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A COMPREHENSIVE REVIEW OF BEHAVIORAL BIASES IN FINANCIAL DECISION-MAKING: FROM CLASSICAL FINANCE TO BEHAVIORAL FINANCE PERSPECTIVES

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Abstract. This paper offers a detailed analysis of the evolution of financial decision-making theories, focusing on the shift from classical finance to behavioral finance. Classical finance theories, including the Efficient Market Hypothesis and Modern Portfolio Theory, assume that investors behave rationally and that the market is efficient. However, these theories have faced criticisms highlighting the importance of considering irrational behaviors in financial markets. Behavioral finance addresses this gap by integrating psychological insights into financial decision-making. This study systematically reviews the literature on behavioral biases that affect individual investors, identifying fundamental biases and their impact on investment decisions. The analysis emphasizes the role of cognitive limitations and psychological tendencies in shaping market dynamics, influencing asset pricing, investment strategies, and market returns. The research also notes a shift in focus from market-level outcomes to the behavior of individual investors, with an increase in publications. The paper concludes that understanding investors' biases is crucial for developing effective risk management strategies and investment recommendations, ultimately leading to improved market performance. The findings underscore the growing importance of behavioral finance in explaining investor behavior and market anomalies, highlighting areas for future research in this evolving field.

Keywords: behavioral finance, investment decision-making, behavioral biases, classical finance theories, pompian's framework, investor personality, rationality in finance.

JEL Classification: G11, G41.

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1. Introduction

Investors' behaviour in investment decision-making is essential because it can significantly affect their investment outcomes. On the one hand, investors consider all the available information and can make rational investment decisions. On the other hand, as Mittal (2022) notes, investors do not always choose a rational way: investors' decision-making uses an intuitive and automatic process rather than a "deliberative and controlled" one. Therefore, the issue of why investors do so is widely debated nowadays.

Pioneer-researchers of the classical approach (Fama, 1965b, 1965a, 1970; Markowitz, 1952; Merton, 1985; Mintzberg et al., 1976) supported the idea of rationality in the decision-making process. Furthermore, the hypotheses of rational investors and efficient markets are supported by theories such as Efficient Market Theory (EMT) (Fama, 1965b, 1965a, 1970) and Modern Portfolio Theory (MPT) (Markowitz, 1952). EMH contends that in a market, "the curfrent prices of a security obviously 'fully reflect' all available information" (Fama, 1970), while MPT focuses on constructing portfolios based on return and risk considerations (Sharma & Sushila, 2020). Under financial decision theory, a rational investor should: (i) make objective decisions to maximise gains and minimise losses; (ii) optimise the risk-return trade-off; (iii) diversify investment portfolio; (iv) seek to be well informed about the characteristics of financial instruments, market conditions, events and trends; and (v) make decisions based on the assumption that financial markets are efficient. However, the criticism expressed by researchers (e.g., Chang, 2008; Kourtidis et al., 2011; Mittal, 2022) highlight that these theories overlook the irrational behaviour present in real markets, resulting in transactions that cannot be explained by traditional finance theories. Consequently, the rise of behavioural finance recognises the importance of incorporating human irrationality into financial decision-making. In this context, human irrationality is defined as behavioural bias. According to Sharma and Sushila (2020), a bias is an irrational assumption or prejudice; it is a human psychological shortcoming. Therefore, the analysis of investor behavioural biases is crucial, as they have a significant impact on market dynamics and outcomes, as Sharma and Kumar (2020) note, "under uncertainty and in a risky environment" (e.g. these biases can lead to mispricing of assets (Chaudary, 2019; Kunjal & Peerbhai, 2021), impact investment strategies (de Dreu & Bikker, 2012; Ahmad et al., 2018) and returns (de Venter & Michayluk, 2008; Mushinada & Veluri, 2020; Sharma & Kumar, 2020). Moreover, at the macro level, it "could help explain the stock market anomalies" (Dhingra et al., 2024; Mittal, 2022).

These biases include various factors that affect decision-making, such as overconfidence, self-attribution, hindsight, representativeness, loss aversion, herding, anchoring, disposition effect (disposition), etc. It is also possible to distinguish a separate group of authors. Firstly, in empirical studies, researchers usually focus on a single bias, sometimes on several biases. For example, Kourtidis et al. (2011) selected four biases: overconfidence, risk tolerance, self-monitoring, and social influence to identify the investor profiles. Rasool and Ullah (2020) examined fourteen behavioural biases to determine the relationship between these biases and the financial literacy of individual investors in Pakistan. Jain et al. (2022) analysed nine behavioural biases to develop the measurement scale for these biases. Baulkaran and Jain (2024) examine six behavioural biases to determine the impact of these biases on the comfort level of financial planners when providing advice. Secondly, a larger number of biases are analysed more in theoretical works, e.g., Zahera and Bansal (2018) studied 17, Sharma and Kumar (2020) – 15, Sharma and Sushila (2020) – 19, Calzadilla et al. (2021) – 18, Badola et al. (2024) – 24 biases. It should be noted, however, that researchers have also conducted systematic reviews of individual biases. For example, Singh et al. (2024) has examined the theories, context and methods used in research on overconfidence. Thirdly, the researchers try to combine the behavioural biases to represent the investor profiles. For example, Kourtidis et al. (2011) selected four biases (as presented above) to identify three main segments of investors (i.e., high, moderate, and low investor profiles). To identify eight possible investor personality types, Pompian (2006) constructed three specific behavioural scales, i.e., "investor personality dimensions" (i.e., Idealist versus Pragmatist, Framer versus Integrator, and Reflector versus Realist). In each dimension, the author contrasted the rational investor with the irrational investor, and in addition, each irrational investor is described by several behavioural biases; the author used a total of 20 biases. Summarising the state of research in behavioural finance, Jain et al. (2022) highlight the need for further research in this area, as the available knowledge base is limited to one or a few behavioural biases that investors face when making investment decisions.

It should be noted that while there is a consensus among researchers that behavioural finance research is growing rapidly, the majority of publications "analyse the behaviour of financial markets and institutional investors" (Calzadilla et al., 2021). Individual investors are less studied (Calzadilla et al., 2021), and this field of behavioural finance is expected to be a key area for future research (Sharma & Kumar, 2020).

As empirical research provides much evidence against EMH, the importance of behavioural finance emerges. The latter tend to develop in two directions: behavioural finance macro (BFMA) and behavioural finance micro (BFMI). Nevertheless, it must be acknowledged that in existing literature little attention is paid to individual and non-financial investors, which raises the need for more detailed research.

This study aims to develop the theoretical analysis that identifies the changes in the approach from the classical approach to behavioural finance, identifies the behavioural biases in financial decision-making, and presents a review of the literature in the field of behavioural finance-related biases. Taking into account that numerous biases are related to investors' behaviour in financial markets and therefore could have significant consequences on the investors' profits and losses, it is crucial, rather than analysing the selected biases in isolation, to analyse them in a grouping that reflects the dimensions of the investor. Furthermore, it is necessary to understand how the biases interact within a single dimension; and what is the interplay between dimensions.

From a theoretical perspective, the study adds to the existing knowledge base by investigating the behavioural biases that affect individual investors in the financial decision-making process and why these decisions deviate from the predictions of traditional theories.

