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Behavioral Biases and Investment Decisions: A Bibliometric Analysis of Global Research Trends

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Abstract

The present study analyzes the evolution and themes of behavioral finance and investment decision-making research through an exhaustive bibliometric analysis. Studies indexed in Scopus and Web of Science since 2000 were analyzed through co-citation, bibliographic coupling, and keyword co-occurrence methods using VOSviewer, while RStudio aided performance and thematic analyses. According to the findings, overconfidence, herding behavior, financial literacy, and investment decisions are major themes in the field with fintech and digital platforms gaining prominence lately. The study highlights a definite move away from early studies centered on the cognitive biases of individuals towards a more integrated approach that involves investment behavior facilitated by technological advancements. Though there were some limitations associated with database selection and language barriers, the present study has provided useful insights regarding contributors and future trends of behavioral finance.

1. Introduction

Behavioral finance makes use of the findings from psychology and economics to explain how investors sometimes stray from the rationality that classical financial theories have assumed (Shiller, 2003). Models like the Efficient Market Hypothesis and Expected Utility Theory assume that investors analyze the situation rationally to maximize their utility (Fama, 1970). Nevertheless, studies have shown that the decision-making process is always characterized by cognitive limitations, emotions, and heuristics, which lead to biases in the outcome (Simon, 1955; Kahneman & Tversky, 1979).

Overconfidence, herding, anchoring, representativeness, availability, loss aversion, and mental accounting have been found to be some of the most extensively researched biases (Barberis & Thaler, 2003; Ritter, 2003). These biases influence investors' assessments of information and risks and portfolio decision-making process. Overconfidence is likely to result in overtrading and inferior investment performance due to overestimation of the abilities of an investor (Barber & Odean, 2001; Glaser & Weber, 2007). Herding tendency might increase volatility in markets when people copy others rather than making their own judgments (Banerjee, 1992; Bikhchandani & Sharma, 2001; Chiang & Zheng 2010).

Anchoring, availability, and representativeness can impact decision making by forcing the investor to take into account certain reference points, new information, or patterns that are possibly irrelevant for the current situation (Fisher & Statman, 2000; Hirshleifer et al., 2009; Kaustia et al., 2008; Tversky & Kahneman, 1974). In a similar manner, mental accounting and the disposition effect can make the investors distinguish between gains and losses which leads to irrational investment decisions (Shefrin & Statman, 1985; Thaler, 1999). All of these findings contradict the assumption about rationality of the financial market and prove the importance of behaviorism in finance (Barberis et al., 1998; Shleifer, 2000).

The interest in behavioral finance has greatly increased over the last two decades, resulting in studies in the fields of finance, economics, psychology, and management (Kumar & Goyal, 2015; Statman, 2019). At the same time, there is an extensive diversity of the literature on the topic, which makes it rather challenging to receive an overview of its history and intellectual structure (Ricciardi & Simon, 2000). The literature review that exists currently tends to be mostly narrative in nature.

The bibliometric approach is a structured way of studying the structure and development of scientific knowledge. The publication data, citation trends, and keyword connections that characterize the field can be used to discover the prominent authors, publications, institutions, countries, and themes within the area of study (Aria & Cuccurullo, 2017; Donthu et al., 2021; Merigó & Yang, 2017). This approach is very helpful in studying the development of research on behavioral bias. Thus, the current research will analyze papers published in Scopus and Web of Science from 2000 to 2025 to present an overall picture of the research area related to behavioral biases and investment decision-making. Through the use of bibliometric methodology such as co-citation, bibliographic coupling, and keywords co-occurrence analysis, the research will explore the intellectual background and structures of the research area as well as research trends in the field.

2. Literature Review, Gap and Research Questions

2.1. Behavioral Biases in Investment Decision-Making

Behavioral finance is an outcome of the realization that the behavior of investors does not always conform to the traditional finance theories. The field borrows ideas from psychology in explaining how biases and heuristics shape the decision-making process in finance (Shefrin, 2000; Tversky & Kahneman, 1974). Biases like overconfidence, herd behavior, anchoring, representativeness, availability, loss aversion, and mental accounting have been extensively discussed by academics (Barber & Odean, 2001; De Bondt & Thaler, 1985; Ritter, 2003; Shiller, 2000).

It is believed that such biases affect the interpretation of information, evaluation of risks, and reaction of investors to market circumstances. Their effect has been related to trading practices, investment decisions, asset pricing problems, and even market results (Banerjee, 1992; Barberis & Thaler, 2003; Bikhchandani & Sharma, 2001; Glaser & Weber, 2007). With the increase in popularity of online and mobile trading services, more attention is being paid to the behavioral factors influencing investment decisions, especially those of retail investors (Barber et al., 2016; Chopra & Strucke, 2017; Dorn et al., 2008; Park et al., 2010). Thus, behavioral biases became an important subject for explaining the behavior of investors and functioning of financial markets.

2.2. Thematic Mapping via Bibliometrics

Bibliometrics analysis has become one of the useful tools that help in analyzing the structure and evolution of research disciplines (Zupic & Čater, 2015). Bibliometrics analysis has been used in the behavioral finance to identify key papers, emerging trends, and relationships among themes. Keyword co-occurrence analysis may be used in behavioral finance to discover relationships among themes like overconfidence, trading behavior, and risk-taking (Liao & Wang, 2018).

Network-based analysis tools, such as co-authoring, co-citation, and bibliographic coupling, are useful in understanding collaboration and the theoretical background of a discipline (van Eck & Waltman, 2014). Moreover, thematic mapping allows the categorization of themes based on their significance and level of maturity in order to differentiate between the well-established themes and new ones. When it comes to the research of behavioral biases, network-based analysis will allow one to understand if the old themes prevail or if the focus is shifting towards the new ones.

2.3. Gaps and Rationale for the Present Study

Despite the extensive studies carried out regarding behavioral biases, literature reviews on the subject are usually narrative and seldom consider a comprehensive analysis of publication trends, conceptual connections, and development of themes. Bibliometric researches in the area of finance have mostly dealt with more general topics like fintech or corporate governance while paying less attention to the topic of behavioral biases during the investment process. Not much has been done to explore the evolution of research themes as a reaction to changes in technology or market shocks.

In order to fill the identified gaps, this current study uses Bibliometrix (Aria & Cuccurullo, 2017) and VOSviewer in order to conduct an exhaustive bibliometric analysis of literature related to behavioral biases and investment decision-making. This analysis will include trends in publications, leading authors, journals, countries, and documents in order to map out the concepts, themes, and collaboration networks of this literature.

2.4. Research Questions

RQ1. *How has research on behavioral biases in investment decision-making evolved over time, and what publication trends characterize the field?*

RQ2. *Which journals and publications form the core knowledge base of this research domain?*

RQ3. *What intellectual, conceptual, and collaborative structures characterize the literature, as revealed through co-citation, bibliographic coupling, and thematic analyses?*

RQ4. *What emerging themes and future research directions can be identified to advance research and practice in behavioral finance?*

3. Data and Methods

3.1. Bibliometric Analysis

The comprehensive survey of the existing literature plays a vital role in advancing the scientific knowledge base and determining new research directions (Donthu et al., 2021; Pritchard, 1969; Tranfield et al., 2003). As opposed to a conventional narrative review that can be affected by personal opinion, bibliometrics offers an objective and systematic method for studying the evolution of a research area (Broadus, 1987; Donthu et al., 2021). Through the use of bibliographic data, this method allows one to trace research patterns and identify knowledge structures.

In this regard, bibliometric methods are especially useful in identifying key themes, intellectual bases, collaborations, and emerging areas of study in the discipline (Cobo et al., 2011; Hallinger & Kovačević, 2019). Therefore, they provide an excellent foundation for assessing the development of the research field and identifying new areas of study (Donthu et al., 2021; Ellegaard & Wallin, 2015).

