International Journal of Economic Practices and Theories (IJEPT)
ISSN: 2247-7225
Volume 2026, Issue 1

Global Research Frontiers in Investor Emotion and Financial Decision-Making: A Bibliometric Investigation

Deepa M

Research Scholar, Presidency University, Bangalore, Assistant Professor, Department of Commerce, Government First Grade College Sulibele,

Hoskote Taluk, Karnataka.

e-mail: deepraj673473@gmail.com

Dr. Krishnakumar K

Research Supervisor, Dean, School of Management, Presidency University, Bangalore, Karnataka.

e-mail: deansoc@presidencyuniversity.in

Abstract

Investor emotions are increasingly recognized as central determinants of financial decision-making, yet the evidence base remains dispersed across behavioral finance, psychology, information systems, and data-driven market analytics. This study maps the intellectual structure, thematic evolution, and emerging research frontiers of scholarship on investor emotions and financial decision-making through a bibliometric investigation of Scopus-indexed publications retrieved using the search string. Also Using performance analysis and science mapping, the study synthesizes annual scientific production, citation dynamics, and source distribution, complemented by co-citation, bibliographic coupling, and keyword co-occurrence networks generated via established bibliometric tools (e.g., VOSviewer and Bibliometrix/Biblioshiny). Results indicate a clear growth trajectory with modest output during 2010–2017, consolidation during 2018–2022, and a sharp expansion during 2023–2025, while average citations per year peak in earlier cohorts, reflecting citation-window effects. The co-citation structure reveals three foundational knowledge bases: (i) behavioral finance and investor psychology, (ii) affective decision science and emotion regulation perspectives, and (iii) digitally mediated sentiment and information effects. Bibliographic coupling identifies active research fronts anchored by highly influential synthesis work and extending into applied bias research and computational sentiment analytics. Keyword co-occurrence further demonstrates three dominant thematic clusters: behavioral finance and investment decision biases; psychological and survey/experimental emotion research; and data-driven sentiment analysis linked to information systems, big data, and electronic trading. Overall, the findings show a field transitioning toward interdisciplinary integration and scalable emotion measurement, with emerging frontiers in social media-driven investing, retail investor psychology, and emotion-aware AI. The study provides a structured roadmap for future theory development, methodological triangulation, and context-specific research in technology-mediated and high-volatility markets.

Keywords: investor emotions; financial decision-making; behavioral finance; sentiment analysis; bibliometric analysis; science mapping; co-citation; bibliographic coupling; keyword co-occurrence; social media sentiment; retail investors; emotional AI

1. Introduction

1.1. Background

For much of the twentieth century, mainstream financial theory was dominated by the rational-investor paradigm, which assumes that market participants process information objectively and make utility-maximizing decisions. However, growing empirical anomalies—such as persistent mispricing, momentum and reversal patterns, excess volatility, and systematic deviations from optimal portfolio behavior—have strengthened the argument that investor decisions are not purely rational but are shaped by psychological and emotional mechanisms. Contemporary behavioral finance therefore positions investor behavior as an interaction between cognition, affect, and contextual cues, emphasizing that emotions (e.g., fear, anxiety, excitement, regret) can influence information processing, risk perception, and trading actions.

Within this behavioral perspective, "investor emotion" is not treated merely as noise; instead, it is increasingly recognized as a measurable driver of market dynamics. Evidence from systematic syntheses shows that behavioral biases and affective tendencies are repeatedly linked to suboptimal investment choices and persistent deviations from normative models (Zahera & Bansal, 2018). At the individual level, emotions such as fear can distort decision frames and intensify reliance on social projection, altering financial judgments in ways that can propagate through collective behavior (Lee & Andrade, 2011). At the market level, emotionally charged environments can amplify herding, speculative behavior, and volatility—particularly in settings where information is ambiguous and uncertainty is high. For instance, sentiment-oriented approaches have been used to model and quantify herding-related dynamics and emotionally driven convergence in investor actions (Ren & Wu, 2020).

