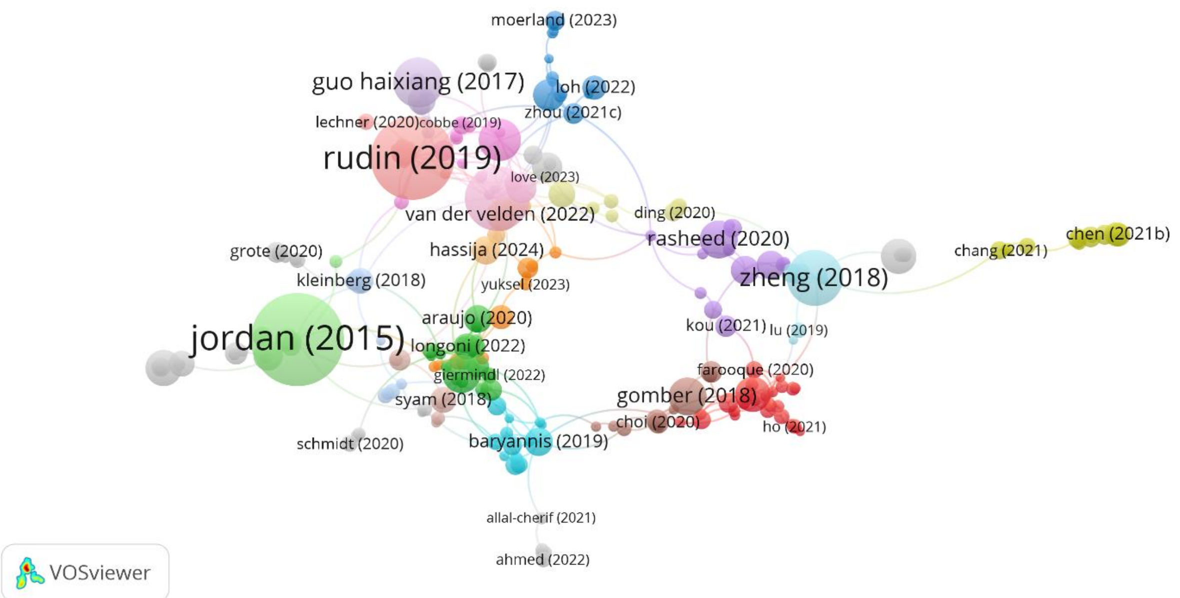

Figure 7: Citation network

Source: Developed by the authors using VOSviewer

A closer examination of the citation network in Figure 8 and of the publications listed in Table 10 reveals a notable pattern in the composition of the most influential works. A substantial share of the highly cited references originates from technology-oriented disciplines rather than from behavioral finance as a discipline. The two leading works, Jordan and Mitchell (2015) on machine learning and Rudin (2019) on interpretable models, illustrate this pattern, and several of the remaining top-cited publications address themes such as blockchain technology, data mining and the application of artificial intelligence to organizational decision-making. By contrast, contributions rooted directly in behavioral finance theory occupy fewer positions in the upper citation tier. This composition is consistent with the multidisciplinary character of the field already noted in the subject-area distribution, and it indicates that the influential anchors of the literature on FinTech and Behavioral Finance are currently sourced more from technological than from behavioral research traditions.

Co-citation analysis

Co-citation analysis is a science mapping technique based on the assumption that publications cited together share thematic similarities (Hjørland, 2013). Figure 9 reveals the co-citation network map generated by VOSviewer. The clustering of nodes in the map represents groups of papers that are often cited together; the results highlight a set of seminal work forming the field. For instance, Kahneman & Tversky (1979) cluster emphasizes decision-making by anchoring the behavioral finance field. On the other hand, research publications such as (Zadeh, 1965) on fuzzy logic represent key contributions bridging computer science with financial applications. Overall, the analysis highlights that fintech and behavioral finance research is supported by a multidisciplinary intellectual foundation that integrates technological science, artificial intelligence, decision sciences and financial theories.

Keyword co-occurrence network analysis

One of the most important elements in bibliometric research is keyword co-occurrence analysis, as it provides a direct understanding of the conceptual and thematic structure of a particular field. This approach examines the occurrence of keywords together to highlight dominant topics that define the current research, and to reveal emerging themes that may shape its future directions. In the context of this study, such analysis is crucial because it captures the dual technological and behavioral aspects of the field, enabling a deep understanding of current research trends and potential future directions. Using VOSviewer, the co-occurrence analysis produced a visual presentation of all available keywords (authors keywords and keywords plus) to offer a more accurate presentation of the intellectual landscape. Given the high number of keywords in the dataset, a minimum keyword occurrence of 50 was applied, resulting in 97 out of 18198 keywords.