The current study uses a bibliometric methodology that encompasses performance analysis and science mapping. Performance analysis involves examining the performance of individuals, journals, organizations, and countries, while science mapping includes the examination of the intellectual, conceptual, and thematic basis of the field (Cobo et al., 2011; Donthu et al., 2021). The analysis will be performed using the Bibliometrix package in R (Aria & Cuccurullo, 2017) and VOSviewer (van Eck & Waltman, 2010). The research framework used in this study is shown in Figure 1.

In this current study, there are two parts to the bibliometric analysis, which are the performance analysis and science mapping. The performance analysis focuses on the productivity and impact of research in terms of the outputs of publications and citations in the main entities of documents, authors, journals, institutions, and countries. The science mapping, on the other hand, focuses on the structure of knowledge in the field. This is done through thematic analysis of the keywords and thematic mapping, as well as social and intellectual connections through collaboration networks, co-citations, and bibliographic coupling.

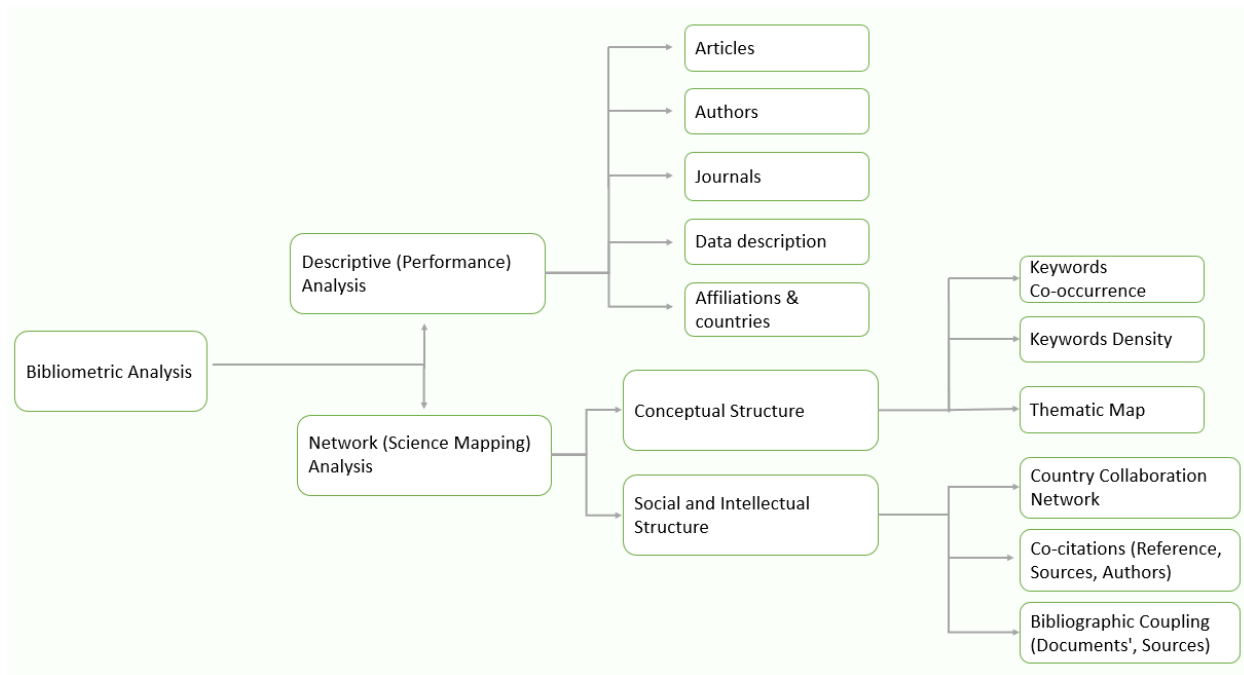


Figure 1. Conceptual framework of the bibliometric analysis

3.2. Data

The bibliographic information was obtained from Scopus and the Web of Science Core Collection (WoS). These are well-known databases that contain quality literature on finance, economics, and management (Donthu et al., 2021). In order to select works that investigate the connection between cognitive biases and financial decision making, a search strategy was formulated with Boolean operators and keywords related to cognitive biases, investors, and financial decisions.

The search string consisted of keywords that described behavioral and cognitive biases (e.g., overconfidence, herding, anchoring, representativeness, mental accounting, loss aversion, confirmation bias, and regret aversion) in combination with various investment terms (e.g., investment decisions, portfolio choice, stock markets, trading, and retail investors). This search strategy ensured the inclusion of a wide variety of scholarly literature on the impact of behavioral biases on financial decisions.

All document types found in both databases (journal articles, reviews, conference papers, book chapters, and editorials) were included in the analysis. The adoption of a more liberal inclusion criterion helped to identify various established and novel research areas in the domain (Zupic & Čater, 2015). Only studies published in English were included in order to ensure consistent metadata, abstracts, and keyword analysis.

The first search returned 489 publications, whereof 414 publications were found from Scopus database and 75 from Web of Science database. Once the datasets have been merged and deduplicated through DOI and title, a total number of 448 unique publications remained for analysis. The bibliographic details of each publication consisted of title, author(s), abstract, keyword(s), affiliation(s), cited references and source. The data analysis was done with help of bibliometrix software in R (Aria & Cuccurullo, 2017), whereas VOSviewer was used to visualize the data (van Eck & Waltman, 2010).

The workflow of data identification, merging, and screening is presented in Figure 2, following a PRISMA-style reporting structure (Page et al., 2021).

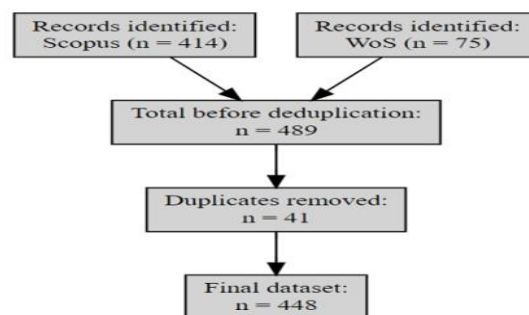


Figure 2. Flow diagram of the data collection and screening process (adapted from PRISMA 2020).

Source: Diagram generated using RStudio (Aria & Cuccurullo, 2017)

3.3. Sample Description

Figure 3 shows the yearly publication on behavioral finance and investors' decisions according to the Web of Science database. The number of publications was rather low until the mid-2010s and then gradually grew, with a particular increase in the period from 2020 to 2022. This pattern demonstrates growing scholarly attention to the field of investor behavior, financial literacy, and behavioral issues in finance. The results coincide with the existing literature that notes that behavioral finance was developed due to periods of instability and high uncertainty in financial markets (Kumar & Goyal, 2015; Shiller, 2003).

A similar trend is observed with respect to the Scopus database (Figure 4). The number of publications was low at the beginning of the 2000s decade, yet it increased gradually after 2010 and significantly after 2015. Growth in the number of publications indicates the growing importance attributed to behavior in making investment decisions due to technological advances in the field of finance.

Table 1 provides information about the area of publication distribution in the literature. The areas of Business Finance (29.51%) and Economics (24.59%) represent the largest percentages of the publications in the WoS database, while Management (9.84%) and Business (9.02%) take the third and fourth places respectively. It is important that there are such areas as Mathematical Methods, Mathematics – Interdisciplinary Applications, Computer Science, Engineering, and Psychology, which confirms the interdisciplinary nature of the topic.

The distribution of papers in the Scopus database is similar, where Economics, Econometrics and Finance comprise 40.07% of total publications, whereas Business, Management and Accounting comprise 30.05%. Other disciplines contributing include Social Sciences, Psychology, Computer Science, and Decision Sciences. The inclusion of psychology disciplines in the list highlights the growing importance of cognitive bias and behavioral aspects of finance decisions (Baker et al., 2019; Zahera & Bansal, 2018).