The relevance of emotions is also evident in studies connecting decision outcomes to dual-process tendencies and emotion regulation strategies. In this view, investors may rely on fast, intuitive processes or more deliberative, reflective processing, with emotion regulation serving as a moderating mechanism that shapes whether biases manifest in observable trading patterns. Empirical evidence indicates that classic behavioral effects, such as the disposition effect, are associated with investors' reliance on different processing systems and their emotion regulation strategies (Richards et al., 2018). Such findings reinforce the proposition that emotions influence not only what investors decide but also how they decide—via attention, interpretation, and response selection under risk.

In parallel, technological and data-driven transformations are reshaping how investor emotions are observed and studied. Digital traces—from online discussions to news sentiment and social media signals—have enabled the large-scale quantification of emotional expressions and their relationship with financial outcomes. Studies increasingly explore whether online emotional signals can predict market movements and volatility patterns, demonstrating that computational approaches can capture emotion–market linkages beyond traditional survey-based methods (Zhou et al., 2016; Zhou et al., 2018). Moreover, the integration of physiological and biosignal measures has extended emotion research into neuro-information systems contexts, offering mechanisms to observe and support emotion regulation in decision environments (Astor et al., 2013). Together, these streams suggest that investor emotions constitute a mature but rapidly evolving domain with interdisciplinary foundations spanning finance, psychology, information systems, and data science.

1.2. Problem Statement

Despite substantial growth in scholarship on investor emotions and investment decision-making, the literature remains widely dispersed across disciplines, methods, and application contexts. Studies appear in finance, marketing, psychology, information systems, computational social science, and engineering venues, often using different constructs (e.g., mood, sentiment, affect, anxiety, fear, arousal), distinct measurement approaches (self-report, behavioral proxies, text-based sentiment, physiological signals), and varied outcome indicators (risk-taking, trading frequency, volatility, price predictability, portfolio performance). This dispersion creates two practical problems for researchers.

First, the field is fragmented, which makes it difficult to consolidate what is already known, compare findings across methodological traditions, and identify durable theoretical anchors. Even where systematic syntheses exist, they tend to focus on subsets of biases or specific empirical contexts, leaving the broader intellectual structure under-specified (Zahera & Bansal, 2018). Second, there is a lack of consolidated knowledge mapping that clarifies (a) the influential sources shaping the domain, (b) the major thematic clusters that organize the research, (c) the evolution of these themes over time, and (d) where new frontiers are forming. Without such mapping, scholars risk duplicating efforts, overlooking influential streams, or drawing conclusions from partial representations of the domain.

1.3. Research Gap

Although prior studies provide important insights into behavioral biases and emotion-linked decision patterns, a comprehensive bibliometric synthesis that systematically maps the intellectual, conceptual, and social structure of investor emotion research remains limited within the present dataset. Important strands—such as evidence on behavioral biases affecting investment decisions in specific contexts (Kartini & Nahda, 2021), validated measurement development for bias-related constructs (Ritika & Kishor, 2022), and the role of emotion regulation in explaining behavioral anomalies (Richards et al., 2018)—coexist with computational approaches linking digital emotions to market outcomes (Shen et al., 2017; Zhou et al., 2016; Zhou et al., 2018). Yet these strands are often treated as parallel rather than integrated, leaving unclear how they connect in terms of shared intellectual foundations, co-citation patterns, and thematic convergence.

Critically, emerging areas appear underexplored from a field-level synthesis perspective. These include:

- FinTech-enabled investing and data-rich decision environments, where emotional cues may be amplified by frictionless trading and continuous information flow;
- AI and machine learning applications, which increasingly operationalize market prediction and investor behavior modeling (e.g., the application of machine learning for price prediction in conference proceedings) (Sarode et al., 2019);
- Social media and news emotion dynamics, which translate collective emotional expressions into quantifiable market signals (Shen et al., 2017; Zhou et al., 2016).

