ABSTRACT

Objective: This study aims to systematically review the existing literature published over the past 42 years on behavioral biases in investment decision-making. Therefore, the current study concentrates on two biases: overconfidence and herding bias of individual and institutional investors.

Theoretical framework: Kahneman and Tversky (1979) formulated prospect theory and concluded that investors make decisions based on possible gains and losses, rather than on final outcomes. Therefore, this study used this theory to understand the influence of behavioral biases on investment decisions.

Methods: This study used a systematic literature review (SLR) and 109 selected articles for review published between 1980 and 2022. Most importantly, this study conducted a content analysis of behavioral biases in investment decision-making.

Result and Conclusion: The volume of research on behavioral bias has increased over the past two decades. The existing literature shows limited research on institutional investors’ overconfidence bias, limited studies on individual herding behavior, ineffective direct measures of overconfidence, the majority of research showed that institutional investors are more inclined to herd than individual investors, and the maximum number of studies showed that individual investors are more susceptible to overconfidence bias than institutional investors.

Implications of the research: This study highlights the influence of behavioral biases in investment decision-making and suggests a future research agenda for future researchers, as well as helpful to investment advisors enabling them to manage biases and select purposeful stocks for their clientele.

Originality/value: This study delineates the behavioral biases of individual and institutional investors. This first study encompasses relevant studies conducted between 1980 and 2022 and lucidly summarizes the behavioral biases, including the ‘overconfidence’ and ‘herding’ tendencies of these different kinds of investors.
Keywords: overconfidence, herding bias, behavioral biases, investment decisions, systematic literature review, content analysis.

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PRECONCEITOS COMPORTAMENTAIS E SUA INFLUÊNCIA NA TOMADA DE DECISÕES DE INVESTIMENTO: UMA REVISÃO SISTEMÁTICA DA LITERATURA E AGENDA DE PESQUISA FUTURA

RESUMO

Objetivo: Este estudo tem como objetivo rever sistematicamente a literatura existente publicada ao longo dos últimos 42 anos sobre vieses comportamentais na tomada de decisões de investimento. Portanto, o presente estudo concentra-se em dois vieses: excesso de confiança e viés de rebanho de investidores individuais e institucionais.

Estrutura teórica: Kahneman e Tversky (1979) formularam a teoria da perspectiva e concluíram que os investidores tomam decisões com base em possíveis ganhos e perdas, em vez de nos resultados finais. Portanto, este estudo usou essa teoria para entender a influência de vieses comportamentais nas decisões de investimento.

Métodos: Este estudo utilizou uma revisão sistemática da literatura (SLR) e 109 artigos selecionados para revisão publicados entre 1980 e 2022. Mais importante ainda, este estudo realizou uma análise de conteúdo de vieses comportamentais na tomada de decisões de investimento.

Resultado e Conclusão: O volume de pesquisas sobre viés comportamental aumentou nas últimas duas décadas. A literatura existente mostra estudos limitados sobre o enviesamento de investidores institucionais, estudos limitados sobre o comportamento individual de rebanho, medidas ineficazes diretas de excesso de confiança, a maioria dos estudos mostrou que os investidores institucionais estão mais inclinados a rebanhos do que os investidores individuais, e o número máximo de estudos mostrou que os investidores individuais são mais susceptíveis de enviesamento de excesso de confiança do que os investidores institucionais.

Implicações da pesquisa: Este estudo destaca a influência de vieses comportamentais na tomada de decisões de investimento e sugere uma agenda de pesquisa futura para futuros pesquisadores, bem como útil para consultores de investimento, permitindo-lhes gerenciar vieses e selecionar estoques propostais para sua clientela.

Originalidade/valor: Este estudo delineia os vieses comportamentais de investidores individuais e institucionais. Este primeiro estudo engloba estudos relevantes realizados entre 1980 e 2022 e resume de forma clara os preconceitos comportamentais, incluindo as tendências de “excesso de confiança” e de “manada” destes diferentes tipos de investidores.

Palavras-chave: excesso de confiança, tendência de pastoreio, tendências comportamentais, decisões de investimento, revisão sistemática da literatura, análise de conteúdo.

1 INTRODUCTION

Traditional finance supported rationality in the decision-making process, justifying decisions based on available information (Fama, 1970). Traditional finance
theories and principles include the Arbitrage Pricing Process of Modigliani and Millar, the Markowitz Principle of Portfolio Management, the Capital Asset Pricing Model given by Sharpe, Linter, and Black, and the Option Pricing theory of Black, Scholes, and Merton (Kumar & Goyal, 2015). These approaches validate the concept of rationality in investment decision-making, assuming investors to be rational decision-makers (Jain et al., 2022).