Figure 10 visualizes the keyword co-occurrence network in the field of FinTech and Behavioral Finance, with 97 nodes grouped in 5 clusters and connected by 3332 links. The size of each node reflects a keyword's frequency, and the links reflect the co-occurrence strength. The map uses various colors to distinguish each cluster, and **Error! Reference source not found.** displays the most frequent keywords in each one of them.

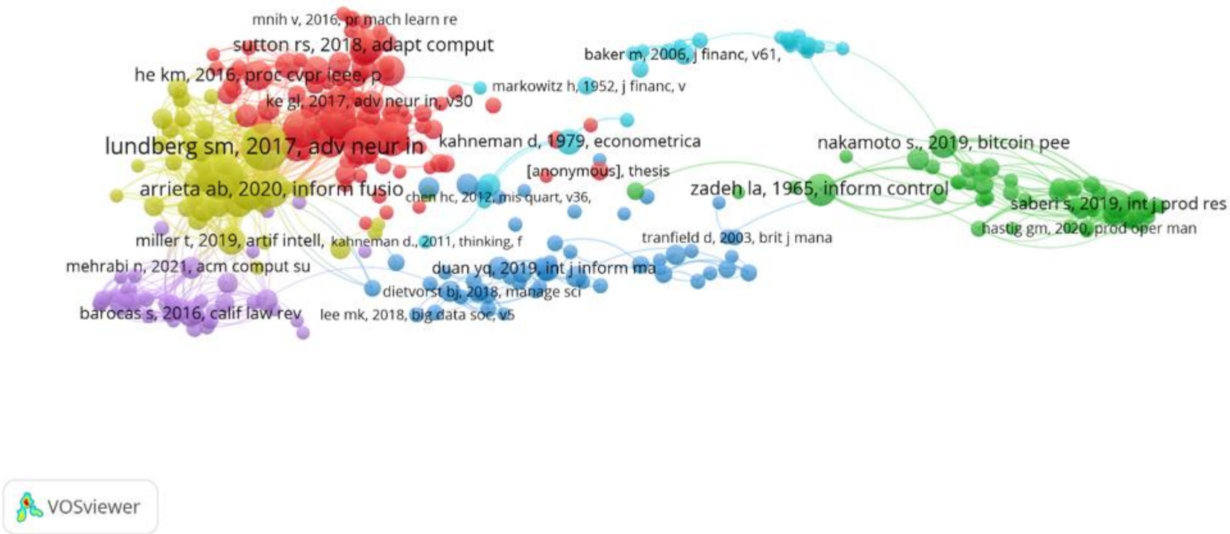

Figure 8: Co-citation network map on FinTech and Behavioral Finance research

Source: Developed by the authors using VOSviewer

Cluster 1 brings together terms such as Machine learning, deep learning and natural language processing. These terms reflect the fundamental role of data-driven approaches in financial technologies. Machine Learning and Deep Learning technologies are increasingly applied to different sectors, from financial prediction to risk assessment, algorithmic trading and fraud detection. Keywords such as classification and predictive commonly appear as they are fundamental in the financial research field.

Cluster 2 or the green cluster entails documents related to terms such as Blockchain technology, big data analytics, supply chain management, Fintech and performance. The grouping highlights the integration of new technologies into business models and organizational context. An example to this lies in the use of big data analytics to provide personalized and unique services to investors (Lee & Shin, 2018).

Cluster 3 includes artificial intelligence, ethics, fairness and transparency. As AI is now embedded in the financial landscape, ethical debates are starting to rise particularly in areas like credit scoring and automated wealth managers (robo-advisors), as these rely on algorithms to propose a mix of assets tailored to a client's profile and preferences ("Ask the Algorithm," 2015) where these recommendations tend to be biased leading to inequality and discrimination. Trust on the other hand demonstrates behavioral and ethical concerns, as investors' confidence in financial innovations depends on whether they are perceived as secure and reliable.

Cluster 4 surrounds the topics of Blockchains, Internet of things (IoT), cloud computing and security, capturing the infrastructural backbone of FinTech. Technologies such as IoT and cloud computing facilitate the application of blockchain in areas including supply chain, digital contract and secure financial transactions.