Furthermore, as methods diversify—from psychometric scale development (Ritika & Kishor, 2022) to sentiment-based herding measurement (Ren & Wu, 2020) and biosignal-driven emotion regulation support (Astor et al., 2013)—there is a need to clarify which approaches dominate, how they cluster, and which themes are emerging as high-growth research frontiers. A bibliometric investigation is well-suited to address these needs by combining performance indicators with science mapping techniques to reveal structural relationships and thematic evolution.

1.4. Research Objectives

To address the above challenges, this study conducts a bibliometric investigation of the scholarly literature on investor emotions and investment decision-making. The objectives are:

1. To map the intellectual structure of the field by identifying influential documents, sources, and foundational knowledge bases through citation-based techniques.
2. To identify dominant themes by examining keyword co-occurrence patterns and thematic clustering across the literature.
3. To detect emerging research frontiers by observing thematic evolution and highlighting rapidly developing topics, particularly those related to digital sentiment, computational methods, and technology-mediated investment behavior (Shen et al., 2017; Zhou et al., 2018).
4. To suggest future research directions by synthesizing gaps implied by thematic coverage, interdisciplinary linkages, and methodological concentration.

1.5. Contributions

This study makes three complementary contributions.

Theoretical contribution: By organizing dispersed evidence into an integrated knowledge architecture, this work clarifies how investor emotion research coheres around key constructs such as behavioral biases (Kartini & Nahda, 2021; Zahera & Bansal, 2018), emotion-linked cognitive processing and decision framing (Lee & Andrade, 2011), and emotion regulation as a mechanism explaining systematic behavioral effects (Richards et al., 2018). The resulting map helps position the field's core theoretical orientations and indicates where integration across disciplines is occurring (e.g., finance–information systems via biosignals) (Astor et al., 2013).

Methodological contribution: The study advances understanding of methodological pluralism in this domain by comparing how evidence is produced across psychometric validation (Ritika & Kishor, 2022), market analytics using digital emotional traces (Shen et al., 2017; Zhou et al., 2016), and computational prediction and machine learning approaches (Sarode et al., 2019). This supports a more systematic assessment of how methods shape findings and where methodological gaps may exist.

Practical implications: By identifying dominant themes and emerging frontiers, the findings can inform scholars, practitioners, and policymakers seeking evidence-based insights into emotionally driven investing. The mapped themes have direct relevance for investor education and debiasing interventions (Zahera & Bansal, 2018), risk communication and decision support design (Astor et al., 2013), and market monitoring approaches that incorporate news and social media emotions as potential early signals of volatility or regime shifts (Shen et al., 2017; Zhou et al., 2018).

2. Theoretical Foundation

2.1. From Rational Finance to Behavioral and Emotional Finance

Traditional finance models largely assume that investors are rational, information is processed objectively, and deviations from optimality are quickly arbitraged away. However, sustained empirical anomalies and repeated evidence of systematic decision errors have strengthened behavioral finance as an alternative explanatory framework. Within this paradigm, investor choices are shaped not only by information and constraints, but also by psychological processes—particularly cognitive biases and affective (emotional) responses that influence perception of risk and return. Syntheses of the behavioral finance literature consistently document that biases (e.g., overconfidence, loss aversion, anchoring, herding tendencies) materially affect investment decisions and can persist in real markets, challenging purely rational models (Zahera & Bansal, 2018).

Importantly, emotional finance extends the behavioral perspective by emphasizing the role of affective states in shaping judgment and choice under uncertainty. Emotions do not merely accompany decision-making; they can alter attention, weighting of information, and the subjective evaluation of outcomes. For example, fear has been shown to heighten social projection and influence financial judgments—mechanisms that help explain why investors may behave similarly under uncertainty even when their private information differs (Lee & Andrade, 2011). In parallel, emotion-driven decision pathways interact with dual-process cognition: intuitive, rapid responses may dominate under stress, whereas deliberative reasoning may emerge under conditions of control and emotional regulation. Empirical work indicates that emotion regulation strategies and reliance on different cognitive systems are associated with classic behavioral anomalies such as the disposition effect (Richards et al., 2018).