Citation analysis further illustrates the intellectual foundations of the field. Within Web of Science, Huang et al. (2020) received the highest number of citations, highlighting the influence of environmental and psychological factors on investor behavior. Other influential studies include Hirshleifer et al. (2019), which examines decision fatigue, and contributions by Badshah (2013) and Praveen et al. (2020), which demonstrate the methodological and thematic diversity of the literature.

In the Scopus dataset, Sterman's (1989) study on dynamic decision-making remains the most cited publication, followed by Chen et al. (2007), which provides evidence of behavioral biases in emerging markets. Kumar and Goyal (2015) also rank among the most influential contributions through their comprehensive review of behavioral finance research. Together, these highly cited works reflect the theoretical development and practical relevance of behavioral approaches to investment decision-making.

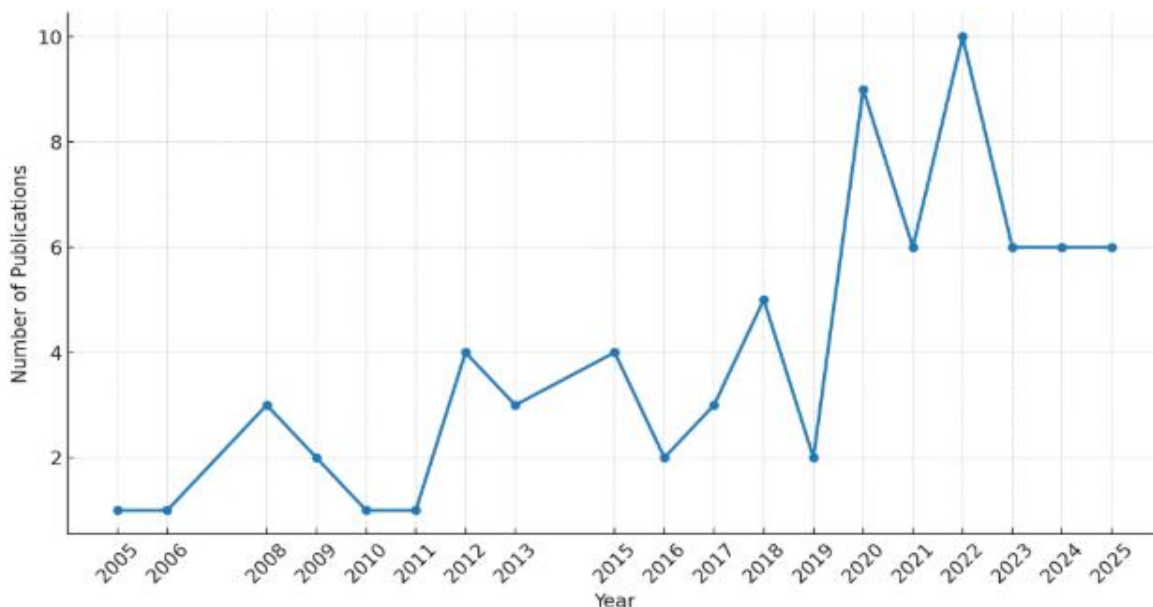


Figure 3. Annual Scientific Production (Source: Web of Science)

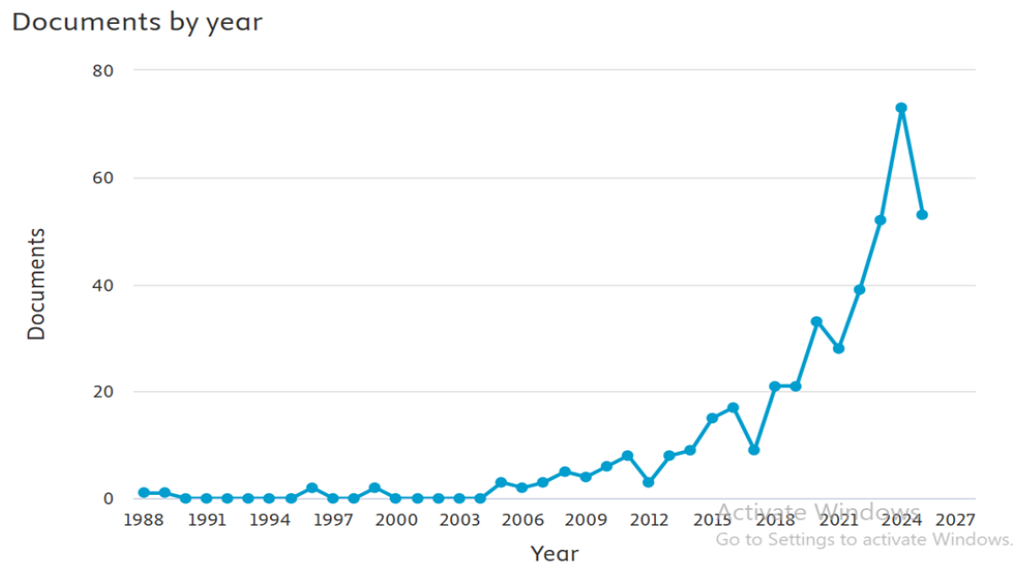


Figure 4. Annual Scientific Production (Source: Scopus)

Table 1. Web of Science categories and most cited papers

Web of Science Category	Number of Records	% of 75
Business Finance	36	29.51%
Economics	30	24.59%
Management	12	9.84%
Business	11	9.02%
Social Sciences, Mathematical Methods	4	3.28%
Mathematics, Interdisciplinary Applications	3	2.46%
Multidisciplinary Sciences	3	2.46%
Operations Research & Management Science	3	2.46%
Psychology, Applied	3	2.46%
Computer Science, Cybernetics	2	1.64%
Psychology, Multidisciplinary	2	1.64%
Social Sciences, Interdisciplinary	2	1.64%
Other Categories (1 each, n = 11*)	11	9.02%
*Includes: Chemistry Multidisciplinary, Computer Science Theory & Methods, Engineering Environmental, Engineering Industrial, Engineering Multidisciplinary, Environmental Sciences, Green & Sustainable Science Technology, Hospitality Leisure Sport Tourism, International Relations, Materials Science Multidisciplinary, Physics Applied, Psychology Experimental, Psychology Social, Public Environmental Occupational Health.		
Article	Authors	Citations
Pollution and Performance: Do Investors Make Worse Trades on Hazy Days?	Huang, Xu, and Yu (2020)	136
Decision fatigue and heuristic analyst forecasts	Hirshleifer, Levi, Lourie, Teoh (2019)	105
Quantile Regression Analysis of the Asymmetric Return-Volatility Relation	Badshah (2013)	67
The Availability Heuristic and Investors' Reaction to Company-Specific Events	Kliger and Kudryavtsev (2010)	57
Exploring market overreaction, investors' sentiments and investment decisions in an emerging stock market	Praveen, Satti, Subhan, Jamil (2020)	52
About the fear of reputational loss: Social trading and the disposition effect	Pelster and Hofmann (2018)	47
Do behavioral biases vary across individuals? Evidence from individual level 401 (k) data	Agnew (2006)	46
Stock salience and the asymmetric market effect of consumer sentiment news	Akhtar, Faff, Oliver, Subrahmanyam (2012)	45
Financial Literacy and Portfolio Diversification: An observation from Tunisina stock market	Mouna and Jarboui (2015)	42
An Analysis of Financial Analysts' Optimism in Long-term Growth Forecasts	Lee, O'Brein, and Sivaramakrishnan (2008)	39

Source: Author's own work.

Because, Scopus and Web of Science attribute multiple subject fields to the same document, the sum of subject field values will be greater than the number of unique documents (Glänzel & Thijs, 2024).

In conclusion, the obtained information demonstrates that behavioral finance is an area lying on the crossroads between economics, finance, psychology, and management. The fact that finance remains the dominant subject field indicates that it represents the primary domain of the discipline, while the increasing role of psychology and decision sciences illustrates the behavioral approach in economics (Shiller, 2003).