After the energy crisis of the 1970s, the empirical study (Kahneman & Tversky, 1979) results were inconsistent with the Efficient Market Hypothesis (EMH) and Expected Utility Theory (EUT). Kahneman and Tversky (1979) developed the renowned concept of prospect theory, which is an alternative to EUT in explaining decision-making under uncertain circumstances. The introduction of this theory instigated a swift and profound transformation in the domain of traditional finance, leading to the emergence of the behavioral finance field by combining the behavioral and psychological aspects of economic and financial decision-making. The traditional concepts of the efficient market hypothesis and expected utility theory capitulated on behavioral finance for inadequate explanations of various irrational decisions. Thus, behavioral finance suggests that behavioral biases are the reason for the irrationality of investment decision-making.

So far, various studies have been conducted to empirically investigate behavioral biases in investment decisions (Bakar & Yi, 2016; Baker et al., 2019; Bhatia et al., 2020). However, little effort has been made to systematically review these studies. This study covers the period from 1980 to 2022 and this study focuses on the behavioral biases of individual and institutional investors in investment decision-making. Here, we consider two common biases: overconfidence and herding. Specifically, proper review procedures have not been effectively followed, including identifying keywords, searching for keywords, and using inclusion and exclusion criteria. In the traditional literature review, there are several issues with openness and bias (Ibrahim et al., 2023).

Thus, this study employed a systematic literature review and content analysis to answer the research questions. A systematic literature review entails identifying keywords, searching for keywords, and determining the appropriate literature by stating the inclusion and exclusion criteria (Kumar et al., 2020). Additionally, content analysis has been used to provide the findings of previous research studies. The research questions of this study are as follows:
What are the key trends in publication over the past four decades in the area of behavioral biases?
What type of data most frequently used?
Which country have more publication?
Which studies have received the most citations?
What are the effects of behavioral biases on both individual and institutional investors’ investment decisions?
What are the predominant knowledge gaps and key ideas for further research?

The outline of the review article is organised as follows. An overview of the literature is followed by presenting and describing the material and methodology, reporting the results and discussion, and concluding with a summary of the future research agenda.

2 LITERATURE REVIEW

This section deals with the theoretical background of behavioral biases in investors’ investment decision-making. “How do investors behave? Why do investors behave in a specific manner? To answer these questions, a new concept of behavioral finance emerged in the fields of economics and finance in the 1980s” (Kumar & Goyal, 2015). “Behavioral finance studies the psychological aspects of financial decision-making and explains the irrationality of investors in investment decision-making” (Kumar & Goyal, 2015). Kahneman and Tversky (1979) developed prospect theory and specified that investors’ decision-making is based on possible gains and losses rather than on final outcomes. This situation is driven by cognitive biases that affect the judgment of these gains and losses (Kumar & Goyal, 2015). Different behavioral biases impact investors’ investment decisions, and we have reviewed two biases in the following sections.

2.1 OVERCONFIDENCE BIAS

Overconfidence bias is a well-known and common bias. Overconfidence causes investors to overestimate their skills and talent and ignore the risk associated to the investment. Some significant studies on this bias, Daniel et al. (1998) observed that investors overreact to private information and underreact to public information, which leads them to be overconfident. Odean (1999) found that overconfident investors tend to
trade too much. Moreover, significant empirical studies have been reviewed for this study, for example, (Barber & Odean, 2000, 2001; Gervais & Odean, 2001; Odean, 1998).

2.2 HERDING BIOAS

Herding is a bias where investors imitate the decisions of others, usually a larger group, while making decisions (Spyrou, 2013). Institutional investors follow herding behavior than individual investors (Dennis et al., 2002; Hsieh, 2013). Chiang and Zheng (2010) found that herding behavior exists in advanced stock markets, except for the US and Asian markets. Chen (2013) observed that herding behavior is present in the global markets.

3 METHODS

This study follows a systematic literature review, which is conducted based on defined protocols that search across various databases using a predetermined search strategy, which improves the quality of the work conducted by making it more transparent, scientific, and comprehensive (Pittway, 2008). A comprehensive systematic literature review reduces the possibility of including irrelevant studies but also improves the reliability of the research (Tang, 2019).