2.2. Investor Emotions, Sentiment, and Market Outcomes

At the aggregate level, investor emotions are frequently operationalized through the construct of "sentiment," which reflects collective optimism/pessimism or affective tone. Sentiment can influence trading intensity, pricing efficiency, and volatility—especially in markets characterized by information ambiguity. Methodological innovations have further strengthened this link by enabling scalable measurement of sentiment from text, media, and online behavior. For instance, evidence shows that emotion signals extracted from news and social media are associated with commodity market dynamics, suggesting that online emotional tone can function as an informative proxy for market-wide affect (Shen et al., 2017). Related work using online emotional indicators also demonstrates relationships with stock market prediction and volatility patterns, supporting the proposition that digitally expressed emotions can contain predictive information, particularly in retail-driven or attention-sensitive environments (Zhou et al., 2016; Zhou et al., 2018).

Beyond prediction, sentiment research also helps explain collective behavioral phenomena such as herding. Advanced sentiment analysis methods have been proposed to quantify herding behavior more precisely, reinforcing the conceptual relationship between emotional convergence and synchronized investor actions (Ren & Wu, 2020). This theoretical linkage is central to markets where rapid information diffusion and emotionally salient narratives contribute to feedback loops between investor mood and price dynamics.

2.3. Technology-Mediated Investing: FinTech, AI, and Social Media Emotion

The last decade has expanded emotional finance into technology-mediated contexts. Digitalisation and FinTech increasingly shape how investors obtain information and execute trades, potentially intensifying emotional responses due to continuous information flow, reduced transaction frictions, and heightened social influence. Recent work points to dynamic relationships between digitalisation and behavioral outcomes, suggesting that technological context is now an important boundary condition for understanding investor emotion and decision-making (Kaur & Badola, 2026).

Concurrently, AI and machine learning approaches have accelerated the extraction and utilization of emotional signals for market analytics. Studies propose models that incorporate sentiment features into prediction pipelines, reflecting the growing convergence of behavioral theory with computational finance (Singh et al., 2025; Sarode et al., 2019). The relevance of these methods is amplified by social media ecosystems, where rumor diffusion and emotionally charged narratives can shape investor attention and price reactions. Research examining rumor sentiment and related emotional features shows that such signals can be analytically decomposed and linked to financial outcomes (Alzahrani et al., 2023). Similarly, microblog-based approaches illustrate how online information streams can be mined for actionable financial opportunities, reinforcing the importance of digital emotion in contemporary market behavior (de Arriba-Pérez et al., 2020). Earlier conceptual work also highlighted how social media may forecast investor sentiment trajectories, foreshadowing the expansion of digital emotion studies now visible in recent empirical work (Lugmayr, 2013).

2.4. Synthesis and Implications for Bibliometric Mapping

Taken together, the theoretical landscape suggests that the investor emotion domain is both interdisciplinary and methodologically diverse: it spans psychological mechanisms (fear, regret, arousal), behavioral biases and decision anomalies, and computational sentiment approaches grounded in digital traces. Systematic syntheses confirm substantial growth in investor psychology research but also indicate dispersion across constructs and methods, motivating integrative mapping efforts to consolidate knowledge and clarify thematic structures (Herathmenike et al., 2025; Zahera & Bansal, 2018). A bibliometric investigation is therefore theoretically justified as a mechanism to reveal how these streams connect, identify dominant paradigms, and detect emerging frontiers (e.g., AI-driven sentiment analytics, FinTech-mediated investing, rumor and microblog dynamics) (Alzahrani et al., 2023; Kaur & Badola, 2026; Singh et al., 2025).

3. Methodology

3.1 Research Design

This study adopts a bibliometric research design to systematically map the knowledge structure of research on investor emotions and financial decision-making. Bibliometric methods are appropriate for consolidating fragmented and interdisciplinary literature because they enable (a) performance analysis (productivity and impact) and (b) science mapping (intellectual and conceptual structure through networks of citations and keywords). The approach aligns with the broader aim of integrating dispersed evidence in investor psychology and behavioral finance, where prior syntheses have highlighted both growth and heterogeneity in constructs and findings (Herathmenike et al., 2025; Zahera & Bansal, 2018).