Table 2. Subject Area in Scopus and most cited papers (589 Records)

Subject Area	Number of Records	%
Economics, Econometrics and Finance	236	40.07%
Business, Management and Accounting	177	30.05%
Social Sciences	48	8.15%
Psychology	26	4.41%
Computer Science	22	3.73%
Engineering	19	3.23%
Decision Sciences	15	2.55%
Arts and Humanities	13	2.21%
Multidisciplinary	10	1.70%
Mathematics	6	1.02%
Environmental Science	5	0.85%
Neuroscience, Energy	3	1.02%
Medicine	2	0.34%
Article	Author(s) (Year)	Citations
Misperceptions of feedback in dynamic decision making	Sterman, J.D. (1989)	422
Trading performance, disposition effect, overconfidence, representativeness bias, and experience of emerging market investors	Chen, G., Kim, K.A., Nofsinger, J.R., & Rui, O.M. (2007)	362
Behavioural biases in investment decision making – a systematic literature review	Kumar, S., & Goyal, N. (2015)	210
Market Efficiency in an Irrational World	Daniel, K., & Titman, S. (1999)	208
Do investors exhibit behavioral biases in investment decision making? A systematic review	Zahera, S.A., & Bansal, R. (2018)	176
Chapter 20 Human behavior and the efficiency of the financial system	Shiller, R.J. (1999)	168
How financial literacy and demographic variables relate to behavioral biases	Baker, H.K., Kumar, S., Goyal, N., & Gaur, V. (2019)	161
Pollution and performance: Do investors make worse trades on hazy days?	Huang, J., Xu, N., & Yu, H. (2020)	146
Heuristic biases in investment decision-making and perceived market efficiency: A survey at the Pakistan stock exchange	Shah, S.Z.A., Ahmad, M., & Mahmood, F. (2018)	129
Evaluation of behavioral biases affecting investment decision making of individual equity investors by fuzzy analytic hierarchy process	Jain, J., Walia, N., & Gupta, S. (2020)	120

Source: Author's own work.

3.4. Method

3.4.1 Search Strategy and Data Collection

The search strategy involved balancing breadth and relevance by using a structured three-block strategy. Block one identified general terms like behavioral or behavioural bias, cognitive bias, and heuristics. Block two identified established behavioral finance constructs like overconfidence, herding, anchoring, availability heuristics, loss aversion, disposition effect, and confirmation bias. Block three narrowed down the findings to the investment area by searching for terms like investment decision, trading decision, portfolio choices, stock market, retail investors, and stock trading platforms.

Scopus and the Web of Science Core Collection searches were done for English articles only, with 414 and 75 articles, respectively. Both these sets of data were extracted in BibTeX and CSV formats. The BibTeX data was useful for constructing PRISMA flow chart, thematic maps, and analysis of performance, while the CSV format was applied for network analyses like bibliographic coupling, co-citation, and keywords co-occurrence.

Before performing the analysis, data consistency was assured via thorough deduplication to ensure that each publication was included once only in the data set. Duplicate records were detected by applying filters in Excel and an R code in R Studio, taking into account such factors as DOI, title, and abstract. It was required to deduplicate data both in these environments because VOSviewer analyzed CSV data and R Studio used BibTeX data.

3.4.2 Data Cleaning and Deduplication Procedure

To make sure that the bibliometric data is of good quality and reliable, a process of deduplication was conducted before the analysis. A dedicated R script was run using RStudio to clean the BibTeX file and remove the duplicates. This process involved using regular expression and string matching to find DOI, title, and abstract fields in each entry. The hierarchy used was:

- DOI-based removal of duplicates: Duplicates were first found based on comparison of normalized DOIs (without case sensitivity).
- Title/Abstract matching: In case of non-existent DOI in any entry, duplicates were found using concatenation of normalized title and abstract (normalized into lower case).
- Removal rule: In case of duplicate, only the first occurrence was kept to ensure uniqueness of the record.
- The procedure was algorithmic, ensuring replicability and scalability. Here follows a simplified form of the R code used:

```
entries <- unlist(strsplit(paste(readLines("data.bib"), collapse="\n"), "(?=@)", perl=TRUE))

extract_field <- function(entry, field) {
  pattern <- paste0("(?i)", field, "\\s*=\\s*\\{([\\^}]*\\}\\s*)")
  m <- regmatches(entry, regexpr(pattern, entry, perl=TRUE))
  if (length(m)>0) tolower(gsub("\\s+", " ", sub(pattern, "\\1", m, perl=TRUE))) else NA_character_
}

dois <- sapply(entries, extract_field, "doi")
titles <- sapply(entries, extract_field, "title")
abstracts <- sapply(entries, extract_field, "abstract")

abstracts[is.na(abstracts)] <- ""
titles[is.na(titles)] <- ""

keys <- ifelse(!is.na(dois) & dois!="",
              paste0("doi:", dois),
              paste0("ta:", titles, "_", abstracts))

unique_entries <- entries[!duplicated(keys)]
writeLines(unique_entries, "data.bib")
```

Figure 5: R Code for Systematic Deduplication Procedure

As shown in the above figure 5, to prepare the bibliometric dataset for analysis, a systematic deduplication procedure was performed using R. First, the BibTeX file was imported, and entries were separated at each @ symbol to isolate individual records (`entries <- unlist(strsplit(...))`). A custom function was then defined to extract key fields—DOI, title, and abstract—using regular expressions (`extract_field <- function(...)`). These fields were converted to lowercase and stripped of extra whitespace to ensure consistency. Missing titles and abstracts were replaced with empty strings to avoid processing errors (`abstracts[is.na(abstracts)] <- ""`, `titles[is.na(titles)] <- ""`). For each entry, a unique key was generated, using the DOI when available or a concatenation of the title and abstract as a fallback (`keys <- ifelse(!is.na(dois)... , paste0("doi:",dois), paste0("ta:",titles,"_",abstracts))`). Duplicate entries, identified by matching keys, were removed while retaining the first occurrence (`unique_entries <- entries[!duplicated(keys)]`). Finally, the cleaned and deduplicated dataset was written back into a BibTeX file for subsequent analysis (`writeLines(unique_entries, "data.bib")`).

3.4.3 Analytical Framework

The bibliometric methodology is based on the multidimensional approach presented by Zupic and Čater (2015), comprising the following three levels of analysis:

- Performance analysis – provides an evaluation of the scientific performance and impact of authors, institutions, journals, and nations using various indicators such as publication frequency, fractional counting, and citations (Aria & Cuccurullo, 2017).
- 2. Intellectual structure mapping – reveals the state of knowledge in the field through co-citations and bibliographic coupling.
- Conceptual structure mapping – analyzes prevalent and emerging topics within the field through keyword analysis and thematic mapping.

Such an approach allows for quantitative and qualitative analysis of the literature at once. In order to study the structure of knowledge, concepts and ideas developed in the research of cognitive biases and investment decisions, this paper used such methods as co-citation analysis, bibliographic coupling, keyword co-occurrence analysis, thematic mapping and performance analysis. Co-citation analysis was used for the identification of the fundamental works and key scientists of the research field, whereas bibliographic coupling showed the contemporary research relationships through the citation of common sources (Boyack & Klavans, 2010; Kovács et al., 2015). Also, keyword co-occurrence and thematic mapping were used in order to identify the key and emergent themes of the research (Su & Lee, 2010). Moreover, the performance analysis was conducted to estimate the productivity and impact of authors, journals and countries.

3.5. Advanced Bibliometric Techniques

3.3.5 Thematic and Performance Analyses

The analysis of the thematic maps divided research themes into four categories, based on two criteria: centrality and density:

- 1. Motor themes – themes which are central and highly developed;
- 2. Basic themes – themes that are foundational, yet not highly developed;

- 3. Themes which are emerging or declining – low-centrality and low-density themes showing growth or decline; and
- 4. Niche themes – specialized and peripheral, but mature themes.