Cluster 5: the final cluster integrates behavior, risk management, cryptocurrency and covid-19. This cluster is unlike the previous ones as it represents the behavioral dimension of the field. Core concepts such as uncertainty and risk management are central for Behavioral finance, as they capture investors and institutions' response to volatile environments. From shaping investors psychology to accelerating digital adoption, the inclusion of Covid-19 highlights the impact of external events on market stability. Together, these five clusters reveal an interconnected and multidisciplinary research landscape, reflecting the technological and behavioral aspects that underscore that FinTech and Behavioral Finance are not parallel domains, but rather complementary components shaping financial innovations. Figure 11 shows the keywords co-occurrence heatmap, where warmer tones (yellow) indicate a higher occurrence frequency and cooler ones (green/blue) marks lower frequency. As shown on the heatmap, artificial intelligence, machine learning, decision making and blockchain are the most prominent and extensively discussed keywords, underscoring their central role in the research field.

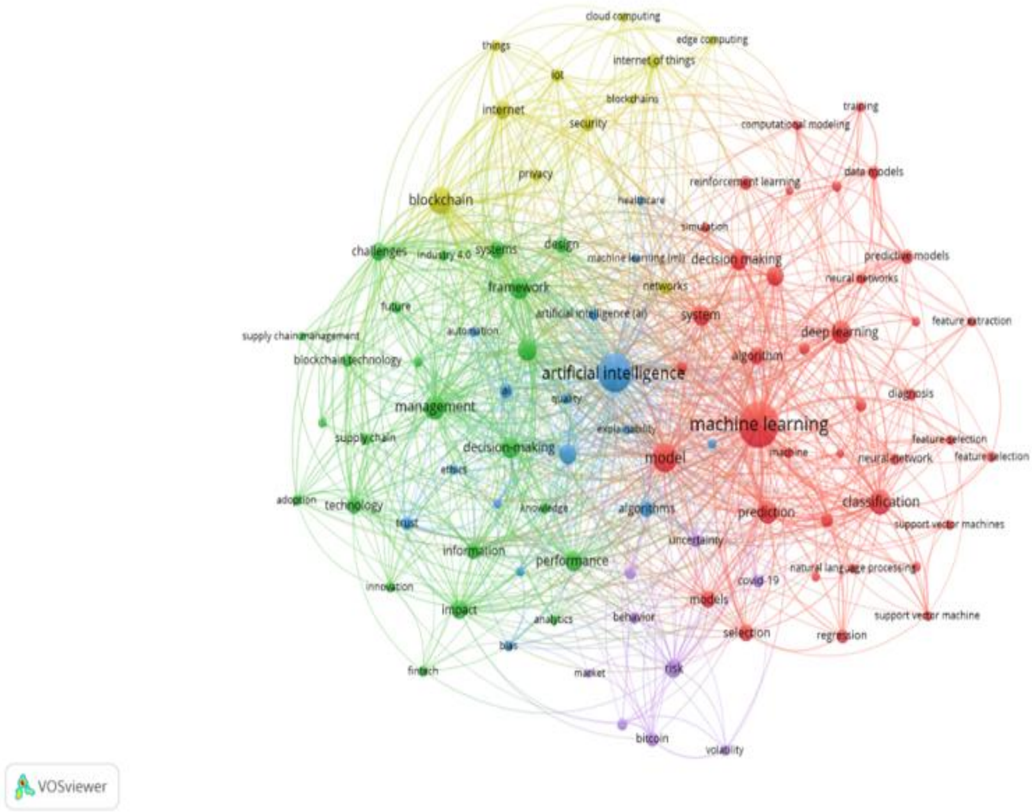

Figure 9: Keyword co-occurrence Network visualization

Source: Developed by the authors using VOSviewer

Table 10: The most occurring keywords within clusters

Clusters	Cluster 1 (Red)	Cluster 2 (Green)	Cluster 3 (Blue)	Cluster 4 (Yellow)	Cluster 5 (Purple)
Keywords	Machine learning, Deep	Blockchain technology, big data	Artificial intelligence,	Internet of things,	Behavior, risk management,

	learning, predictive models, natural language processing	analytics, performance, supply chain management, innovation, FinTech, performance	ethics, transparency, trust, fairness	blockchains, security, cloud computing	market, risk, covid-19, volatility, uncertainty, cryptocurrency