The findings of this study could contribute to the understanding of investors' biases and their investment decisions, which could help to develop more accurate risk management strategies, models, and investment recommendations that account the complexity of individual behaviour in financial markets.

In summary, as Jain et al. (2022) state, knowledge of behavioural biases and their implementation in investment decisions will increase the logic of investment decisions and create the scope for higher market performance.

The remainder of this paper is organised as follows: Section 2 describes the changes in two different approaches: classical and behavioural finance. Section 3 describes the systematic literature review methodology, and Section 4 presents the analysis and critical evaluation of financial behavioural biases. Finally, Section 5 presents the analysis of network map. In the end, we stated conclusions.

2. The changes in approach from the classical approach to behavioural finance

2.1. The classical approach

The study by Sharma and Kumar (2020) can be considered as one theoretical research that reviews the theories supporting the Efficient Market Hypothesis (EMH), "discusses the evolution of the concept of market efficiency and how EMH came into being and became a widely accepted explanation of the market movements," and analyses studies that provide the stock market evidence of the failure of EMH to understand emerging trends in behavioural finance (Sharma & Kumar, 2020).

Psychological insights have not been applied to explain economic and financial decision-making for a long time. However, as observed in scientific studies (Mittal, 2022), the human decision-making process is influenced by many factors and biases that could be explained by behavioural finance.

From the perspective of behavioural finance as a new direction in finance, the development of finance science can be divided into several phases. Before Williams's (1938, as cited in Graham, 1939) issue, "old-time investment, with its emphasis on book value and the past record, was short-sighted and naive"; the financial markets were not considered appropriate markets (Sharma & Sushila, 2020); it was considered to be analogous to casinos (Sharma & Sushila, 2020), i.e., at that time, "investment, as practiced by investment trusts and everyone else, is not much more than an undisciplined wagering upon the future and as such logically indistinguishable from speculation" (Graham, 1939). Firstly, according to Sharma and Sushila (2020), John Burr Williams was "first to challenge the casino concept": in the book "The Theory of Investment Value" in 1938, he considered the quantitative and forward-looking technique of common-stock investment, and he detailed that "the investment value of a stock is the present worth of all future dividends" (Graham, 1939), i.e. argued the Dividend Discount Model (DDM).

Secondly, in 1952, Markowitz created the Modern Portfolio Theory, which became one of the traditional finance theories (Kourtidis et al., 2011; Mittal, 2022; Mushinada, 2020; Sharma & Sushila, 2020) and a milestone in the field of financial mathematics (Yin, 2019). In this theory, the selection of assets is based on return and risk, where the term 'return' is frequently identified with discounted future cash flow and 'risk' with the uncertainty of expected outcome (Sharma & Sushila, 2020). Furthermore, the understanding of risk has changed from qualitative to quantitative, i.e., for the first time, the researcher used mathematical tools to quantify risk (Yin, 2019).

Thirdly, Eugene F. Fama proposed the efficient market hypothesis (EMH), which has the following main assumptions. First, we analyse a market in which prices give accurate signals about the allocation of resources, assuming that security prices "fully reflect" all the available information at any time. As Fama (1970) states, a market in which prices always "fully reflect" the available information is called "efficient" (Fama, 1970). Second, the author identifies the following market conditions that are consistent with efficiency (Fama, 1970): (i) "there are no transactions costs in trading securities," (ii) all market participants have access to available information costlessly, and (iii) "all agree on the implications of current information for the current price and distributions of future prices of each security." Fama (1970) summarises that, in such a market, "the current price of a security obviously "fully reflects all available information" (Fama, 1970). In the same way, Alrabadi et al. (2018) refer that, according to the EMH, "stock prices reflect all past, publicly available and insider relevant information". Furthermore, the researchers point to investor behaviour, i.e. (i) the EMH "is not concerned with the actual investor behaviour and its consequences" (Ates et al., 2016); (ii) it states that the investor is "rational" i.e., "explain what investors should do" (Mittal, 2022) or "discuss how the rational investor should behave" (Ates et al., 2016), etc.

2.2. A criticism of the classical approach

According to researchers e.g. Chang (2008), Kourtidis et al. (2011), traditional finance theories like the EMH and the MPT "support the hypotheses of rational investors and efficient markets" (Kourtidis et al., 2011). However, irrational investors exist in the market, making random transactions (Chang, 2008) that "cannot adequately be explained by traditional finance theories" (Kourtidis et al., 2011). Sharma and Kumar (2020) stated that (i) the EMH, characterised by idealistic assumptions based on a perfectly rational world, has faced growing criticism. (ii) Analysis of theoretical and empirical research papers reveals numerous instances where the EMH is not confirmed. It suggests that markets are irrational. (iii) Therefore, an alternative theory, such as behavioural finance, is needed to acknowledge the irrational nature of human behaviour and its impact on decision-making. To summarise the discussion, it should be noted that traditional financial theories reflect a hypothetical situation (Mittal, 2022), and they are supported by the hypotheses of efficient markets and "rational" investors (Kourtidis et al., 2011; Mittal, 2022; Mushinada, 2020; Sharma & Sushila, 2020). However, in the real markets, irrational investors also transact, and their behaviour cannot be adequately explained by traditional finance theories (Chang, 2008; Kourtidis et al., 2011), i.e., these theories cannot explain what investors really do but could be explained by behavioural finance (Mittal, 2022).

2.3. Changes in approach

Researchers have challenged the concept of rationality in decision-making. According to Sharma and Sushila (2020), in 1957, Herbert Simon introduced the concept of "Bounded Rationality," highlighting that humans are limited by "their abilities and available information," i.e. human decision-making is not "fully rational." In the 1970s, Amos Tversky and Daniel Kahneman applied psychological biases to the analysis of economic decision-making in situations of uncertainty (Sharma & Sushila, 2020). In 1979, Daniel Kahneman and Amos Tversky developed the Prospect theory (Sharma & Sushila, 2020). Daniel Kahneman applied psychological insights to economic decision-making (Sharma & Sushila, 2020), and won the Nobel Memorial Prize in Economics in 2002 "for having integrated insights from psychological research into economic science, especially concerning human judgment and decision-making under uncertainty" (Nobel Prize Outreach AB, 2023a). In 2017, Richard Thaler won the Nobel Memorial Prize in Economics "for his contributions to behavioural economics" (Nobel Prize Outreach AB, 2023b; Sharma & Sushila, 2020). He has paid particular attention to the following psychological factors: the tendency not to "behave completely rationally," concepts of "fairness and reasonableness, and lack of self-control" (Nobel Prize Outreach AB, 2023b).

2.4. Behavioural finance and behavioural biases

Previous research (Ossareh et al., 2021) has shown that the psychological characteristics of stock market investors have always been of interest to behavioural scientists who aim to understand the investors' decision-making processes "based on their attitudes and specific attributes." Other authors also provide a similar definition of behavioural finance. For example, Anjum et al. (2019) state that theories within behavioural finance are based on psychology, seeking to understand how their emotions and cognitive errors influence the behaviour of individual investors. Similarly, Sharma and Sushila (2020) describe "behavioural finance as a sub-field of behavioural economics" that combines psychology with finance and explains how investors' cognitive and emotional biases impact their investment decisions. Bikas et al. (2013)

suggest that behavioural finance draws upon human and social cognition and emotional tolerance research to identify and comprehend economic decision-making. Thaler (1999) defined behavioural finance as "an integration of classical economics and financial theories," focusing on the studies of psychology and decision-making (Bikas et al., 2013).