Thematic maps were created through the use of the Bibliometrix R package, followed by qualitative triangulation through the manual coding of abstracts of 50 most cited papers in order to determine whether clusters identified via algorithms have theoretical meaning (such as cognitive or emotional biases).

3.3.6 Visualization and Network Diagnostics

VOSviewer was used for network visualization and diagnostics. Apart from its visualization capacities, the clustering algorithm used in VOSviewer delivered numerical measures of the network, such as strength of links and modularity, to evaluate the degree to which thematic groups were cohesive (Van Eck & Waltman, 2010).

3.3.7 Methodological Contribution

Unlike the previous bibliometric studies that provide only descriptive accounts, the current one uses a mixed bibliometric-thematic approach incorporating time analysis, qualitative validation, and network analysis. Such an approach makes methodological contribution since it allows not only for the development of a map but also for the study of intellectual and conceptual evolution of behavioral biases in investment decisions.

Table 3 Description of Tool/ technique used and their purpose.

Analytical Stage	Technique / Tool	Purpose
Data Collection	Scopus, Web of Science (WoS)	Comprehensive coverage of global research
Data Cleaning	RStudio, Excel	Deduplication and normalization of bibliographic records
Performance Analysis	Bibliometrix (R package)	Identify influential authors, journals, and contributing countries
Intellectual Mapping	Co-citation Analysis & Bibliographic Coupling	Discover theoretical foundations and current research frontiers
Conceptual Mapping	Keyword Co-occurrence & Thematic Evolution	Detect core and emerging research themes
Validation	Manual Abstract Review	Ensure theoretical and conceptual consistency
Visualization	VOSviewer	Perform network clustering and bibliometric diagnostics

Source: Author's Own work

4. Results

4.1. Co-Citation Analysis

A co-citation study helps in determining the intellectual base of a research area by considering the number of times two authors have been cited together in the same publications. Co-citation of the author network is shown in figure 6 based on the dataset. The visualization of network map has been done through VOSviewer. The visualization of network depicts the clusters and connections of the authors which provide an insight into the intellectual base of the field.

It is clear from the analysis that there are several prominent authors who constitute the intellectual base of behavioral biases and investment decisions research. Some prominent authors include Daniel Kahneman, Richard Thaler, Hersh Shefrin, Werner De Bondt, Shleifer, Barber, and Odean who have made seminal contributions to the field of behavioral finance and psychology. The larger size of nodes reflects their higher frequency of co-citations in the literature.

The clusters obtained correspond to different research lines, although all of them are interconnected. The red one deals mainly with behavioral economics and cognitive psychology (Kahneman, Slovic, Tversky). The green one deals with financial anomalies and issues of market efficiency (Shleifer, Fama, French). The blue cluster is related with investors' behavior and trading activities (Odean, Barber, Statman). Finally, the yellow one refers to new relations in the literature, incorporating ideas related to risk perception and decision science (Weber, Dhar).

All in all, co-citation analysis has proven once again that the field of behavioral finance is highly connected to the fields of psychology and economics, and its main contributors are Kahneman and Thaler. As can be seen from the co-citation map presented below (Figure 6), the intellectual foundation of the behavioral finance field and of the processes of investment decision-making becomes obvious. Among the references which play the biggest role for the development of the field, Kahneman and Tversky's (1979) Prospect Theory and Heuristics and Biases by the same authors (Tversky & Kahneman, 1974) should be named first. This shows the high connection between the area in question and the field of cognitive psychology. Another important articles are those of Shefrin and Statman (1985) and Odean (1998).



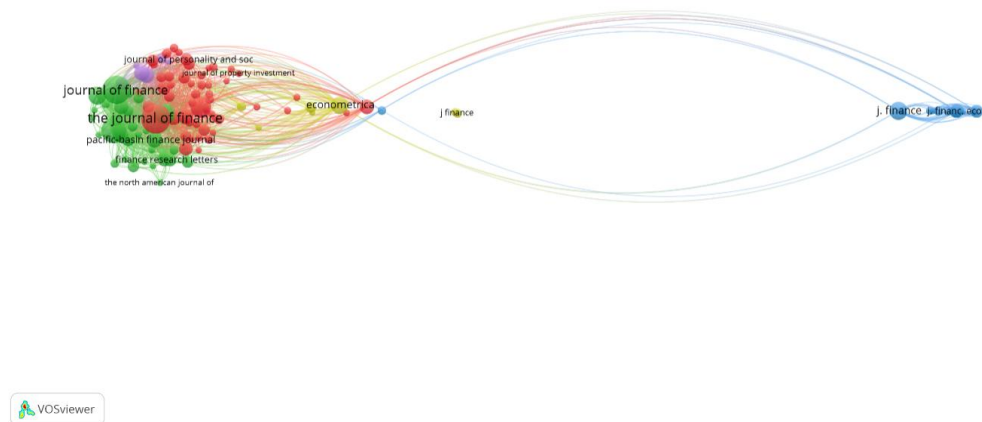
Figure 6. Co-Citation Analysis

Table 4: Co-Cited References (Threshold: ≥ 20 Citations)

Article	Author	Citation	Link Strength
Prospect theory: An analysis of decision under risk	Kahneman and Tversky (1979)	21	10
Are Investors Reluctant to Realise Their Losses?	Odean (1998)	26	28
The dispositions to sell winners too early and ride losers too long: Theory and evidence	Shefrin and Statman (1985)	25	27
Judgement under uncertainty: heuristics and biases	Tversky and Kahneman (1974)	48	23

The co-citation results at the reference level are provided in Table 4 below using the criterion of 20 or more citations. It is clear from the findings that there are some seminal works in behavioral decision-making and finance which form the knowledge base of the area. For instance, Judgement under Uncertainty: Heuristics and Biases by Tversky and Kahneman (1974) (48 citations, link strength 23) and Prospect Theory: An Analysis of Decision under Risk by Kahneman and Tversky (1979) (21 citations, link strength 10) demonstrate the psychology behind behavioral finance. In a similar vein, Are Investors Reluctant to Realize Their Losses? by Odean (1998) (26 citations, link strength 28) and The Disposition to Sell Winners Too Early and Ride Losers Too Long: Theory and Evidence by Shefrin and Statman (1985) (25 citations, link strength 27) explain the importance of the trading activity of investors especially the disposition effect.

From all the above results, it is quite evident that the co-cited references are seminal articles which have played an instrumental role in the development of finance through psychology. The theories of biases developed by Kahneman and Tversky form the theoretical base while the work of Odean, Shefrin, and Statman provide the practical aspect of the same.

**Figure 7. Source: Co-citation by Cited Sources****Table 5: Co-Cited Sources (Threshold: ≥ 20 Citations)**

Rank	Journal Name	Citations	Total Link Strength
1	The Journal of Finance	401	13773
2	Journal of Finance	363	10264
3	Journal of Financial Economics	298	9899
4	Qualitative Research in Finance	207	6515
5	The Journal of Behavioural Finance	190	6559
6	Econometrica	141	4094
7	Pacific-Basin Finance Journal	110	3817
8	Review of Behavioural Finance	111	4140
9	Quarterly Journal of economics	98	3506
10	Journal of Behavioural and Experimental Finance	87	3425

Tables 5 and 7 jointly demonstrate the findings from the co-citation analysis by cited references. The table ranks the top ten co-cited journals based on the criterion of at least 20 references. According to Table 5, the two most co-cited references include The Journal of Finance with 401 citations and total link strength 13,773 and Journal of Finance with 363 citations and total link strength 10,264. Other important journals like the Journal of Financial Economics, Qualitative Research in Financial Markets, and Journal of Behavioral Finance emphasize the dual perspective of traditional finance and behavioral finance.

The network diagram (see Figure 7) helps to see how these journals relate to each other in the context of knowledge map. Large size of nodes such as The Journal of Finance and Journal of Financial Economics reveals higher citation counts, while the thicker line denotes stronger co-citation linkages between them. As seen from the clustering of journals, it can be said that the field of behavioral finance uses theories not only from behavioral outlets such as Journal of Behavioral Finance and Review of Behavioral Finance, but also from established finance and economics journals (Econometrica, Quarterly Journal of Economics).