3.2 Data Source and Search Strategy

The Scopus database was selected due to its broad multidisciplinary coverage and consistent indexing of bibliographic metadata needed for bibliometric analysis. Data retrieval employed the following Scopus query, as specified:

"TITLE-ABS-KEY (investor AND emotion AND financial AND decision-making) AND PUBYEAR > 2009 AND PUBYEAR < 2027"

This search strategy captures publications from **2010 to 2026 (inclusive)** and operationalizes the domain using four core concepts: investor, emotion, financial, and decision-making. The period selection is justified by the rapid expansion of digital sentiment research and computational approaches in finance over the last decade, including social media emotion analytics, rumor sentiment features, and AI-based market prediction (Alzahrani et al., 2023; Shen et al., 2017; Singh et al., 2025; Zhou et al., 2018).

3.3 Screening, Eligibility, and Data Cleaning

A structured screening process was applied to enhance relevance and analytical consistency:

Inclusion criteria	**Exclusion criteria**
1. Publications indexed in Scopus within 2010–2026 based on the query.	1. Records where investor emotion is peripheral or unrelated to financial decision-making outcomes.

2. Studies explicitly linking emotion/sentiment/affect to financial decision-making at the investor or market level.	2. Non-scholarly items and documents lacking sufficient bibliographic metadata for network analysis.
3. Peer-reviewed outputs (e.g., journal articles; conference papers where relevant to computational methods).	

Data cleaning steps typically involved standard bibliometric procedures such as harmonizing author names (where variants exist), normalizing keywords (e.g., merging "sentiment analysis" and "investor sentiment" when conceptually aligned), and checking for duplicates. This step is important in domains where overlapping constructs (emotion vs. sentiment) can lead to fragmented keyword networks, even when studies address common mechanisms (Ren & Wu, 2020; Shen et al., 2017).

3.4 Bibliometric Techniques and Analytical Workflow

The analysis proceeded in two integrated phases:

3.4.1 Performance Analysis

Performance analysis quantified the productivity and impact of the literature, including:

a) Annual publication trends,
b) Leading journals and sources,
c) Most cited documents.

This stage helps contextualize growth patterns—particularly in technology-facing subdomains such as social media emotion analytics and AI-driven prediction models (Alzahrani et al., 2023; Singh et al., 2025; Zhou et al., 2016).

3.4.2 Science Mapping and Network Analyses

To uncover intellectual and conceptual structures, science mapping techniques were applied:

a) Co-citation analysis to identify foundational works and the intellectual base shaping investor emotion research (e.g., behavioral bias synthesis and emotion-linked decision theory) (Lee & Andrade, 2011; Richards et al., 2018; Zahera & Bansal, 2018).
b) Bibliographic coupling to detect current research fronts by grouping documents that cite similar references—particularly useful for identifying emerging technology-mediated themes (Kaur & Badola, 2026; Singh et al., 2025).
c) Keyword co-occurrence analysis to identify dominant thematic clusters such as behavioral biases, fear/greed dynamics, sentiment and volatility, herding, and digital emotion signals (Ren & Wu, 2020; Shen et al., 2017; Zhou et al., 2018).

3.5 Tools and Reporting

Network visualization and thematic clustering were conducted using standard bibliometric visualization software (e.g., VOSviewer) and complementary bibliometric workflow tools (e.g., Bibliometrix/Biblioshiny) to generate co-authorship, co-citation, and keyword maps. Findings are reported through a combination of tables (top authors, journals, and documents) and network figures (collaboration, co-citation, and keyword clusters). Consistent with the study's theoretical orientation, interpretation of clusters emphasizes emotional mechanisms (fear, sentiment), behavioral outcomes (herding, disposition), and emerging digital contexts (FinTech, microblogs, rumor sentiment, and AI prediction) (Alzahrani et al., 2023; de Arriba-Pérez et al., 2020; Kaur & Badola, 2026; Ren & Wu, 2020; Singh et al., 2025).