Source: Developed by the authors

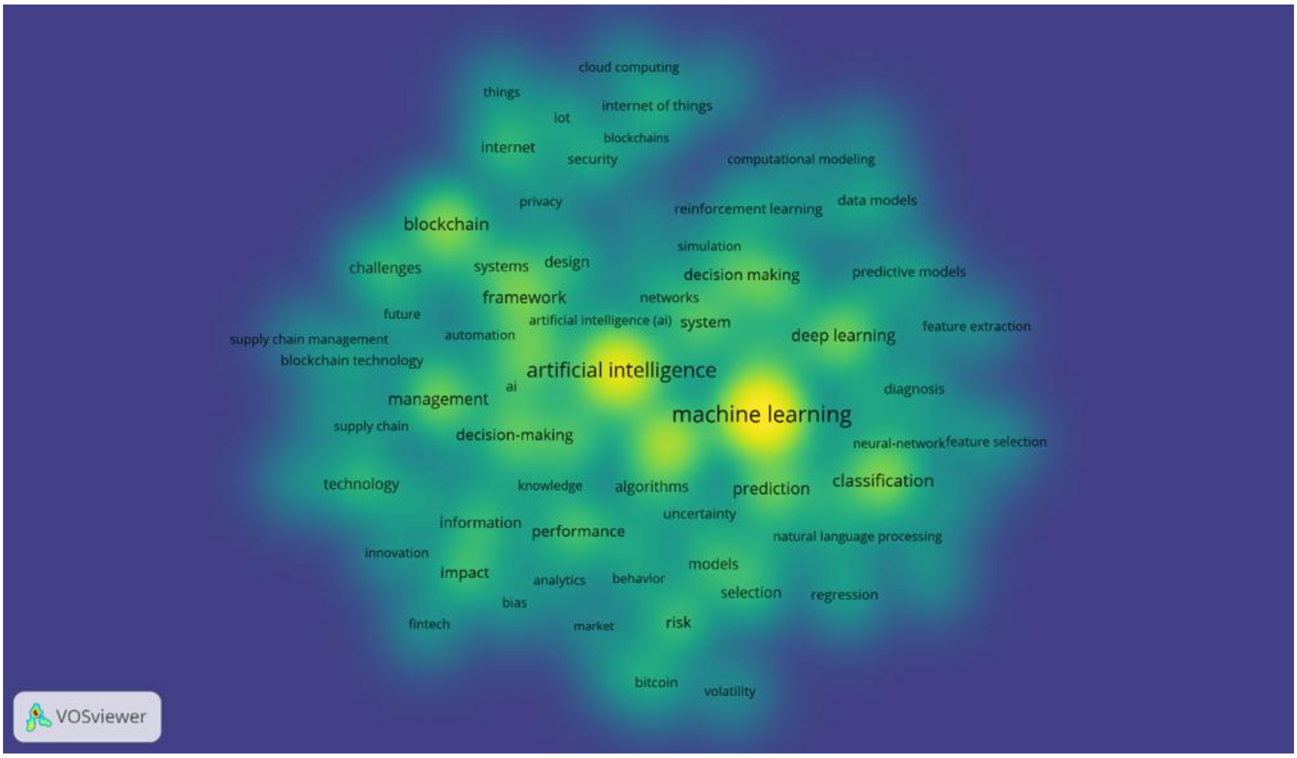

Figure 10: Keyword co-occurrence Density visualization

Source: Developed by the authors using VOSviewer

DISCUSSION

The bibliometric results presented above offer more than a descriptive picture of academic production; they invite a deeper reading of how the intellectual foundations of FinTech and Behavioral Finance are taking shape. Interpreting these findings through the theoretical lenses that have long structured both fields helps to clarify why the literature has grown in particular directions, and where the conceptual stakes of this convergence lie.

The acceleration of publications observed after 2019 cannot be reduced to a purely technological response to the Covid-19 pandemic. Prospect theory provides a useful framework for understanding this surge (Kahneman & Tversky, 1979). In periods of heightened uncertainty, investors deviate more strongly from the rational benchmark assumed by classical finance, and loss aversion, herding and emotional reactions to losses become especially visible. The pandemic functioned as a large-scale natural experiment that exposed these biases at a moment when digital platforms had become the dominant channel of access to financial markets. Kou et al. (2021) showed that the disruptions caused by lockdowns accelerated the adoption of FinTech services, and the parallel growth in academic output suggests that this practical shift drew scholarly attention toward the behavioral mechanisms that mediate technology use under stress. Read in this light, the post-pandemic surge is not a statistical artifact of citation databases but a delayed academic recognition that financial technologies and investor behavior cannot be studied separately when both are reshaped by the same shock.