It can be concluded that the intellectual basis of behavioral finance is multidisciplinary, combining insights from the mainstream finance journals with behavioral and experimental findings.

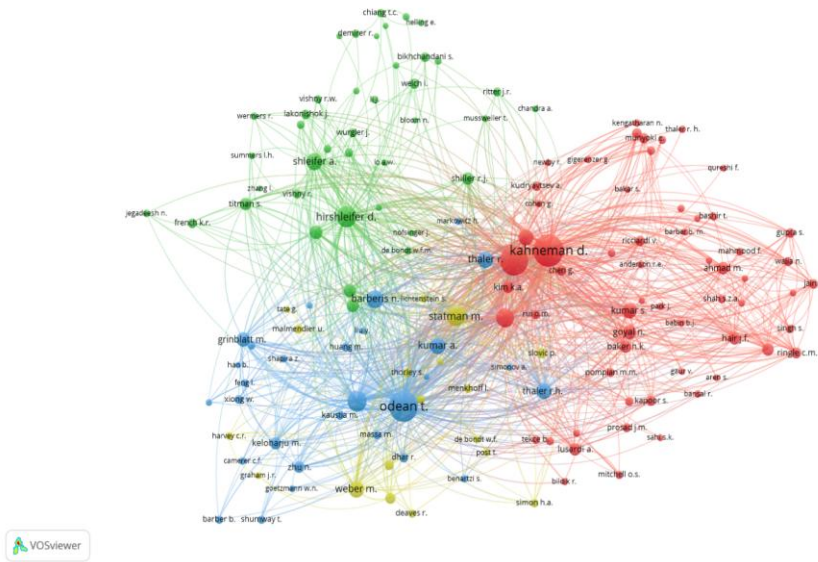


Figure 8. Co-citation by Cited Authors

The co-citation analysis performed by the cited authors reveals the most eminent authors in the field of behavioral finance, as depicted in Table 6 and network visualization (Figure 8). The authors Kahneman, Odean, and Tversky are revealed to be most co-cited authors due to their basic contributions to decision-making theories and prospect theory. Meanwhile, the other cluster is comprised of authors Hirshleifer, Barber, and Statman and reveals their importance in explaining behavioral biases in trading and investment decisions. Another cluster consists of Shefrin, Barberis, Shleifer, and Thaler and reveals the contributions made by them in theorizing market inefficiencies, investors’ sentiments, and the integration of psychology into financial models. Thus, the network visualization indicates that these clusters are closely interconnected, implying that the works of these authors are mostly co-cited.

Table 6: Co-Cited Authors (Threshold: ≥20 Citations)

Rank	Author	Citation	Total Link Strength
1	Kahneman .d	450	16746
2	Odean t.	414	17166
3	Tversky a.	401	14826
4	Hirshleifer d.	196	8048
5	Barber b.m.	185	8513
6	Statman m.	179	7171
7	Shefrin h.	168	6760
8	Barbaris n.	138	5570
9	Shleifer a.	131	4859
10	Thaler r.	122	4736

4.2. Bibliographic Coupling of Documents and Sources

It is possible to note that bibliographic coupling reveals how influential publications from the sphere of behavioral finance and investment decisions are interconnected.

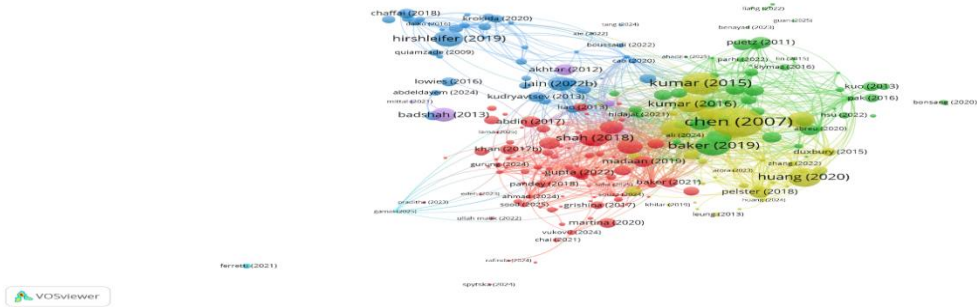


Figure 9. Source: Bibliographic Coupling by Documents

In particular, according to Figure 9 and Table 7, the most connected papers are Chen (2007), Kumar (2015), and Baker (2019). The publications have not only high citation numbers but also strong link numbers, which means that they have been used by other authors in their research and therefore are central in the development of research. For example, Chen (2007) and Kumar (2015) have proved to be the most cited and most connected publications. In addition, Shah (2018) and Ahmad (2022) have high total link numbers. Thus, even though their citations are lower, these papers can be seen as important connectors in the research literature. Moreover, the clustering found in the visualization shows that there are a number of core papers, which form the foundation of further discussions, whereas new publications (for example, Jain (2022) and Hirshleifer (2019)) continue discussions.

Table 7. Bibliographic Coupling of documents

Rank	Document (First Author, Year)	Citations	Total link Strength
1	Chen (2007)	362	744
2	Kumar (2015)	210	794
3	Baker (2019)	161	645
4	Huang (2020)	146	221
5	Shah (2018)	129	821
6	Jain (2022)	120	697
7	Kumar (2016)	118	755
7	Hirshleifer (2019)	112	52
8	Linnainmaa (2010)	99	414
9	Ahmad (2022)	88	787
10	Jain (2022)	88	690

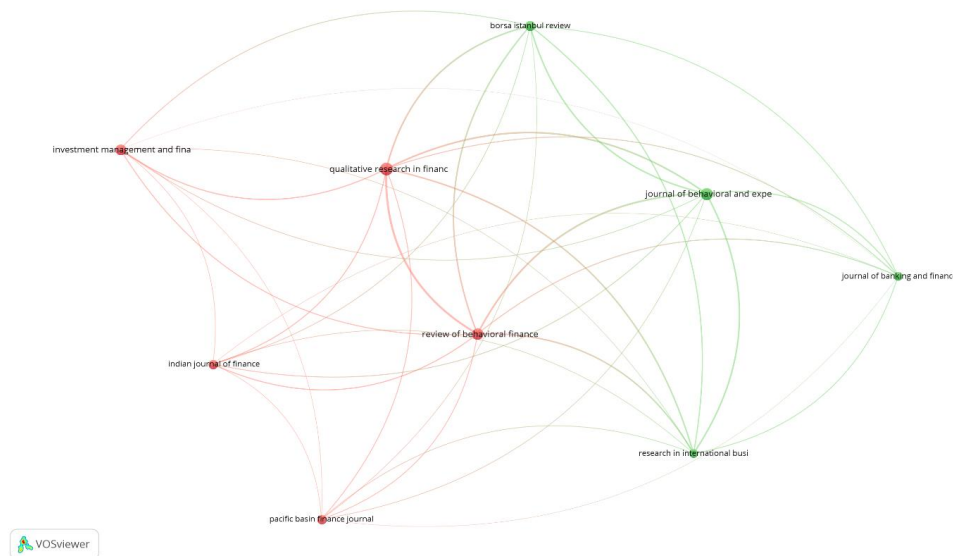


Figure 10. Bibliographic Coupling by Sources

Based on the bibliographic coupling analysis of sources (Table 8; Figure 10), it can be noticed that the qualitative research in financial markets (11 papers, TLS = 1133) and the review of behavioral finance (9 papers, TLS = 1110) are key hubs for the network. Moreover, the journal of behavioral and experimental finance (10 papers, TLS = 969) represents an important source of connections in the network. From the graphical representation, two clear clusters have been identified where one includes investment management and financial innovations, Indian journal of finance, and Pacific basin finance journal as dominant sources, while the second cluster includes Borsa Istanbul Review, research in international business and finance, and journal of banking and finance as key sources. Therefore, although the research is published in several journals, certain journals represent important bridges of knowledge from a regional and international perspective on behavioral finance and investments.