4. Data analysis

The data analysis was conducted using a two-stage bibliometric workflow designed to capture both the productivity–impact profile of the literature and its intellectual and conceptual structure. First, a performance analysis was performed to summarize annual publication trends and identify the most influential journals, authors, institutions, countries, and highly cited documents within the dataset retrieved from Scopus (2010–2026). Second, science mapping techniques were applied to uncover the underlying knowledge architecture of investor emotion research through network-based analyses, including co-authorship (collaboration patterns), co-citation (intellectual foundations), bibliographic coupling (current research fronts), and keyword co-occurrence (thematic clustering and topic prominence). Visualisation and clustering were generated using standard bibliometric tools (e.g., VOSviewer and Bibliometrix/Biblioshiny), and results were interpreted by linking each network cluster to behavioral finance constructs (e.g., emotional biases, risk perception, herding, sentiment-driven decision-making) and to emerging technology-mediated themes (e.g., FinTech contexts, AI-enabled sentiment analytics, and social media emotion signals).

4.1. Performance Analysis

4.1.1 Annual publication trends

The annual scientific production (Figure-1), for the Scopus dataset (2010–2026) indicates a clear progression from a low-output niche to a rapidly expanding research stream on investor emotions and financial decision-making. As shown in the annual counts—2010 (3), 2011 (3), 2012 (2), 2013 (3), 2014 (3), 2015 (5), 2016 (4), and 2017 (1)—the early period reflects limited but consistent scholarly attention, followed by a noticeable step-change from 2018 (8) and 2019 (8), with output remaining comparatively elevated in 2020 (7). This pattern suggests that the field began consolidating after 2017, likely reflecting broader acceptance of affect-driven explanations within behavioral finance and the growth of empirical approaches capturing emotion-related signals.

A second, more pronounced acceleration occurs from 2022 (6) onward, with production increasing sharply to 2023 (11), 2024 (20), and peaking at 2025 (25)—indicating a strong recent surge and positioning 2023–2025 as the dominant high-growth window in the dataset. The apparent decline in 2026 (6) should be interpreted cautiously in line with Scopus reporting conventions, as the most recent year often reflects partial-year coverage and indexing lag, rather than a confirmed reduction in research activity. Overall, the trajectory demonstrates a maturing and fast-expanding literature base, providing strong justification for bibliometric mapping to identify the field's dominant clusters and emerging frontiers.