A second observation concerns the imbalance between the technology-oriented clusters (Clusters 1, 2 and 4) and the behavioral cluster (Cluster 5). Three of the five thematic groups are anchored in computational concepts such as machine learning, deep learning, blockchain and the Internet of Things, while only one cluster centers explicitly on investor behavior, risk perception and external shocks. This pattern is consistent with the field's intellectual sourcing: the most cited references identified in the citation analysis, including Jordan and Mitchell (2015) on machine learning and Rudin (2019) on interpretable models, originate in computer science rather than in finance. The convergence of FinTech and Behavioral Finance is therefore being built primarily on imported technological scaffolding, with behavioral interpretation entering the field gradually rather than driving its formation. This finding extends the observation made by Gomber et al. (2018) that the FinTech revolution has been technology-led, and suggests that integrating behavioral foundations into the field remains an open task rather than an accomplished synthesis.

The emergence of Cluster 3 around artificial intelligence, ethics, fairness, transparency and trust is particularly informative when read against behavioral finance theory. Trust has long been recognized as a central determinant of investor behavior, shaping participation in markets and willingness to delegate decisions to intermediaries (Mahmood et al., 2024). The prominence of explainable and trustworthy artificial intelligence in the bibliometric map reflects the same concern transposed to a new context: investors are now asked to delegate decisions not to human advisors but to algorithmic systems whose internal logic is opaque. Rudin (2019) argued that high-stakes decisions should rely on interpretable rather than black-box models, and Miller (2019) developed the link between explanation and human reasoning. Goodman and Flaxman (2017) anticipated the regulatory translation of this concern through the European framework on algorithmic decision-making. Taken together, these contributions indicate that explainability is not only a technical requirement but a behavioral one. It addresses the cognitive and emotional conditions under which trust in financial technologies can be sustained, and it explains why this cluster has gained empirical weight despite the relatively recent age of its constituent works.

The position of Cluster 5 in the network also deserves a theoretical reading. Its co-occurrence of behavior, risk management, cryptocurrency and Covid-19 captures the moment at which behavioral finance enters the FinTech literature, no longer as a distant theoretical reference but as an active analytical lens applied to technology-mediated decisions. Within FinTech adoption research, established models such as the Technology Acceptance Model and the Unified Theory of Acceptance and Use of Technology have repeatedly identified perceived risk and trust as critical predictors of user behavior. Jafri et al. (2024) confirmed the role of trust and perceived security in driving the adoption of FinTech services in banking, and Mohammed and Hassan (2024) identified perceived risk among the most influential factors shaping continuous use. The bibliometric evidence shows that these constructs, long established in the adoption literature, are now being absorbed into the wider intersection between FinTech and Behavioral Finance, where they connect with classical behavioral biases such as overconfidence and loss aversion (Ahmad & Shah, 2020). Cluster 5 should therefore be read not as a peripheral group within the technology-heavy map, but as the conceptual hinge through which behavioral theory enters and reshapes the FinTech research agenda.

Read jointly, these interpretations indicate that the convergence between FinTech and Behavioral Finance is structurally asymmetric. The technological side provides the methods, the data and most of the highly cited foundations, while the behavioral side provides the questions that increasingly orient the field toward issues of trust, ethics, risk perception and resilience under external shocks. The bibliometric map captures a moment of transition rather than a settled synthesis, and the most productive future research is likely to emerge where the two sides are forced into closer dialogue, particularly around explainability, behavioral profiling in robo-advisory platforms, and the regulation of algorithmic decision-making in finance.

CONCLUSION

Today, the financial landscape is being reshaped by two of the most transformative forces, the proliferation of Financial Technologies (FinTech) and the expanding role of Behavioral Finance. However, despite their shared relevance, their integration remains limited in academic research. The literature does not yet provide a systematic and comprehensive mapping of how technological innovations and behavioral insights converge; to address this gap, the present study conducts a bibliometric analysis that offers a structured and up-to-date overview of the field while uncovering its intellectual foundations and its emerging directions.

The study's dataset was retrieved from the Web of Science (WoS) database, restricted to the last ten years and limited to only English articles and review articles, resulting in a final sample of 4975 documents. The analysis was conducted using Bibilometrix to clean and process the data, and VOSviewer to construct and visualize scientific networks. The study employs a combination of performance analysis and science mapping techniques to examine publication patterns, influential institutions, countries and authors, as well as collaboration, co-citation and keywords co-occurrence networks.