Table 8. Bibliographic coupling of sources

Rank	Source	Documents	Total Link Strength
1	Qualitative Research in Financial Markets	11	1133
2	Journal of Behavioral and Experimental Finance	10	969
3	Review of Behavioral Finance	9	1110
4	Investment Management and Financial Innovations	8	314
5	Borsa Istanbul Review	7	756
6	Indian Journal of Finance	6	324
7	Pacific Basin Finance Journal	6	236
8	Research In International Business and Finance	5	734
9	Journal of Banking and Finance	5	342

4.3. Author Keywords Co-occurrence

The network and bibliographic co-occurrence analysis of the author keywords is displayed in Figure 11 and Table 9. It can be seen that there is a high concentration of clusters of such concepts as overconfidence, behavioral finance, herding, and investment decision, which are typically discussed simultaneously within the scope of behavioral finance research. Among them, the keyword overconfidence takes first place by number of occurrences (45) and total link strength (114). The other keywords connected with overconfidence are behavioral finance (38 occurrences, link strength 78) and disposition effect (27 occurrences, link strength 54). These connections confirm that research in behavioral finance focuses on multiple biases. In addition, herding (24 occurrences) and anchoring (11 occurrences) appear to have quite strong connections, which is also an indication of their significance in forming of investors' behavior. Finally, the presence of financial literacy and individual investor among the top 10 keywords indicates that the researches pay much attention to the study of moderators and demographical factors.

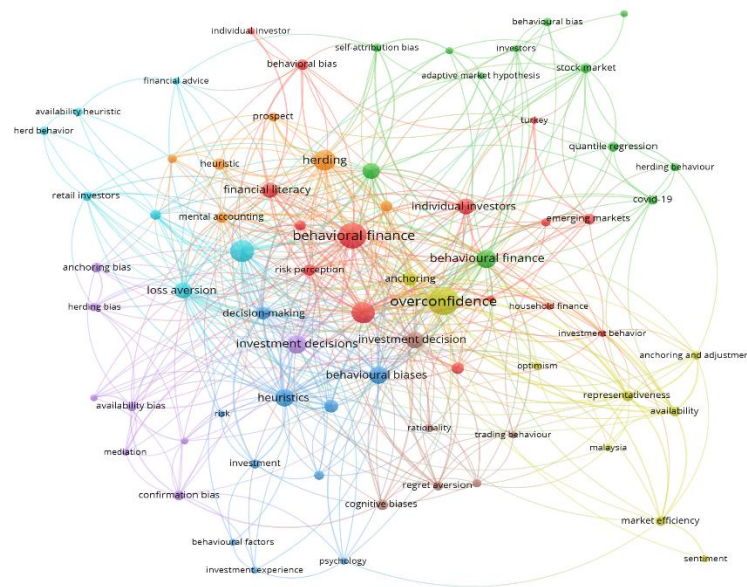


Figure 11. Author Keyword Co-occurrence Network Visualization (VOSviewer)

Table 9. Authors Keywords Co-occurrence

Rank	Keywords	Occurrence	Total Link Strength
1	Overconfidence	45	114
2	Behavioral Finance	38	78
3	Disposition Effect	27	54
4	Behavioral Biases	25	62
5	Herding	24	45
6	Investment Decision	19	40
7	Heuristic	17	55
8	Individual Investor	14	32
9	Financial Literacy	13	32
10	Anchoring	11	44

Figure 12 demonstrates the density map of author keywords in behavioral finance literature. The density map was created using VOSviewer based on the analysis of keyword co-occurrence with a minimum number of co-occurrences set at 3. In this map, colors symbolize the importance and prevalence of keywords. That is, the yellow areas correspond to dense places where keywords occur frequently and are well-connected to each other, the green areas are characterized by medium density, whereas the blue areas stand for low density or weakly connected keywords. From the figure, one can see that such keywords as “behavioral finance,” “overconfidence,” and “herding” are present in the brightest yellow area, which means that these are the most popular topics in the literature.

The above mentioned keywords constitute the intellectual framework for behavioral finance studies based on the prevalent cognitive biases that have been studied in the field of behavioral finance. Around these densely occurring keywords, medium density keywords such as “investment decision,” “financial literacy,” “anchoring” and “loss aversion” (highlighted in green color) occur, which depict topics of research that receive steady research interest to a lesser degree. On the other hand, keywords such as “COVID-19,” “market efficiency,” “sentiment,” “optimism,” “Turkey” and “Malaysia” (highlighted in blue color) emerge around these keywords, depicting topics of research that do not receive much research interest at the moment.

The density map offers a good insight into the level of intensity and focus in behavioral finance research. With the existing research themes on topics like overconfidence and herding bias, there appears to be an emerging trend of research into areas such as financial literacy, behavior of investors during crises like that of coronavirus, and comparative research across countries.

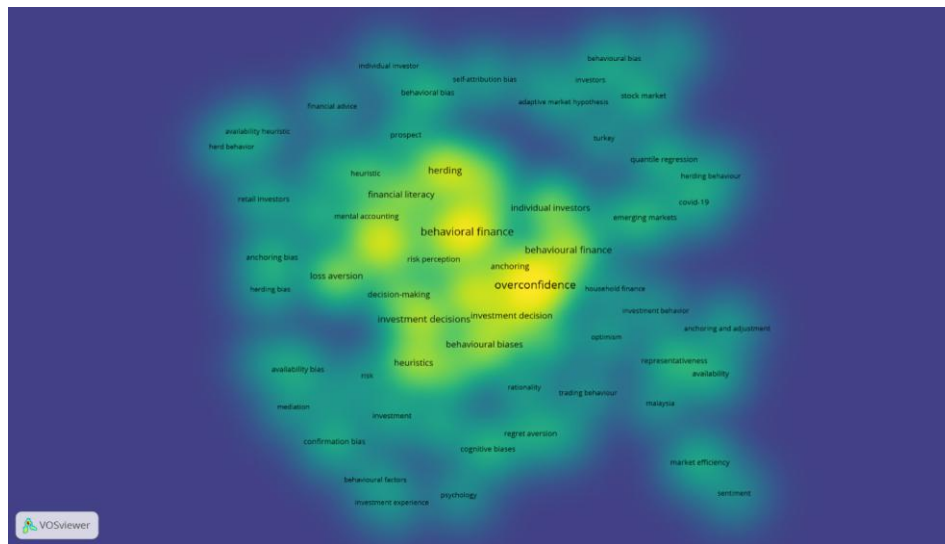


Figure 12. Keyword Co-occurrence Density Visualization (VOSviewer)

4.4. Performance Analysis

In order to examine the impact made by authors, journals, and countries, a performance analysis was done using bibliometric indicators, which include the number of publications, fractionalized contribution, and citations.

Table 9 displays the top performing authors for the study on behavioral biases and investment decisions. Ahmad M. and Singh S. dominate the list with eight publications each, proving to be very dedicated to the research topic. Fractionalized authorship reveals the extent of collaborative work being done, where the authors like Kumar S. and Baker H. have made considerable contributions.