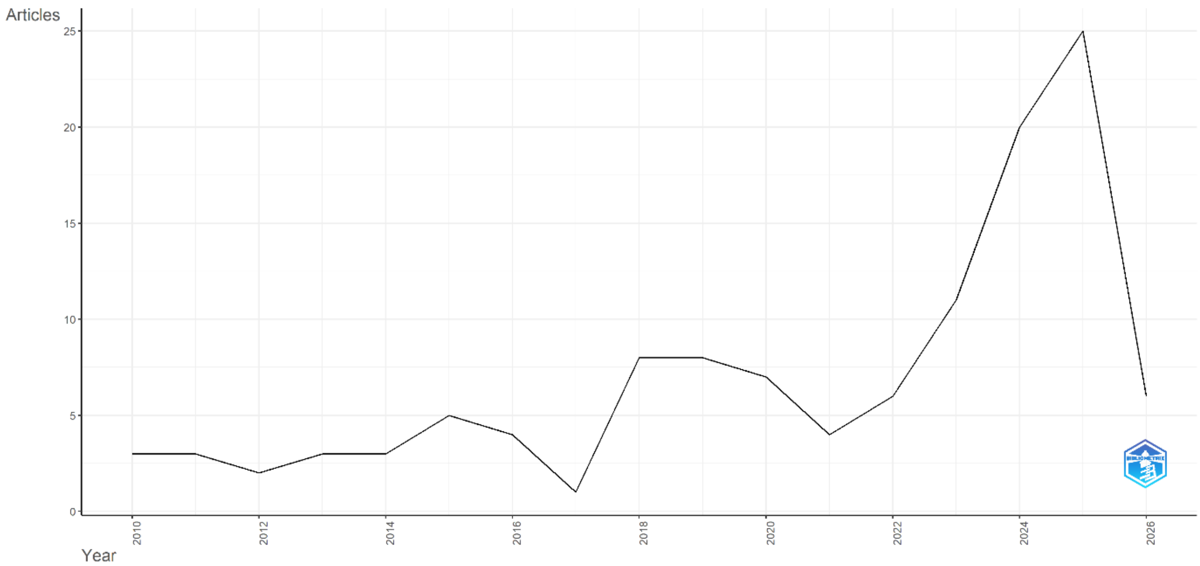

Figure-1: Annual Scientific Production Trend

Source: Researcher own compilation using Bibliometrix R

4.1.2 Average Citations Trend Analysis

The average citations per year indicator (Figure-2), reflects the annualised impact of articles published each year and therefore corrects—at least partially—for differences in publication age. As shown in the table and trend line, the citation intensity is comparatively strongest for several mid-period cohorts: 2013 (3.48 citations/year), 2017 (2.80 citations/year; note N=1), and especially 2018 (4.10 citations/year), which represents the highest annualised influence in the dataset. After this peak, the indicator moderates in 2019 (1.31) and then strengthens again during 2020 (2.00) and 2021 (3.62), followed by 2022 (2.23) and 2023 (1.86). This pattern suggests that foundational and consolidation-phase studies (roughly 2013–2021) have accumulated stronger citation momentum, indicating the presence of influential contributions and more "settled" citation trajectories during those years.

In contrast, the sharp decline in average citations per year for the most recent cohorts—2024 (0.93), 2025 (0.24), and 2026 (0.50; N=6)—should be interpreted cautiously in line with Scopus-standard bibliometric interpretation, because citation-based indicators are highly sensitive to citation window length and indexing lag. The table explicitly shows shrinking citable years for recent publications (e.g., 2024: 3 years; 2025: 2 years; 2026: 1 year), meaning these articles have had substantially less time to accrue citations. Therefore, the lower values in 2024–2026 do not indicate reduced scholarly relevance; rather, they reflect recency effects typical of bibliometric datasets. Overall, the figure supports a Scopus-consistent conclusion: the field's volume has surged recently (as seen in annual production), while citation impact is currently concentrated in earlier cohorts with adequate time for citations to mature, underscoring the importance of combining productivity trends with normalised citation indicators in the results interpretation.