3.1 DATABASE, KEYWORDS, AND INCLUSION CRITERIA

In this paper, the literature search focuses on the research conducted in the field of behavioral finance. The study sample covers the period from 1980 to 2022. Scopus and Google Scholar are used as databases to search the existing relevant literature. Scopus, Google Scholar, and CSA Illumina, which offer citation indexing of social sciences, found significant results. Scopus provides the best coverage of these databases and may be used as an alternative to the Web of Science as a tool to measure research impact in the social sciences (Norris & Oppenheim, 2007). Google Scholar can be used as an advanced search (Sakka & Ghadi, 2023).

While conducting a systematic literature review, there is a possibility that certain research work is ignored; Therefore, Tranfield et al. (2003), a three-stage search strategy has been used to remove this uncertainty. The three stages were segmented into database searching, reviewing abstracts, and checking references and citations.
This study focuses on restrictive words rather than a broader keyword search, which further contributes to a better understanding of the specific literature search and draws conclusions about what we know and do not know about a given question or topic. The present study followed the suggestions of Chen et al. (2017) and Singh and Walia (2002) to guarantee thorough coverage of the extant literature. Thus, keywords are divided into two categories. The first set of keywords related to behavioral biases such as "overconfidence", "herding" and "herding behavior". The second set of keywords comprises the various components related to individual and institutional investors, such as "investors", "institutional investors", "measures of overconfidence", "trading activity", "gender differences in trading activity", "institutional investor herding", "individual investor herding", "institutional herding", "individual herding" and "market conditions". With the use of Boolean operators, authors merged each search term from the first category with each search term from the second category to perform the search queries. In addition to the combination search method indicated above, the study also executed independent searches using keywords from two categories. This study included only papers whose titles, abstracts, and keywords contained the above search terms. No time restrictions were imposed by the authors. The search was conducted at one point (December 2022) to prevent any potential bias caused by the ongoing update of the Scopus database. (Jain et al., 2022). During the initial search, 175 research articles were retrieved. Subsequently, the following inclusion and exclusion criteria were adopted to select the research papers.

- Peer-reviewed English-language research papers are considered. This study did not include any studies relevant to other languages (Saggese et al., 2016).
- This study includes articles and book chapters and excludes conference paper, erratum, and note.
- Articles published between 1980 and 2022.

3.2 SELECTION OF THE PAPERS

The inclusion criteria offer a broad, reliable, and informed foundation for studies to be included (Bhatt et al., 2020). The inclusion criteria were implemented and scrutinized based on the titles, abstracts, and keywords of research papers. A detailed reading was performed to provide additional insights into the research conducted in this
study. After skimming through the full reading of research studies, a base of 45 papers was shortlisted (Jain et al., 2022). However, there is a possibility that some papers pertinent to the study's topic may not be included (Jain et al., 2022). To achieve this, the snowball technique was adopted (Eduardsen & Marinova, 2020). Additionally, 64 research works from Google Scholar were included by referring to the forward and backward citations. Figure 1 depicts the methodological process in detail.

Figure 1 Methodological approach

Source: Prepared by the authors (2023)

4 RESULTS AND DISCUSSION

In this section, we have systematically categorized the selected articles based on trends in publication, type of data used, collection of sample data based on country, citation analysis, and content analysis.

4.1 TRENDS IN PUBLICATION

Figure 2 illustrates the evolution of publication in behavioral bias research. 17 documents were published between 1980 and 2002, followed by 38 documents between 2003 and 2012. Finally, a significant increase occurred, with 54 articles published between 2013 and 2022. Figure 2 depicts a noticeable rise in publication trends and an increase in research output in the field of behavioral bias.
4.2 TYPE OF DATA

Table I illustrates that in the field of behavioral bias, the frequency of usage is higher in secondary data, whereas the primary data are less frequently used. Therefore, there is more scope to investigate investors’ behavioral biases using primary data.

<table>
<thead>
<tr>
<th>Type of data</th>
<th>Number of articles used</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Primary</td>
<td>18</td>
<td>16.51</td>
</tr>
<tr>
<td>Secondary</td>
<td>91</td>
<td>83.49</td>
</tr>
<tr>
<td>Total</td>
<td>109</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)

4.3 COLLECTION OF SAMPLE DATA BASED ON COUNTRY

Table II highlights the frequency of sample data collection from different countries; it is evident that the majority of research articles were conducted in developed nations, primarily the United States of America, followed by developing nations such as Taiwan and China.