Finally, based on theoretical analysis, Bikas et al. (2013) summarise that behavioural finance emerges from the convergence of different sciences: (i) psychology, which studies behavioural and cognitive processes influenced by the physical, psychical, and external environment; (ii) finance, which includes the formation, distribution, and use of resources; and (iii) sociology, which explores the socio-behavioural aspects of individuals or a group, emphasising the impact of social relationships on attitudes and behaviour.

Behavioural finance covers a broad area of research: "from individual investor conduct to market-level outcomes" (Pompian, 2006); or, as Sharma and Kumar (2020) state, the theoretical framework of behavioural finance "embraces investor irrationality and market inefficiency." Therefore, the researcher (Pompian, 2006) proposes two 'themes' of behavioural finance: behavioural finance macro (BFMA) and behavioural finance micro (BFMI), where BFMA "detects and describes anomalies in the efficient market hypothesis," and BFMI examines "behaviours or biases of individual investors," which we discuss in more detail.

According to Sharma and Sushila (2020), a bias is an irrational assumption or prejudice; as the authors state, it is a human psychological shortcoming. On the one hand, Alrabadi et al. (2018) state that "behavioural biases denote irrationality in decision-making." Moreover, the empirical findings in the finance literature show that "investors do not act rationally." According to Sharma and Sushila (2020), "In the process of decision-making, of several biases arise." However, as Ossareh et al. (2021) point out, not all are related to investors' behaviour in financial markets. Therefore, these biases should be classified. Michael M. Pompian (2006) classified these biases into (i) cognitive and (ii) emotional biases (Sharma & Sushila, 2020). On the other hand, as Sharma and Sushila (2020) note, cognitive biases are caused by errors in information processing or the use of heuristics. The economic, psychological, and sociological literature contains a wide range of cognitive biases. For example, Blawatt (2016) identifies almost 100 different biases of this type. Cognitive biases are essential research mediators and moderators for investor decision-making (Mushinada, 2020). Major cognitive biases are adjustment, anchoring, confirmation, conservation, hindsight bias, mental accounting, etc. (Sharma & Sushila, 2020). According to Mushinada (2020), self-attribution and overconfidence are biases that are widely discussed in the literature.

Emotional biases arise because of the emotions an individual feels when making a decision. Major emotional biases are loss-aversion, overconfidence, regret aversion and status-quo bias, etc. (Sharma & Sushila, 2020). Alrabadi et al. (2018) summarise that psychological research has documented different behavioural biases. These biases can affect various decision-making behaviours. However, they are particularly relevant for investment.

As biases might be unavoidable in the investment decision-making process, there is a discussion about minimizing their impact on investment results. In this way, it might seem that only humans suffer from behavioural biases, while robots, on the other hand, are completely rational and emotionless. However, a systematic review of the literature on investment advisors by Wagner (2024) shows that both conventional and digital advisors may deviate from rational behaviour due to unconscious factors: conventional advisors may have misguided beliefs, while digital advisors may be affected by programmer bias.

Although, as Dhingra et al. (2024) note, behavioural biases influence the investment decisions of individual and institutional investors in different countries. Our study focuses on the

BFMI, i.e., it analyses the behaviour of individual investors. More precisely, it aims to analyse the investor personality types and simultaneously the behavioural biases of irrational investors. As summarised by Alrabadi et al. (2018), the importance of this issue stems from the consequences that these behavioural biases could have on the investors' profits and losses, i.e., at the micro level and on the stock market, i.e., at the macro level.

Finally, when analysing the importance of behavioural finance for individual investors by Calzadilla et al. (2021), the authors highlight two moments: (i) the volume of published papers related to behavioural finance has increased exponentially since 2010, and (ii) many published papers analyse the behaviour of financial markets and institutional investors, while individual and non-financial investors receive less attention. Thus, this topic of individual investor behavioural finance is less researched and requires further investigation.

3. Systematic literature review methodology

The systematic literature review methodology is applied to review and analyses publications related to behavioural biases in investment decision-making. This research consists of two main stages. Firstly, the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) method is used, following the methodology used in previous systematic literature analysis studies, such as the approach of Dičpinigaitienė and Kanapickienė (2019), Calzadilla et al. (2021), Wagner (2024). Secondly, the text analysis technique is employed to identify the key behavioural biases in financial decision-making.

The literature identification and selection are carried out with a strategy that includes various criteria for the systematic literature review. The search was conducted by employing relevant keywords, selecting the appropriate database, setting a specific time frame, and developing other inclusion and exclusion criteria (Figure 1).

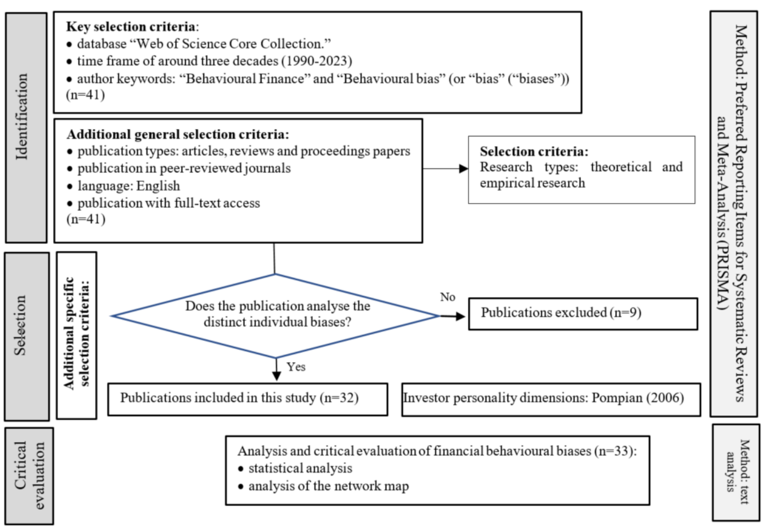


Figure 1. Algorithm for the systematic literature review methodology

To search for the paper, we used the following author keywords: "behavioural finance" and "behavioural bias" (or "bias" ("biases")) within the "Web of Science Core Collection" database.

The selected time frame for the search encompassed approximately three decades, from 1990 to 2023. We chose 1980 as the initial year, as suggested by Kumar and Goyal (2015), because it marked the development of the prospect theory by Kahneman and Tversky (1979), "which was the first theoretical base of behavioural finance." Thus, empirical studies in this field have primarily emerged after 1980. However, the "Web of Science Core Collection" information has been available since 1990. In addition, we selected information from the "Web of Science Core Collection" until June 2023, specifically until 18 June 2023. Furthermore, the scope of publications includes theoretical and empirical articles, reviews, and proceedings.

The database search was conducted on 18 June 2023, including all the publications that met the criteria above. As a result, forty-one research papers were selected based on these criteria, i.e., 29 articles, five reviews, and seven proceedings papers (the database search protocol can be offered upon request). After reviewing, nine publications were excluded from the study because they did not analyse individual bias. Thus, the further analysis includes 32 publications: 24 articles, five reviews, and three proceedings papers (see Table 1).

4. Analysis and critical evaluation of financial behavioural biases

Firstly, the results present a statistical analysis of the selected sample of publications. Secondly, the network map results analysis is provided, showing the key aspects of behavioural bias conception to clarify the depth of these studies.