The findings have revealed significant growth in academic production over the past decade, most notably in the period following the Covid-19 pandemic, which accelerated the adoption of digital technologies, thereby reinforcing scholars' attention on FinTech and Behavioral Finance aspects. Furthermore, the study has explored the contribution of multiple countries to this field; with China dominating as the most productive one, while its strong collaboration with USA positions both counties at the center of international collaboration networks. In addition, several high-impact journals like IEEE Access and Scientific Reports have emerged as leaders for FinTech and Behavioral Finance research, while institutions including Chinese Academy of Science and Egyptian Knowledge Bank stand out as key contributors. Most importantly, five major thematic clusters were identified by keyword co-occurrence analysis, capturing both the technological and behavioral dimensions of the field. These clusters highlighted current research hotspots and emerging themes such as explainable AI, sustainability, ethical governance and behavioral implications of external shocks.

Implications for Practice and Policy

For FinTech providers and the financial institutions that increasingly rely on algorithmic platforms, the findings carry direct managerial relevance. The dominance of artificial intelligence and machine learning in the bibliometric map indicates that competitive advantage in the sector now depends as much on the behavioral design of digital interfaces as on their underlying technical capability. Robo-advisory platforms and automated portfolio managers operate at the point where investors are most exposed to biases such as overconfidence and loss aversion (Ahmad & Shah, 2020); their effectiveness therefore depends on the accuracy of their predictions and equally on whether their interfaces help users to recognize and counteract these biases rather than amplifying them. Practical implications include the design of decision aids that introduce reflection at moments of market volatility, the calibration of recommendation systems to investor profiles that incorporate behavioral indicators alongside risk tolerance, and the careful framing of portfolio changes in ways that do not exploit cognitive vulnerabilities. Lee and Shin (2018) emphasized that FinTech business models succeed when they align with how users actually decide, and the present findings reinforce that the integration of behavioral insight has become a strategic rather than a peripheral concern for the industry.

At the policy level, the prominence of explainability, fairness and trustworthy artificial intelligence among the field's research hotspots signals an emerging regulatory agenda that financial authorities cannot postpone. The work of Goodman and Flaxman (2017) on the European framework for algorithmic decision-making was an early step in this direction, but the bibliometric evidence shows that the academic conversation has now expanded well beyond it, addressing questions of bias, accountability and the right of investors to understand how automated decisions affecting their portfolios are produced. Policymakers should consider transparent disclosure requirements for the logic of algorithmic recommendations in financial services, auditing standards adapted to machine learning systems used in credit scoring and wealth management, and consumer protection rules tailored to digital investment platforms where behavioral nudges can operate at scale. The strong international character of the literature, visible in the collaboration networks involving China, the United States, the United Kingdom and India, also indicates that coordinated regulatory approaches are likely to prove more effective than purely national frameworks, particularly as cross-border FinTech services continue to expand.

A third set of implications concerns educational and institutional actors. The asymmetry highlighted in the bibliometric map, in which technological themes substantially outweigh behavioral ones, suggests that the formation of professionals in the financial sector should evolve in two directions at once. Business schools and finance curricula need to integrate the operational logic of artificial intelligence and digital platforms into the training of analysts and advisors, while engineering and computer science programs oriented toward finance need to give greater weight to the behavioral dimensions of the products they design. Mahmood et al. (2024) showed that financial literacy moderates the influence of behavioral biases on investment decisions, and the rapid migration of investment activity to digital platforms makes literacy programs that address biases in technology-mediated contexts more pressing than before. For financial institutions themselves, the implication is that internal training on cognitive biases needs to be updated to reflect how those biases manifest in algorithmic environments, where attention, framing and the design of choice architectures shape the quality of investor decisions in ways that traditional pedagogy on behavioral biases has not yet fully addressed.

Like all bibliometric studies, this work has limitations. First, it is solely based on Web of Science (WoS) database, which may have excluded certain sources indexed elsewhere like IEEE Xplore and Scopus. In addition, this study considered only journal articles and review papers dismissing other relevant materials such as books, chapters and conference proceedings that could have contributed to the analysis. Finally, it is important to recognize that research at the intersection of Financial Technology and Behavioral Finance continues to develop at a rapid pace, from ongoing technological advancements to evolving patterns of investors' behavior. Therefore, it is essential for scholars to remain up to date on the latest developments in the field. Despite these limitations, this study's findings equip scholars and practitioners with a clear understanding of the field's evolution and a roadmap for future research.

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