<table>
<thead>
<tr>
<th>Country</th>
<th>Number of studies</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Austria</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>China</td>
<td>13</td>
<td>11.93</td>
</tr>
<tr>
<td>Dutch</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>Finland</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>Germany</td>
<td>3</td>
<td>2.75</td>
</tr>
<tr>
<td>Greece</td>
<td>1</td>
<td>0.92</td>
</tr>
<tr>
<td>India</td>
<td>6</td>
<td>5.50</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)
4.4 CITATION ANALYSIS

We analyzed the selected articles with respect to their citations to identify the most important papers on behavioral biases. These articles have 60212 cited references, with an average of 552 per article. To avoid a long list of articles, we have identified the citations for the top 10 most cited research articles for overconfidence and herding bias, respectively. This is presented in Tables III and IV. The following research articles were found to be the most cited on overconfidence bias: Daniel et al. (1998), which contains total citations of 7363, followed by Barber and Odean (2001) with 6765 citations, and the most cited papers on herding bias: Grinblatt et al. (1995), with 2807 total citations, followed by Lakonishok et al. (1992), with 2780 total citations.

<p>| Table III Overconfidence bias articles listed based on their citations |
|-------------------------------- |----------------- |----------------- |</p>
<table>
<thead>
<tr>
<th>SI.no</th>
<th>Article</th>
<th>No. of citations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Daniel et al. (1998)</td>
<td>7363</td>
</tr>
<tr>
<td>2</td>
<td>Barber and Odean (2001)</td>
<td>6765</td>
</tr>
<tr>
<td>3</td>
<td>Barber and Odean (2000)</td>
<td>4516</td>
</tr>
<tr>
<td>4</td>
<td>Odean (1999)</td>
<td>3172</td>
</tr>
<tr>
<td>5</td>
<td>Odean (1998)</td>
<td>2664</td>
</tr>
<tr>
<td>6</td>
<td>Gervais and Odean (2001)</td>
<td>2379</td>
</tr>
<tr>
<td>7</td>
<td>De Bondt and Thaler (1995b)</td>
<td>1441</td>
</tr>
<tr>
<td>8</td>
<td>Barber (2009)</td>
<td>1089</td>
</tr>
<tr>
<td>9</td>
<td>Statman et al. (2006)</td>
<td>1083</td>
</tr>
<tr>
<td>10</td>
<td>Barber and Odean (2002)</td>
<td>1023</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)
4.5 CONTENT ANALYSIS

Content analysis is used as a methodology to present the content of previously conducted research in objective, systematic and quantitative manner (Berelson, 1952). Content analysis provides information about the empirical findings of previous research studies. In this section, we systematically constructed a content analysis on behavioral biases, such as overconfidence and herding in investment decision-making.

4.5.1 Overconfidence bias

This section illustrates the impacts and empirical results of overconfidence bias. The empirical results are classified into six categories:

1. Table V shows overconfidence and trading activity
2. Table VI shows overconfidence and gender differences in trading activity
3. Table VII shows measures of overconfidence
4. Table VIII shows overconfidence and individual investors
5. Table IX shows overconfidence and institutional investors
6. Table X shows a comparative study of individual and institutional investors.

4.5.2 Herding bias

This section shows the impacts and empirical results of herding bias. The empirical results are divided into four categories:

1. Table XI shows institutional investor herding
2. Table XII shows individual investor herding
3. Table XIII shows a comparative study between institutional and individual investors.
4. Table XIV shows herding and market conditions.

Table V Empirical results on overconfidence and trading activity

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overconfidence and excess trading</td>
<td>De Bondt and Thaler (1995a) first proposed the impact of overconfidence on excessive trading by individuals and observed that overconfidence is a crucial behavior factor to understand the puzzle of trading. Odean (1999) concluded that overconfident investors trade excessively. Due to excessive trading, the estimated trade earnings are insufficient to pay transaction expenses. Similar findings were found in the previous studies (Chuang &amp; Lee, 2006; Hsu &amp; Shiu, 2010; Khan et al., 2016; Meier, 2018; Statman et al., 2006). However, the findings of Barber et al. (2009) are inconsistent with the excess trading influenced by overconfidence.</td>
</tr>
<tr>
<td>Overconfidence and information</td>
<td>Daniel et al. (1998) stated that investors overreact to their private information while underreacting to publicly available information, which leads them to overestimate their accuracy and make them overconfident. Similarly, Barber and Odean (2000) found that investors become overconfident when they overestimate their private information, which drives them to trade excessively and, subsequently, earn less in return. Furthermore, information influences investors’ trading behavior and makes them overconfident and non-overconfident. This evidence is supported by the findings of Abreu and Mendes (2012) showed that when overconfident investors use information from their friends and family, they trade less frequently. However, when they rely on specialized information sources, non-overconfident investors engage in excess trading. Boussaidi, (2020) found that investors’ overreaction to the level of private information increases and subsequently, a rise in trading activity. Recently, it has been shown that information factors increase trading and significantly reduce returns. These findings are consistent with those of Bregu (2020). Ho (2011) observed that overconfident investors with private information, hold loser stocks for a long time.</td>
</tr>
<tr>
<td>Overconfidence and demographic variables</td>
<td>Tekçe and Yılmaz (2015) revealed that investors who were male, young, had lower portfolio values, lower incomes, and lower levels of education showed more overconfidence behavior. Moreover, they stated that overconfidence affects portfolio wealth.</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)