Table 10: Most Productive Authors

Rank	Author(s)	Articles	Fractionalized Contribution
1	Ahmad M.	8	4.50
2	Singh S.	8	3.00
3	Jain J.	7	2.33
4	Kumar S.	6	2.25
5	Baker H.	5	1.75
6	Goyal N.	5	1.92
7	Khan M.	5	2.00
8	Kudryavtsev A.	5	3.33
9	Kumar A.	5	1.92
10	Shah S.	5	1.75

Table 11: Top Countries by Number of Publications and Citations

Rank	Country	Articles	Total Citations	Average Citations per Article
1	India	71	1505	21.20
2	China	24	246	10.25
3	Pakistan	16	421	26.31
4	Indonesia	15	88	5.87
5	USA	15	569	37.93
6	Malaysia	11	151	13.73
7	United Kingdom	10	82	8.20
8	Tunisia	7	160	22.86
9	Turkey	6	136	22.67
10	Brazil	5	0	0

Figure 13 and Table 11 represent the international distribution of research outputs along with citations in this area. India emerges as a leading contributor to the number of outputs by providing 71 documents and 1,505 citations. This country demonstrates the significant research productivity as well as scholarly visibility. The USA is not the most prolific country, since it only produces 15 documents, however, this country reaches the highest citation impact with the mean of 37.93 citations per document that speaks about the significance and high quality of the outputs. Some other countries like Pakistan (26.31), Tunisia (22.86), and Turkey (22.67) also provide a high citation efficiency with respect to their outputs. On the contrary, China (24 articles, 10.25 citations on average) and Indonesia (15 articles, 5.87 citations on average) demonstrate increasing research productivity with the low citation impact. Brazil (five papers with zero citations) illustrates little scholarly impact.

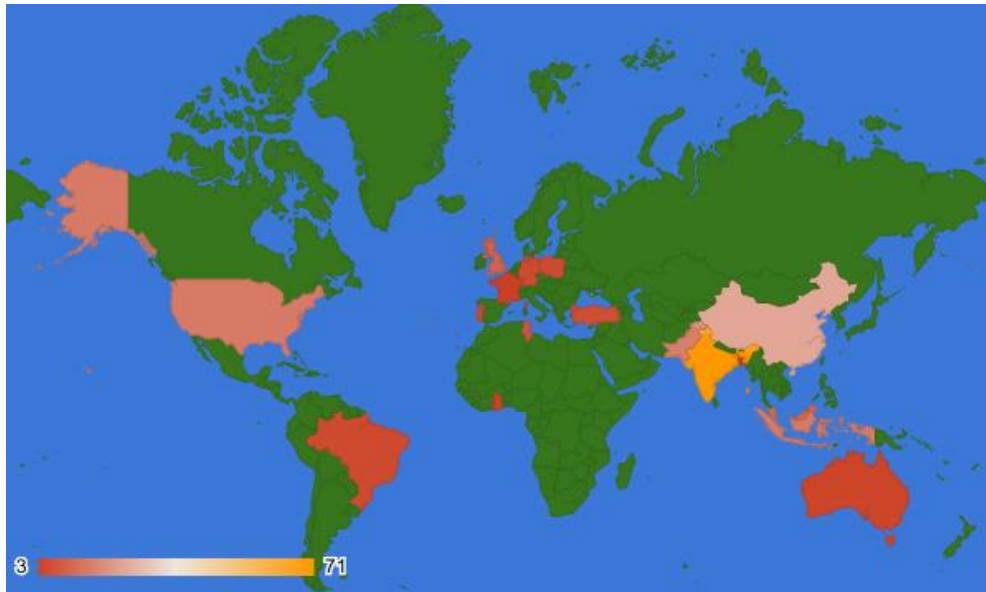


Figure 13. International Distribution of Research Outputs

4.5. Thematic Analysis

In order to reveal the conceptual structures of research on behavioral finance and investor decisions, a thematic map has been made on the basis of two dimensions of centrality (relevance of theme in the field) and density (theme development) (Cobo et al., 2011). According to this approach, themes can be classified into four main categories, which are: motor themes, basic themes, emerging/declining themes and niche themes.

Motor Themes: Overconfidence, herding and investment decision making are identified as motor themes, since they reflect the maturity and high impact of these themes on behavioral finance. In other words, they are characterized by high internal development and close connections with other research areas.

Basic Themes: Financial literacy, disposition effect and behavioral biases belong to the category of basic themes. Despite their importance for studying investors, they still have poor integration into the network of research and possess great potential for academic investigation.

Emerging Themes: Issues relating to the influence of environment on investment decisions, mobile trading platform, and decision fatigue are cited as emerging and/or declining issues. This is due to their emerging nature, especially in the context of technology, sustainability, and cognitive heuristics.

Niche Themes: Other more specialized topics, which include cross cultural analysis of heuristics and sophisticated modeling techniques, are mature in terms of their development but remain marginal within the larger topic.

This can be seen in Figure 14 below, where the motor themes are placed in the top right quadrant (high centrality and high density), basic themes in the bottom right quadrant, emerging and/or declining themes in the bottom left quadrant, and niche themes in the top left quadrant.

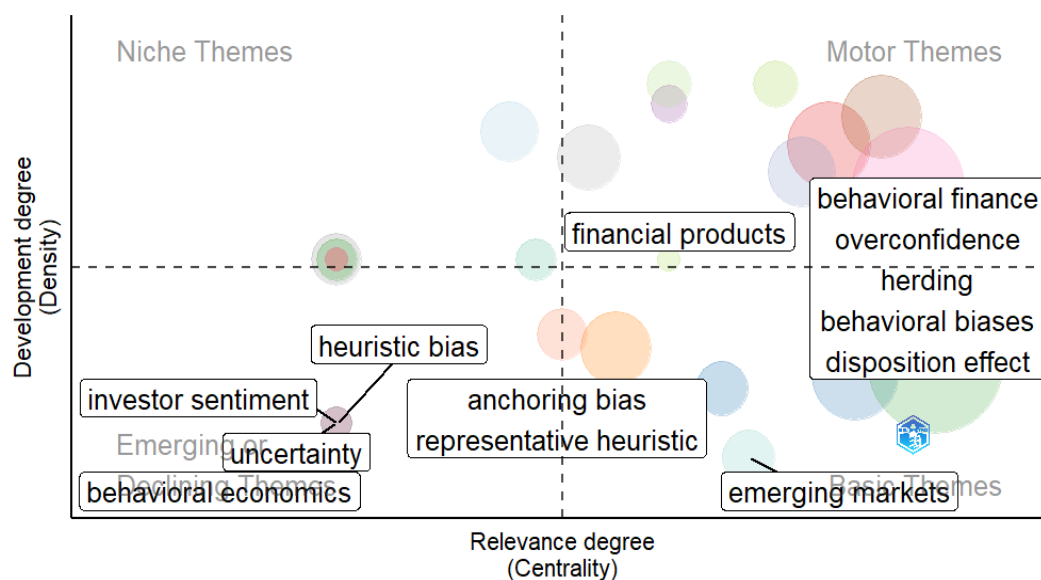


Figure 14. Thematic Map of Research on Behavioral Biases and Investment Decision-Making

5. Limitations

Despite the methodological strength of this bibliometric study, there are several weaknesses that need to be mentioned. First, the analysis is based on articles written in the English language and indexed in Scopus and WoS. Though these databases are highly reliable sources known for their coverage, the exclusion of papers from other languages and other databases like Google Scholar and ProQuest may result in loss of regional and interdisciplinary literature. Second, the very nature of bibliometrics implies that the main focus is made on quantitative factors such as the number of citations and co-occurrences. Third, thematic classification and mapping based on keywords use the metadata provided by authors and may involve overlaps and inconsistency in the representation of emerging themes. Lastly, this study provides an overview of history and structure of research but does not establish any causal relations between the behavioral bias and investment performance.

6. Conclusions

This study provides an extensive account of scholarly work related to behavioral biases and investment decision-making. The results reveal that the current state of this field is based on the pioneering works by Kahneman, Tversky, and Thaler but remains vibrant due to the ongoing research related to overconfidence, herding, and the disposition effect. In addition, there is an increasing attention in this field to such areas of research as technology, specifically, digital trading, fintech, and algorithmic detection of behavioral patterns. The study indicates that there are several promising research directions in this field, which can include cultural differences among investors, sustainable finance, and the role of artificial intelligence and digital platforms in making financial decisions. The findings of this review also demonstrate the significance of financial literacy. Thus, the literature reveals several interesting features of this field that should be considered when conducting research in behavioral finance.

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