Figure 2 illustrates the distribution of publications between 1990 and 2023, revealing a substantial increase in interest in the topic, particularly in the last decade. It should be noted that no studies were included in the "Web of Science Core Collection" between 1990 and 2004.

In the subsequent period from 2005 to 2009, only one article was published focusing on empirical research. From 2010 to 2014, the number of publications increased to six, comprising three articles and three proceedings papers. Among these, one article focused on theoretical research, and the remaining five on empirical research. Between 2015 and 2019, the number of publications increased to 12, encompassing seven articles and four proceedings papers. The distribution of research types is the following: 16.6% of publications were theoretical, while the other publications (83.4%) encompassed empirical research. The most recent period, from 2020 to 2023, exhibited a substantial increase in publications: 18 were articles, and the remaining four were reviews. Interestingly, 27.2% of publications involved theoretical research, while the majority, 72.8%, centred around empirical research. The progressive rise in the number of studies indicates the growing recognition of the significance of a behavioural approach in investors' financial decision-making.

The 32 publications analysed 47 behavioural biases, 19 of which were analysed by Pompian (2006) to identify dimensions of investor personality. It should be noted that Pompian (2006) uses one more bias – Ambiguity – which is not mentioned in the investigated studies.

The analysis of publications measures the importance of each behavioural biases category referenced within the selected publications (see Table 1). Overconfidence (65.6% of all publications) and Self-attribution (31.3%) are the top categories. Such biases as Anchoring, Disposition effect (Disposition), Hindsight, Representativeness, and Herding (Herd behaviour) were analysed in 21.9% of the publications. Confirmation and Loss aversion were analysed in 18.8% of the publications. All other biases were studied in 15.6% or less of publications. It should be noted that all the most frequently analysed biases (except Herding (Herd behaviour) and Disposition effect (Disposition)) are included in Pompian (2006), investigating investor personalities.

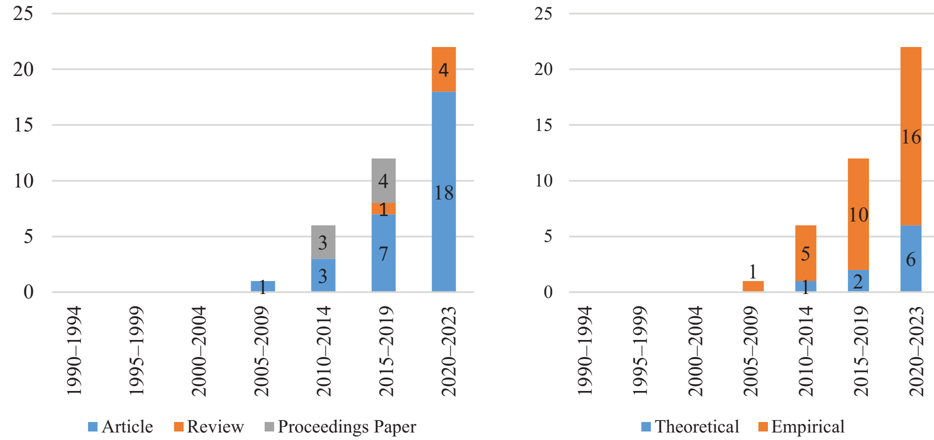


Figure 2. Number of citations and publications (source: Web of Science, recovered on 18 June 2023)

Among the 47 analysed behavioural biases, 41 biases were not analysed in 2005–2014. Already, 37 biases were explored in 2020–2023 (i.e., 78.7% of all biases). Finally, the bias "Ambiguity" is not analysed (except for Pompian, 2006). In the following, we will explore the biases studied in 20% of publications in more detail.

Overconfidence is a bias that has been analysed across all periods and shows the highest growth (Figure 3). On the other hand, as Figure 3 shows, all the other biases, i.e., Self-attribution, Anchoring, Hindsight, Representativeness, Herding (Herd behaviour), and Disposition effect (Disposition), have only recently started to be examined in the last two periods.

During the 2015–2019 period, compared to the 2010–2014 period, Self-attribution demonstrated the highest growth, with the number of publications increasing from 0 to 4. The Anchoring, Disposition effect (Disposition), and Representativeness biases increased from 0 to 2 publications. Only one study examined the Hindsight bias.

In the 2020–2023 period, compared to the 2015–2019 period, the Hindsight bias showed the highest growth, with the number of publications expanding from 1 to 6 (i.e., six times). The Anchoring, Representativeness, Hindsight, and Disposition effect (Disposition) biases increased by 2.5. The Self-attribution bias showed the lowest growth (1.5 times).

The next dimension of the analysis is based on publications analysing behavioural biases (see Figure 4). As mentioned above, a total of 32 publications were analysed.

Fourteen publications (i.e., 43.8% of all publications) examined one bias each. We will analyse which sub-group biases (A or B sub-groups as shown in Figure 4) are more extensively analysed. 8 publications (i.e., 57.1% of the publications with 1 bias) focused on biases from the A sub-group. Eight publications (i.e., 57.1% of the publications with 1 bias) focused on biases from the A sub-group. Most frequently, authors investigated overconfidence and confirmation.

Table 1. Behavioural biases analysed in publications

Behavioural bias:	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	Total (without 0)
Sub-group A																																		
Ambiguity	1																																	0
Anchoring	1								1				1					1		1	1	1						1						7
Availability	1																	1			1					1		1		1				5
Cognitive dissonance	1																	1			1													2
Confirmation	1				1						1		1							1		1				1								6
Conservatism	1												1							1	1	1												4
Endowment (Endowment effect)	1												1							1	1	1												4
Framing	1												1							1	1	1												4
Hindsight	1												1					1		1	1	1	1							1				7
Illusion of control	1								1									1																2
Loss aversion	1												1					1			1	1	1			1								6
Mental accounting	1												1					1			1	1						1						5
Optimism (excessive optimism)	1																				1												1	2
Overconfidence	1	1	1			1			1	1		1	1		1	1	1	1	1	1	1	1	1		1			1		1	1	1		21
Recency	1												1																					1
Regret (Regret aversion)	1												1					1				1						1						4
Representativeness	1					1							1					1			1	1	1					1						7
Self-attribution	1							1				1	1		1	1	1	1			1	1								1				10
Self-control	1								1																									1

Continued Table 1

Behavioural bias:	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	Total (without 0)
Status quo	1								1												1													2
Sub-group B																																		
Aversion																												1						1
Bandwagon effect																										1								1
Bias of growth opportunity																								1										1
Certainty effect										1										1														2
Disappoint-ment aversion																				1														1
Discounting																						1												1
Disposition effect (Disposition)						1							1							1	1	1					1			1				7
Dunning–Kruger effect																										1								1
Familiarity bias								1						1															1					3
Gambler's fallacy																		1			1					1		1						4
Guru effect							1																											1
Herding (Herd behaviour)								1					1					1			1	1						1		1				7
Home bias				1									1								1	1												4
Hot-hand fallacy																										1								1
House money effect													1							1		1												3
Ignorance of probability laws																				1														1
Isolating effect										1																								1