Table VI Empirical results on overconfidence and gender differences in trading activity

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overconfidence and gender differences in trading activity</td>
<td>Barber and Odean (2001) found that men trade excessively because they are more overconfident than women. Similarly, Shu et al. (2004) stated that, compared to women, men trade more. Kumar and Goyal (2016) show that male investors are more prone to limited information and private information and became more confident than female investors. Kufepaksi (2011) observed that female investors are more likely to behave</td>
</tr>
</tbody>
</table>
overconfidently than male investors when the market provides positive news, which is inconsistent with the findings of Kumar and Goyal (2016).

There is no evidence of differences in gender and trading activity (Biais et al., 2005; Cuevas et al., 2019; Deaves et al., 2009; Fellner-Röhl & Krügel, 2014). These findings are inconsistent with those of Barber and Odean (2001) and Kumar and Goyal (2016).

Variable asymmetric information has been studied previously (Biais et al., 2005; Cuevas et al., 2019; Deaves et al., 2009; Fellner-Rohling & Krügel, 2014). Interestingly, Yang and Zhu (2016) used symmetric information and found that overconfidence and gender have no impact on trading volume.

Table VII Empirical results on measures of overconfidence

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Measures of overconfidence</td>
<td>Glaser and Weber (2007) assessed overconfidence through measures that are better than average effect, volatility estimates, and miscalibration and found that trade volume has no relation to miscalibration. Similar conclusions have been reported in previous studies (Biais et al., 2005; Fellner-Rohling &amp; Krügel, 2014). Fellner and Krügel (2012) showed that perception of signal precision and miscalibration is not significantly related to overconfidence. Khan et al. (2019) examined whether overconfidence manifested as better-than-average, miscalibration, and illusion of control mediates the relationship between perception of past portfolio returns and investment behavior and found that through the mediating channel of better-than-average. Kirchler and Maciejovsky (2002) applied two measurements of overconfidence, subjective confidence intervals, and differences between objective accuracy and subjective certainty, and observed that participants were classified as overconfident based on the comparison of objective accuracy to subjective certainty. Huisman et al. (2012) proposed a new measurement for overconfidence namely the Parkinson volatility measure and found that investors exhibit overconfidence bias. Greço (2020) used a meta-analysis to examine the relationship between overconfidence and financial decision-making, and the results showed that indirect measures of overconfidence have a stronger effect than direct measures on financial decision-making (overestimation, over-precision, and over-placement).</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)

Table VIII Empirical results on overconfidence and individual investors

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overconfidence and individual investors</td>
<td>Barber and Odean (2002) online trading reinforces the investors’ overconfidence and thereby increases trading, more speculative and less profitable. Chen et al. (2004) studied brokerage account data in China and found that Chinese individual investors show overconfidence. Similarly, Huisman et al. (2012), using survey data, found that individual investors exhibit a significant overconfidence bias. Gervais and Odean (2001) revealed that overconfident investors trade very aggressively, thus, causing the anticipated trading volume to rise. Glaser and Weber (2007) observed that the greater the investors’ overconfidence, the greater the trading volume. Significant empirical studies have been conducted on overconfidence and trading volume (Chen et al., 2007; Grinblatt &amp; Keloharju, 2009; Merkle, 2017). Overconfidence leads to an increase in trading volume and causes lower expected utility (Odean, 1998). Overconfident investors underestimate the noise variance in private signals and tend to overestimate the expected returns (Chen et al., 2019). Abreu and Mendes (2020) showed that overconfident investors trade warrants more than stocks. Naveed and Taib (2021) examined the association of overconfidence bias and information acquisition with individual decisions, and found that overconfidence bias with individual decisions is greatly influenced by information acquisition. In contrast to the above-mentioned findings, Kirchler and Maciejovsky (2002) tested individual overconfidence in an experimental asset market and concluded that participants are not vulnerable to overconfidence.</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)
Table IX Empirical results on overconfidence and institutional investors

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overconfidence and institutional investors</td>
<td>Menkhoff et al. (2013) evidence showed that institutional investors are less likely to be overconfident.</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)

Table X Empirical results of overconfidence tendency on individual versus institutional investors

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overconfidence tendency in individual versus institutional investors</td>
<td>Chuang and Susmel (2011) showed that compared to institutional investors, individual investors are more vulnerable to overconfidence bias. Liu et al. (2016) observed that individual investors tend to be more overconfident in their trading behavior compared to institutional investors. Khan et al. (2019) conducted a survey and found that individual investors tend to be overconfident, whereas institutional investors are not inclined to it. Similarly, Li et al. (2020) documented that overconfidence is much more dominant among individual investors than institutional investors. Both individual and institutional investors are overconfident (Lai et al., 2013; Lin &amp; Chiang, 2015).</td>
</tr>
</tbody>
</table>

Source: Prepared by the authors (2023)

Table XI Empirical results on institutional investor herding

<table>
<thead>
<tr>
<th>Impacts</th>
<th>Empirical results</th>
</tr>
</thead>
<tbody>
<tr>
<td>Institutional investors and herding behavior</td>
<td>Lakonishok et al. (1992) used the US tax-exempt funds, with the help of LSV, examined the herding behavior and found that pension fund managers are less inclined towards herd behavior when trading with large stocks. Grinblatt et al. (1995) studied that US mutual funds of momentum investors and their herding behavior are inconsistent. Wermers (1999) found insufficient evidence of herding behavior in mutual fund trading with average stocks; however, herding behavior exists in trading with small stocks and growth-oriented funds. Wylie (2005), using data from the portfolio holdings of 268 equity mutual funds, found that in the largest and smallest individual UK stocks, fund managers exhibit a reasonable amount of herding. Furthermore, herding behavior is less pronounced in other stocks. Apart from the LSV measure, Sias (2004) employed a cross-sectional correlation to measure herding, revealed that the demand for security among institutional investors, the demand in the current quarter is favorably related to the demand in the preceding quarter and also showed that institutional investors herd infer information from one another's trades. Similarly, Choi and Sias (2009) found that institutions followed the same industry-trade strategy, resulting in institutional industry herding.</td>
</tr>
<tr>
<td>Herding behavior and market returns</td>
<td>Li and Yung (2004) found a strong association between institutional ownership changes and ADR returns, and concluded that the correlation is still positive, even when the impact of momentum trading is considered. Dasgupta et al. (2011) observed that institutional herding accurately predicts short-term returns but inaccurately predicts long-term returns.</td>
</tr>
<tr>
<td>Institutional herding in the global market</td>
<td>Kim and Nosfinger (2005) documented that, comparatively, in Japan, institutional herding is less prevalent than in the USA. However, this significantly impacts price movements. Furthermore, economic conditions and the regulatory environment affect the consequences and behavior of institutional herding. Choi and Skiba (2015) studied the herding behavior of institutional investors in international markets and found that in markets with low information asymmetry, institutional investors are more likely to herd.</td>
</tr>
<tr>
<td>Effect of institutional herding on the stock price</td>
<td>Walter and Moritz Weber (2006) found that German mutual fund managers engaged in herding and positive feedback trading. Gutierrez and Kelley (2008) found that institutional investors suffer from buying and continue to gain returns from selling. Moreover, buying herd destabilizes the prices. Whereas, selling herd stabilizes it. Lu et al. (2012) examined the price impact of foreign institutional investors’ herding and found that investors are more likely to have large-size stocks. As a result, there is a subsequent increase in the stock price.</td>
</tr>
</tbody>
</table>
Institutional herding and idiosyncratic volatility

Chang and Dong (2006) found that institutional herding and firm profitability are both positively related to idiosyncratic volatility.

Herding behavior of foreign institutional investors and domestic investors

Chang (2010) analyzed the herding of qualified foreign institutional investors (QFIIs) and concluded that they increase/decrease their holdings in particular sectors. Bowe and Domuta (2004) studied both foreign and domestic investors in the Jakarta stock exchange and found evidence for herding before, during, and after the Asian crisis of 1997. Fang et al. (2017) revealed that investigative herding is the major cause of herding among FIIs in the Taiwan stock market. Tayde and Nageswara Rao (2011) found that FIIs were involved in herding as well as positive feedback trading in the Indian stock market. Garg and Mitra (2015) revealed that in the Indian stock market, FIIs participate in inadvertent herding, resulting in short-term volatility. Similarly, studies on the Indian stock market have also been conducted (Choudhary et al., 2019; Garg et al., 2016; Madaan & Shrivastava, 2020).