End of Table 1

Behavioural bias:	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	Total (without 0)
Limiting the choices																				1														1
Market bias																		1																1
Preference reversal																						1												1
Reliance on expert bias									1																									1
Risk tolerance,			1																															1
Self-monitoring			1																															1
Self-serving																							1											1
Social bias																				1														1
Social influence			1																															1
Socially responsible investing bias									1																									1
Sunk cost fallacy																				1	1													2
Total Sub-group A	20	1	1	0	1	2	0	1	5	1	1	2	13	0	2	2	2	11	1	7	14	12	4	0	1	3	0	6	0	4	1	1	1	
Total Sub-group B	0	0	3	1	0	1	1	2	2	2	0	0	4	1	0	0	0	3	0	8	5	6	1	1	0	4	1	3	1	2	0	0	0	
Total	20	1	4	1	1	3	1	3	7	3	1	2	17	1	2	2	2	14	1	15	19	18	5	1	1	7	1	9	1	6	1	1	1	

Note: 0 – Pompian (2006); 1 – de Venter and Michayluk (2008); 2 – Kourtidis et al. (2011); 3 – de Dreu and Bikker (2012); 4 – Duong et al. (2014); 5 – Toma (2015); 6 – Keller and Pastusiak (2016); 7 – Al-mansour and Arabyat (2017); 8 – Sahi (2017); 9 – Tufan et al. (2017); 10 – Majewski (2018); 11 – Mushinada and Veluri (2018); 12 – Zahera and Bansal (2018); 13 – Chaudary (2019); 14 – Mushinada and Veluri (2019); 15 – Mushinada (2020); 16 – Mushinada and Veluri (2020); 17 – Rasool and Ullah (2020); 18 – Rzeszutek and Szyszka (2020); 19 – Sharma and Kumar (2020); 20 – Sharma and Sushila (2020); 21 – Calzadilla et al. (2021); 22 – Gerth et al. (2021); 23 – Gong et al. (2022); 24 – Kunjal and Peerbhai (2021); 25 – Ossareh et al. (2021); 26 – Bansal and Jacob (2022); 27 – Jain et al. (2022); 28 – Maknickienė and Rapkevičiūtė (2022); 29 – Mittal (2022); 30 – Mundi et al. (2022); 31 – Mundi et al. (2022); 32 – Nyakurukwa and Seetharam (2022).

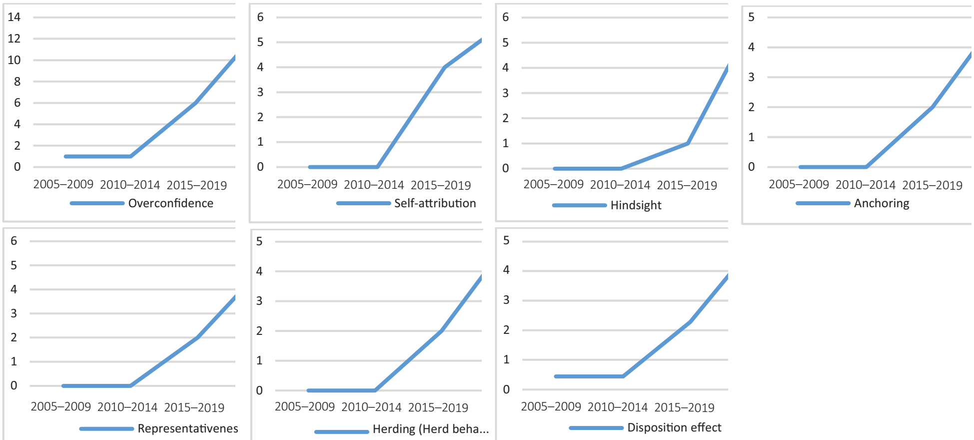


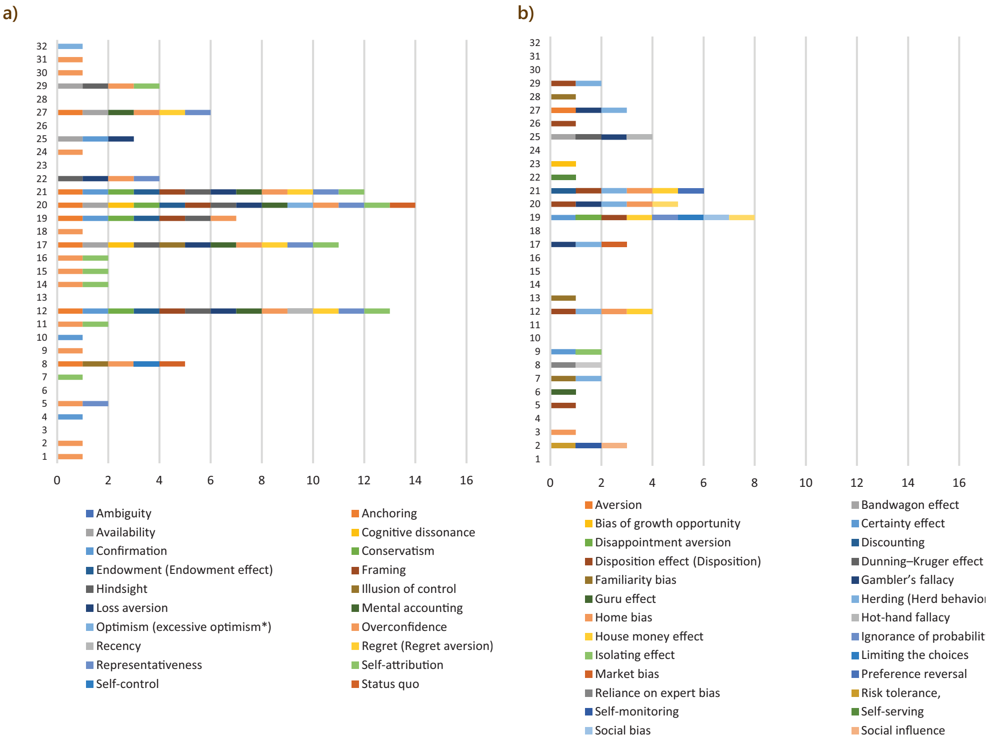
Figure 3. Trend of behavioural biases analysed in publications over time

In sub-group B, no specific trend can be identified: in this sub-group, six publications analysed one bias each: (i) 2 publications investigated the Familiarity bias; (ii) one paper each delved into the following biases: bias of growth opportunity; disposition bias, the Guru effect, home bias. The number of publications analysing multiple biases in a single study decreases significantly. For example, four publications investigated two biases each (these biases are from subgroup A, specifically overconfidence and self-attribution). Three publications investigated three biases each. In a single publication, these researchers examined a larger number of biases: Sharma and Sushila (2020) examined 19 biases; Calzadilla et al. (2021) – 18 biases; Zahera and Bansal (2018) – 17 biases; A. Sharma and Kumar (2020) – 15 biases. All these publications are literature reviews (based on publication type) and theoretical research (based on research type). It should be noted that empirical research analyses fewer biases. When investigating which sub-group A or B biases are more frequently studied in publications (examining more than two biases), it was found that 64.3% of these publications (9 publications) dominantly focused on biases in sub-group A.

5. Analysis of the network map

The network map analysis shows the key aspects of behavioural bias conception in researchers' studies. For this purpose, we analyse and compare two aspects: (i) authors' keywords and (ii) behavioural biases analysed in researchers' studies.

According to Lis (2018), the analysis of keyword co-occurrence, as a bibliometric method, could be used to characterise the research field. Carrión-Mero et al. (2020) describe the author keyword co-occurrence network as a content analysis technique that "uses author keywords to construct semantic visual maps that reveal the cognitive structure of the investigated area". Therefore, the VOSviewer software (version 1.6.19 (van Eck & Waltman, 2023)) has been used for the creation of keyword networks and keyword clusters. Van Eck and Waltman (2014, as cited in Carrión-Mero et al., 2020) point out that graphs connected by nodes and links represent the relationships between words. The nodes represent the keywords. Their size is related to the number of occurrences the keyword appears in the documents. A larger size indicates a higher frequency of occurrence (and vice versa). The links (edges) show the



Note: numbers 1–32 as in Table 1.

Figure 4. Publications analysing the behavioural biases: a – publications analysing the behavioural biases identified by Pompian (2006); b – publications analysing the behavioural biases not examined by Pompian (2006)

relationship between a pair of nodes. The strength of this relationship is measured by the width of the link. A larger width indicates a more significant link.

Firstly, 97 authors' keywords are provided in the research sample publications, i.e., in 32 review documents. The network shows those keywords that form 17 clusters (Figure 5). Furthermore, the eight clusters (i.e., 47% of all clusters) consist of keywords that occur only once and only in that particular cluster: (1) trading behaviour, psychological bias, personality traits; (2) factor analysis, financial satisfaction, individual investor bias; (3) anomaly, asset pricing, the bias of growth opportunity; (4) analyst optimistic bias, analyst recommendation changes, South Africa; (5) disposition bias, equity market, investor behaviour, price path; (6) diversification, heaping, home bias, investment policy, pension funds, portfolio choice; (7) judgment bias, financial planning; (8) market turnover, market return, an exchange-traded fund. It can be assumed that the large number of such clusters indicates the specificity of the topics chosen by the authors.

Secondly, the keywords 'behavioural finance' (29 occurrences, 91 links) and "behavioural bias" (9 occurrences, 26 links) are among the most frequently cited. However, "behavioural finance" and "behavioural bias" (also "bias") have been excluded from this list because they are the main terms used in the keyword search. In this case, the map shows (Figure 6) the 11 independent clusters, i.e. they are not connected to each other: (i) 6 clusters are the first 6 clusters listed in the previous paragraph, i.e. clusters that consist of keywords that occurred

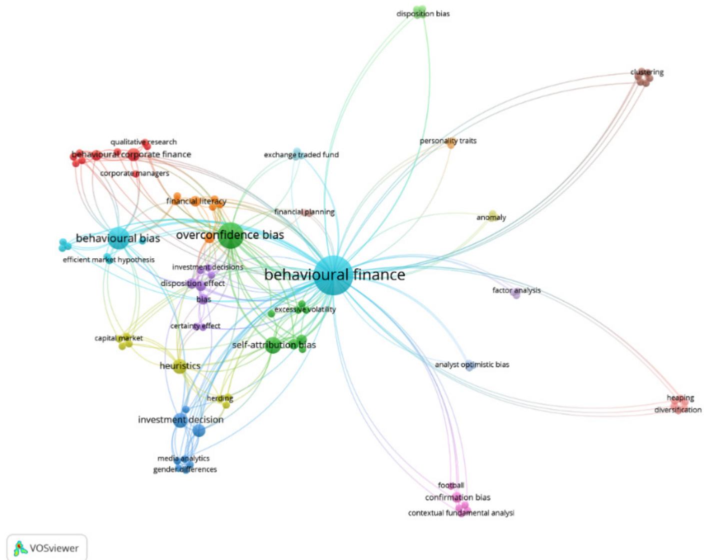


Figure 5. Bibliometric co-occurrence map of authors' keywords

only once and only in that particular cluster) and (ii) 5 new clusters ((1) confirmation bias, contextual fundamental analysis, financial statement analysis, football, market efficiency, value-glamour investing; (2) investment management; (3) efficient market hypothesis, market inefficiency; (4) clustering, cognitive bias, investor's profile, stock market, Teheran stock exchange, unsupervised learning; (5) ordinary investors, systematic review, web of science). This again confirms the observation made in the previous paragraph that authors choose original, specific topics for their research. Furthermore, the authors' keywords that are connected to each other are categorised into 10 clusters (Figure 7).

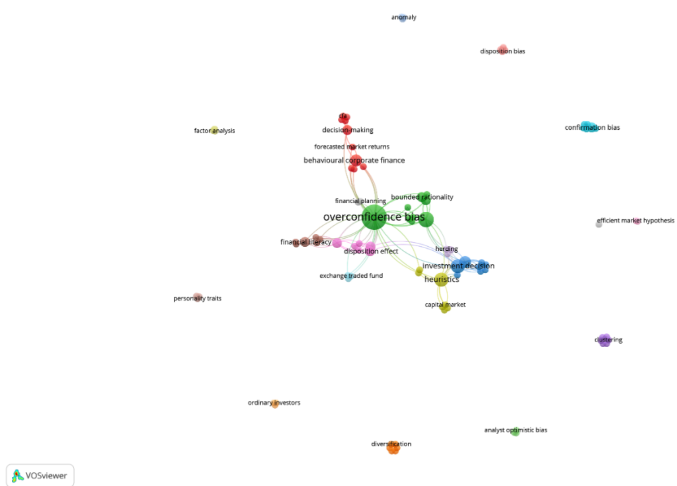


Figure 6. Bibliometric co-occurrence map of authors' keywords ("behavioural finance", "behavioural bias", and "bias" were excluded)

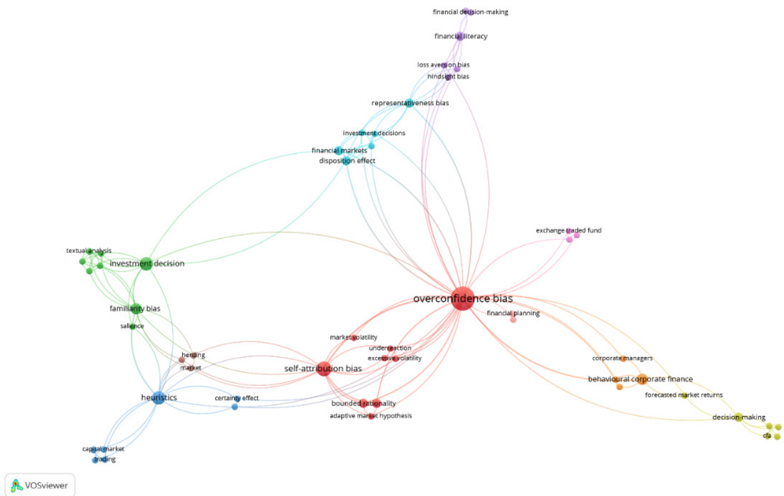


Figure 7. Bibliometric co-occurrence map of authors' keywords ("behavioural finance", "behavioural bias", and "bias" were excluded) without independent clusters

Thirdly, we analyse authors' keywords that appear more than once in the studies. This threshold is met by 14 keywords that can be categorised into 5 clusters: (i) 13 keywords are connected to each other and form 4 clusters (Table 2), (ii) the keyword "confirmation bias" forms a separate independent cluster.