Herding based on intentional and spurious

Holmes et al. (2013) found that institutional herding is influenced intentionally. Gavriilidis et al. (2013) found that institutional herding behavior in the Spanish market is intended for both the market and the sector. Guo et al. (2020) showed that spuriousness has an impact on institutional herding.

Mutual fund herding

Hung et al. (2010) revealed that mutual funds in the Taiwan stock market exhibit herding. Caglayan et al. (2021) found that mutual fund herding considerably reduces return co-movement in Chinese equities. Revealed that Wang et al. (2021) documented that herding is evident in all types of funds other than income funds, and that non-fundamental factors primarily influence herding behavior. Hudson et al. (2020) examined the role of investor sentiment that affects institutional investor herding, and found that they tend to herd based on market portfolio, size, and value factors.

Institutional herding and short selling

Bohl et al. (2014) analyzed short-selling restrictions impact on herding behavior and found that restrictions have no impact on herding behavior. Moreover, it showed a higher dispersion of returns across market.

Institutional herding and Information

Lin et al. (2013) found that institutional investors show herding rationally based on superior information.

Herding and robust return efficiency (RRE)

Lu et al. (2022) empirically tested the relationship between herding behavior and robust return efficiency (RRE) and found that fund managers’ herding behavior benefits the RRE of their funds.

Source: Prepared by the authors (2023)

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<tr>
<th>Impacts</th>
<th>Empirical results</th>
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<tbody>
<tr>
<td>Individual herding in global markets</td>
<td>Chen and Zheng (2022) documented that individual investor herding behavior occurs in both the Chinese and US stock markets, and the Chinese stock market is predominantly influenced by behavioral sentiment dynamics as a result of investor switching patterns, while fundamental factors have an impact on the US market.</td>
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<td>Herding behavior and Google Search Volume Index</td>
<td>Hsieh et al. (2020) found that the Google Search Volume Index can be used to predict the information needs of inexperienced individual investors. Moreover, they observed that in bull markets, individual investors’ buying herd tendency is greater for small-cap companies, whereas selling herd behavior is stronger for large-cap companies. Wanidwaranan and Padungsaksawasdi (2022) analyzed the Google Search Volume Index and revealed that investors unwittingly follow the same trading patterns, which results in unintentional herding behavior.</td>
</tr>
<tr>
<td>Effect of idiosyncratic volatility on the herding behavior</td>
<td>Vo and Phan (2019a) analyzed the impact of idiosyncratic volatility on individual investors’ herding behavior in the Vietnam stock market and found that herding exists in the market.</td>
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Source: Prepared by the authors (2023)
Table XIII Empirical results on the herding of institutional versus individual investors

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<th>Impacts</th>
<th>Empirical results</th>
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<td>Herding of institutional versus individual</td>
<td>Nofsinger and Sias (1999) documented that institutional investors’ herding affects the stock prices more than individual investors. Dennis et al. (2002) found that institutional investors tend to follow herd behavior more than individual investors do when large market prices swing. Similarly, Hsieh (2013) found that compared to individual investors, institutional investors are more inclined to herd. Li et al. (2017) trading volume-based indicator was used to analyzed the variations in herding between individual and institutional investors and observed that less-informed individuals invest their money in a variety of stocks, whereas better-informed institutional investors trade more selectively.</td>
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Source: Prepared by the authors (2023)