Table 2. The 13 high-occurrence authors' keywords and bibliometric co-occurrence map of authors' keywords (notes: (i) the minimum number of occurrences of the keywords is two; (ii) the keywords are related to each other)

Author's keyword	Cluster	Links	Total link strength	Occurrences
Disposition effect	1	4	6	2
Financial literacy	1	2	2	2
Financial markets	1	4	6	2
Representativeness bias	1	4	5	2
Bounded rationality	2	3	6	2
Self-attribution bias	2	5	10	5
Structural equation modeling	2	3	6	2
Behavioural corporate finance	3	2	4	3
Decision-making	3	2	2	2
Overconfidence bias	3	11	21	13
Familiarity bias	4	3	5	3
Heuristics	4	4	5	4
Investment decision	4	5	6	4

Another aspect of the study is to map the financial behavioural biases analysed in the publications. As mentioned above, the authors analysed 48 biases. The financial behavioural biases can be grouped into 10 clusters using the co-occurrence analysis method. In Figure 8, the network shows 46 behavioural biases forming 8 clusters (46 items, 455 links, 968 link strength). The remaining two groups have only one behavioural bias each: (i) the "bias of growth opportunity" analysed by Gong et al. (2022), and (ii) the "guru effect" analysed by Keller and Pastusiak (2016). This shows that these biases have been analysed by only one author, which means that the analysis of these biases is not well-developed.

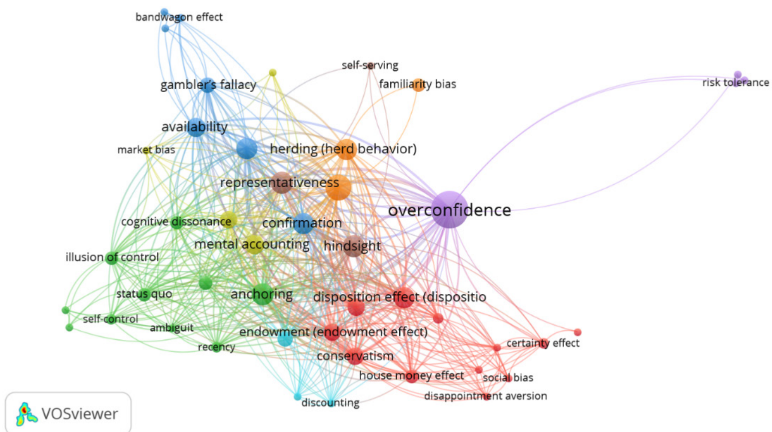


Figure 8. Bibliometric co-occurrence map of financial behavioural biases

In more detail, we analyse high-frequency behavioural biases, i.e., they are repeated in at least 10% of the articles analysed, i.e., at least three times. This threshold is met by 23 biases that can be categorised into 3 clusters (Table 3, Figure 9).

Table 3. The 23 high-occurrence financial behavioural biases (notes: (i) the minimum number of occurrences of the financial behavioural biases is three; (ii) the financial behavioural biases are related to each other)

Financial behavioural bias	Occur-rences	Total link strength	Financial behavioural bias	Occur-rences	Total link strength
Cluster 1 (12 items)			Cluster 2 (8 items)		
Anchoring	8	93	Confirmation	7	57
Availability	6	60	Conservatism	5	71
Optimism (excessive optimism)	3	33	Disposition effect (disposition)	7	62
Gambler's fallacy	4	39	Endowment (endowment effect)	5	71
Illusion of control	3	31	Framing	5	71
Loss aversion	7	81	Hindsight	8	91
Mental accounting	6	82	Home bias	4	47
Cognitive dissonance	3	45	House money effect	3	38

End of Table 3

Financial behavioural bias	Occur-rences	Total link strength	Financial behavioural bias	Occur-rences	Total link strength
Cluster 1 (12 items)			Cluster 2 (8 items)		
Overconfidence	22	107	Cluster 3 (3 items)		
Regret (regret aversion)	5	65	Familiarity bias	3	2
Representativeness	8	87	Herding (herd behaviour)	7	73
Status quo	3	36	Self-attribution	11	86

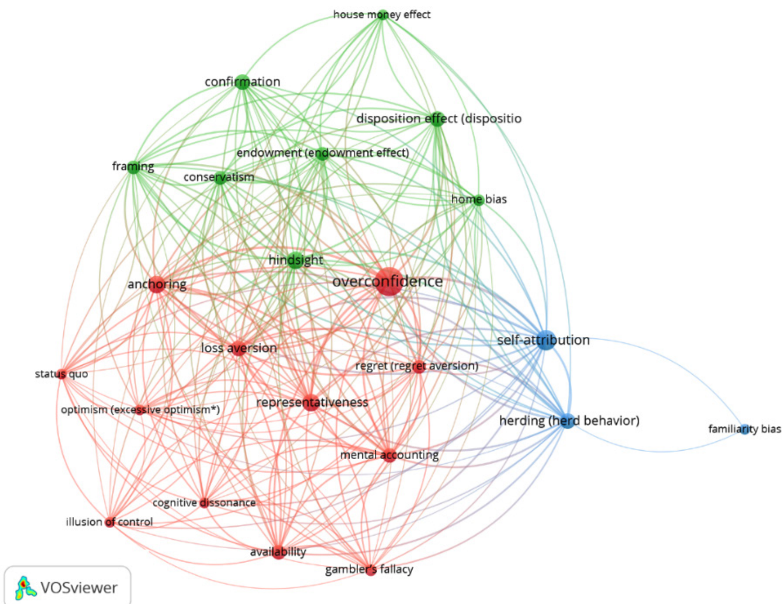


Figure 9. Bibliometric co-occurrence map of financial behavioural biases (notes: (i) the minimum number of occurrences of the financial behavioural biases is three; (ii) the financial behavioural biases are related to each other)

Before analysing high-occurrence financial behavioural biases in research studies (Table 3), it should be noted that Pompian (2006) uses inherent biases to describe the irrational investor in three specific behavioural scales, i.e. "investor personality dimensions". According to the author, the irrational investor-idealist could have eight inherent biases (i.e. overconfidence, optimism, availability, self-attribution, the illusion of control, confirmation, recency, representativeness), the irrational investor-framer could have five (i.e. anchoring, conservatism, mental accounting, framing, ambiguity), and the irrational investor-reflector – seven (i.e. cognitive dissonance, loss aversion, endowment, self-control, regret, status quo, hindsight). In this way, Pompian (2006) examines investor behaviour based on 20 biases.

The 17 biases that were analysed by Pompian (2006) are included in 3 clusters of the high-frequency behavioural biases in research studies. The following observations could be made here. Firstly, of the biases examined by Pompian (2006), there are three biases that have received little analysis in research studies. Only Pompian (2006) investigated the ambiguity bias that characterises the investor-framer. In addition to Pompian (2006), the recency bias, which characterises the investor-idealist, is studied by Zahera and Bansal (2018). Self-control bias, which describes the investor-reflector, is studied by Sahi (2017). Therefore, it can be assumed that other researchers believe these biases could be compensated by other biases describing the relevant investor personality dimension. Secondly, Cluster 1 (contains 12 biases (see Table 3), marked in red in Figure 9) is centred around the nodes of "Overconfidence", "Anchoring", "Loss aversion", and "Representativeness" (the biases describe investors: Idealist, Framer, Reflector, and Idealist, respectively). This indicates that the researchers are interested in all types of irrational investors. In addition, this cluster contains only one bias, the Gambler's fallacy, which is not included in Pompian's (2006) classification of irrational investors. Thirdly, Cluster 2 (contains 8 biases (see Table 3), marked in green in Figure 9) is centred around the node of "Hindsight" (the bias describes investors-idealist). Although occurrences and total link strength of others' biases are lower, they describe all types of irrational investors. This also indicates that the researchers are interested in all types of irrational investors. In addition, this cluster contains three biases, i.e. Disposition effect (disposition), Home bias, and House money effect, which are not included in Pompian's (2006) classification of irrational investors. Fourthly, Cluster 3 (contains 3 biases (see Table 3), marked in blue in Figure 9) is centred around the node of "Self-attribution" (the bias describes investors-idealists). Finally, while the studies analyse the biases of all investors, the authors are most interested in the biases of investors-idealists.

After discussing high-occurrence financial behavioural biases in research studies, it is also appropriate to examine whether the financial behavioural biases investigated by the authors are adequately reflected in the authors' keywords. This is important because authors' keywords increase the discoverability of studies. Moreover, when constructing keywords, authors usually mix generic and more specific terms related to the article's topic.

An analysis of the 13 high-occurrence authors' keywords (in this case, the minimum number of occurrences of the keywords is two) (see Table 2) shows that the authors' keywords reflect only 5 financial behavioural biases. Only research of familiarity bias is fully reflected in the authors' publications keywords. However, not all researched biases are reflected in the authors' keywords of publications. Authors reported Overconfidence bias as a keyword in only 13 studies, i.e., 59% of all publications, even though it is the most studied bias in scientific papers (22 publications). Other biases are similar: self-attribution bias (11 research, present as an authors' keyword in 5 studies, i.e., 45% of all publications), disposition effect (7, 2, 29%), and representativeness bias (8, 2, 25%).

If we analyse the six high-occurrence authors' keywords (in this case, the minimum number of occurrences of the keywords is three), we can see that the authors' keywords reflect only three financial behavioural biases, which are grouped into two clusters. Cluster 1 (marked in red in Table 2 (Figure)) contains one bias – familiarity bias (see Table 2), as well as two generic terms – "heuristics" and "investment decision". This highlights that financial behavioural biases are analysed in the context of individuals' investment decisions; and that this research is conducted using a heuristic method. Cluster 2 (marked in green in Figure 6) contains two biases – overconfidence and self-attribution, i.e. biases that are usually used as the authors' keywords to identify the main behavioural biases in financial decision-making. A generic term – "behavioural corporate finance" – is also included in this cluster. The term "behavioural corporate finance" describes the research direction that examines the financial behavioural biases of corporate managers and their impact on financial decisions, e.g., the studies by Moutzouris and Nomikos (2020), Mundi et al. (2022).

Finally, we can argue that the authors' keywords do not fully reflect the scope of the research of biases, and we consider that meta-analysis needs to be complemented by text analysis of publications.

6. Conclusions

Our investigation elucidates a paradigmatic evolution in financial theory, transitioning from traditional, deterministic frameworks to a more sophisticated and multidimensional paradigm that intricately weaves psychological constituents into the fabric of financial understanding. This paradigmatic shift underscores the imperative for augmented, methodologically rigorous research endeavors in the expansive field of behavioral finance.

In the course of our analytical odyssey through the labyrinth of behavioral biases, it became manifest that certain biases, such as the ambiguity, recency, and self-control biases, remain underexplored in the academic milieu, whilst others have been the subject of more thorough scholastic scrutiny. Most frequently, authors investigated overconfidence and confirmation. In our view, it is not appropriate to analyse individual biases, but rather to group them in such a way that they represent investor profiles. An example of such clustering is Pompian's framework, which measures the irrational investor on three specific behavioural scales, i.e. "investor personality dimensions". Thus, the irrational investor can be the idealist, the framer or the reflector. Our investigative focus primarily orbits around elucidating biases emblematic of various dimensions of irrational investors. We found that the majority of studies emphasised the biases typical of investor idealists. However, studies that have focused on all dimensions of irrational investors are in the minority.

Through a meticulous examination of extant scientific literature, we have discerned a conspicuous incongruity between the spectrum of behavioral biases that have been the focal point of scholarly research and the lexicon of keywords deployed in academic publications. This dichotomy underscores a potential epistemological gap, as the comprehensive gamut of studied biases is not efficaciously encapsulated within the employed terminological frameworks, thereby potentially obfuscating the accessibility and discoverability of these pivotal studies.

We advocate for a holistic, integrative approach that synergizes the methodological rigor of meta-analytic procedures with the depth and granularity afforded by textual analysis of scholarly publications. This approach is indispensable for engendering a more profound and nuanced comprehension of research's extensive and multifaceted terrain in financial behavioral biases.

The significance of acquiring a profound understanding of behavioral biases in the realm of financial decision-making is paramount. This understanding is critical to individual investors, corporate strategists, and institutional decision-makers, as it profoundly influences investment decision paradigms and the dynamics of market behavior.

Our research is based on bibliometric analysis, a quantitative approach to assessing academic literature and publications, which provides valuable insights into the trends, impact, and structure of research within various fields. However, it also has several limitations. Firstly, data source dependence. Our research relies only on the Web of Science Core Collection database, meaning that all other scientific papers from Scopus and other databases are not included. Focusing on high citation counts also have some risks and limitations because the most cited articles are not always the best and the reasons for citations are unclear. High levels of citations sometimes can be because of self-citations or even critisim of the research. The other essential aspect that must be mentioned in the limitations area is the citation time lag. It can take many years for a publication to accumulate many citations, so it is a considerable risk to focus on older research and skip the impact of newer research. From the practical area, bibliometric analysis typically focuses on academic impact and may not capture the broader societal and practical impact of research, especially in fields where practical applications are significant, as in our case focusing on investment decisions.

There exists a difficult and unfulfilled need for further investigative forays into the domain of behavioral finance, particularly in domains that have hitherto been relatively uncharted, such as the behavior of individual investors. Such investigative endeavors are essential for fostering a more comprehensive and granular understanding of how psychological biases insidiously permeate and influence financial decision-making processes at both the micro and macro-economic strata.

This research differs from other studies in the field in that it examines the biases of investors based on the approach of classifying biases into groups rather than analysing individual biases.As a counterpoint to the analysis of individual biases, further research could be directed towards an integrated study of a large number of biases, seeking to discover the interaction of biases within the same dimension, identify the most important biases in each dimension of the investor profile, and evaluate the interaction of biases across dimensions.

For further research and trying to solve some limitations, it is essential to continue this research with practical insights, conducting a survey among investors, doing expert analysis among portfolio managers, and comparing the results from academic papers with survey results in different economic cycles.

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Author contributions

Conceptualization RK, DV, GKS, RŠ, AKO, and TK; methodology RK, TK, GKS; formal analysis RK, TK, AKO; investigation RK, RŠ, and TK; data curation RK, TK, AKO; writing – original draft preparation RK, TK, GKS writing – review and editing DV, AKO; visualization RŠ and TK; supervision RK and DV; project administration RK; funding acquisition RŠ, RK, DV and GKS. All authors have read and agreed to the published version of the manuscript.

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