Table XIV Empirical results on herding and market conditions

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<th>Impacts</th>
<th>Empirical results</th>
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<td>Herding and market conditions</td>
<td>Avery and Zemsky (1998) found that herding behavior exists, which leads to short-run mispricing of assets. Christie and Huang (1995) stated that herding is most likely to occur under an extreme down market. Similarly, Choi and Yoon (2020) revealed that herding behavior occurs in the Korean stock market during downturns. Caparrelli et al. (2004) documented that herding behavior occurs during extreme market conditions. Zhou and Anderson (2013) found that herding occurs under unstable market conditions. Messis and Zapranis (2014) documented that stocks showed more herding or adverse herding exhibit high volatility. Litimi et al. (2016) found that herding behavior leads to an increase in market volatility as well as excessive bubbles in the US stock market at a sectoral level. Hwang and Salmon (2004) studied the herding behavior in South Korean and US stock markets by using a cross-sectional dispersion of factor sensitivity of assets and found a positive correlation between herding and significant market movements. Tan et al. (2014) showed that herding exists in both A and B share markets in the Chinese stock market. Lao and Singh (2011) examined herding behavior in the Indian and Chinese stock markets and found that herding behavior exists in both markets. Bahadur et al. (2019) analysed herding in leveraged exchange-traded funds and found that herding is more widespread in bear LETFs in daily trading, asymmetric market situations, and the global financial crisis period. Hong et al. (2020) showed that both bull and bear markets exhibit herd behavior. Dhall and Singh (2020) documented that herding exists post-COVID-19 in both bull and bear markets. Similarly, Mishra and Mishra (2023) found that herding occurred during the COVID-19 Pandemic. Jirasakuldech and Emekter (2021) showed that herding behavior occurs in a bear market with high trading volume, and during an economic crisis. Wu et al. (2020) reported that herding is dominant in bull market movement, low trading volume, and low market volatility under COVID-19. Indārs et al. (2019) examined herding behavior through fundamental and non-fundamental factors and observed that investors’ herding behavior varied under different market environments namely, liquidity, market trends, oil price volatility, the arrival of new information, and uncertainty. Gabbori et al. (2021) documented that herding occurs on OPEC meeting days, and more importantly, independent oil market volatility influences herding behavior. Mobarek et al. (2014) stated that most continental nations experienced a strong herding effect during the global financial crisis, and Nordic nations also experienced it during the Eurozone crisis. Bekiros et al. (2017) observed that under extreme market conditions, herding becomes highly pronounced. Ansari and Ansari (2021) stated that herding is absent in all market conditions. Demirer and Kutan (2006) analyzed the formation of herding in Chinese markets using return dispersions and concluded the absence of herding behavior.</td>
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Source: Prepared by the authors (2023)

5 CONCLUSION AND FUTURE RESEARCH AGENDA

From the findings of the systematic review, it is clear that research on behavioral bias has emerged over the past two decades. The frequency of usage is higher in the secondary data
than in the primary data. Majority of the research was conducted in the United States of America, followed by Taiwan and China. Daniel et al. (1998) and Grinblatt et al. (1995) have produced the most cited articles in overconfidence and herding consequently. Most importantly, behavioral biases in both individual and institutional investors’ investment decisions are predominantly influenced, and thus, investment advisors should focus on this bias so that individual investors can minimize their losses while making investment decisions.

This study identified various research gaps for future research to work on. Most studies focus on institutional investors’ herding, but few cover individual investors’ herding (Chen & Zheng, 2022; Vo & Phan, 2019b). Studies examining the overconfidence bias among individual investors are the most frequent. However, overconfidence bias towards institutional investors has received very little attention from researchers (Menkhoff et al., 2013). Researchers have focused only on direct measures of overconfidence. However, direct measures of overconfidence have a lower effect on financial decision-making than indirect measures (Grežo, 2020). Therefore, indirect measures may be useful in addressing this behavior. The majority of studies revealed that compared to individual investors, institutional investors are more inclined to herd (Dennis et al., 2002; Hsieh, 2013). On the other hand, the majority of research articles concluded that, in comparison to institutional investors, individual investors are more probable to be impacted by overconfidence bias (Chuang & Susmel, 2011; Liu et al., 2016; Khan et al., 2019; Li et al., 2020). However, only these studies show that both individual and institutional investors exhibit overconfidence (Lai et al., 2013; Lin & Chiang, 2015).

To sum up, the primary objective of this systematic review is to contribute to the body of knowledge on behavioral bias and investment decisions. Significant academic research conducted over the years was carefully scrutinized, selected, and evaluated. The analysis compiled data on relevant studies to identify trends in publication, type of data used, collection of sample data based on country, most cited papers, and content analysis employed.

First, the authors of this study opted for Scopus database to enrich scholars with an overview of recent investigations as a base for further research. Second, this review is limited to articles published in English language. Third, this study included articles and book chapters but did not consider other scholarly outputs such as conference papers, erratum, and notes. Fourth, this investigation is limited to only two behavioral biases. Despite its limitations, the findings of this study highlight the importance of systematic review in improving our understanding of behavioral biases and investment decisions. Future reviews can work on other behavioural biases in investment decision-making.
REFERENCES


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