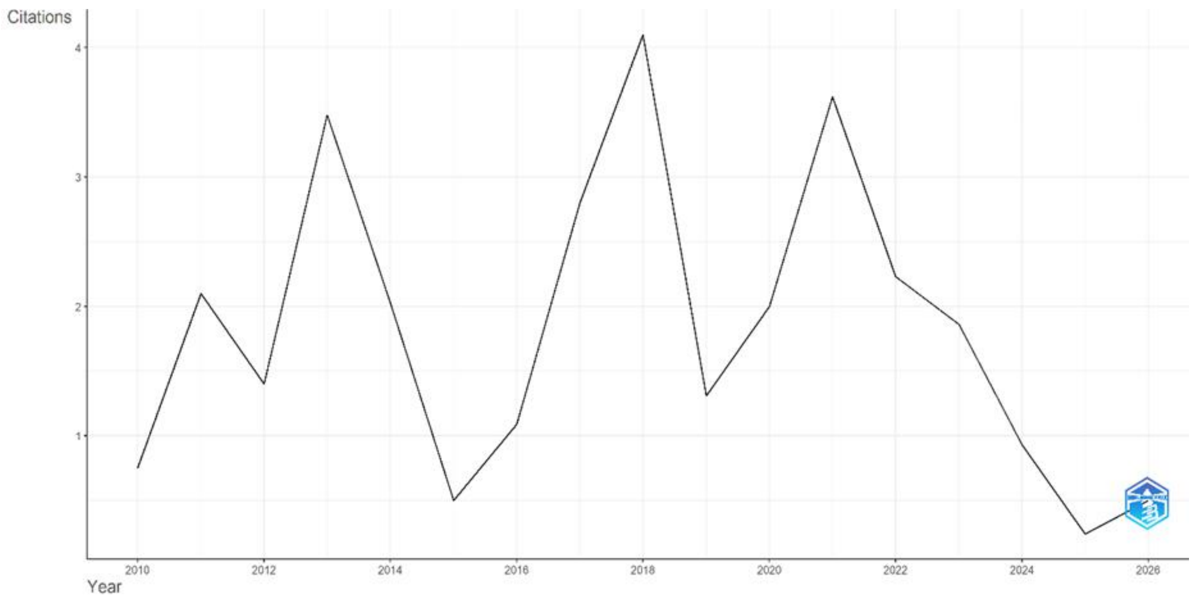

Figure-2: Average citations Trend

Source: Researcher own compilation using Bibliometrix R

4.1.3. Most Relevant Sources

The most relevant sources analysis shows that research on investor emotions and financial decision-making is dispersed across an interdisciplinary set of outlets rather than concentrated in a single dominant journal: Qualitative Research in Financial Markets leads with 5 documents, followed by Acta Psychologica (3), IEEE Access (3), and PLOS ONE (3), while several other sources contribute two documents each (e.g., F1000Research, Review of Behavioral Finance, Scientific Reports, and Lecture Notes in Computer Science). This pattern is consistent with Scopus-standard interpretations of an expanding, cross-disciplinary domain in which behavioral and psychological foundations coexist with computational and data-driven approaches (e.g., sentiment analytics, AI/FinTech), resulting in publication spread across finance, psychology, and technology venues and further justifying bibliometric mapping to integrate fragmented evidence.

Table-1: Most Relevant Sources

Sources	Articles
QUALITATIVE RESEARCH IN FINANCIAL MARKETS	5
ACTA PSYCHOLOGICA	3
IEEE ACCESS	3
PLOS ONE	3
DEEP LEARNING TOOLS FOR PREDICTING STOCK MARKET MOVEMENTS	2
F1000RESEARCH	2
INTERNATIONAL JOURNAL OF ADVANCED SCIENCE AND TECHNOLOGY	2
INVESTOR BEHAVIOR: THE PSYCHOLOGY OF FINANCIAL PLANNING AND INVESTING	2
LECTURE NOTES IN COMPUTER SCIENCE (INCLUDING SUBSERIES LECTURE NOTES IN ARTIFICIAL INTELLIGENCE AND LECTURE NOTES IN BIOINFORMATICS)	2
PSYCHOLOGICAL DRIVERS OF HERDING AND MARKET OVERREACTION	2
REVIEW OF BEHAVIORAL FINANCE	2
SCIENTIFIC REPORTS	2
2016 INTERNATIONAL CONFERENCE ON INFORMATION SYSTEMS, ICIS 2016	1
2019 4TH IEEE INTERNATIONAL CONFERENCE ON BIG DATA ANALYTICS, ICBDA 2019	1
2024 4TH INTERNATIONAL CONFERENCE ON COMPUTER COMMUNICATION AND ARTIFICIAL INTELLIGENCE, CCAI 2024	1
40TH INTERNATIONAL CONFERENCE ON INFORMATION SYSTEMS, ICIS 2019	1
ACADEMY OF ACCOUNTING AND FINANCIAL STUDIES JOURNAL	1
ACCOUNTING PERSPECTIVES	1

Source: Researcher own compilation using Bibliometrix R

4.1.4: Most cited documents.

The top-cited documents as in Table-2, indicate that the field is anchored by a small set of highly influential works that combine theoretical consolidation with methodological innovation. The most impactful publication is Zahera and Bansal's systematic review in Qualitative Research in Financial Markets (TC = 203; 22.56 citations/year; normalized TC = 5.51), confirming that integrative syntheses have played a central role in shaping subsequent research. Strong citation performance is also evident for foundational interdisciplinary contributions linking emotion regulation and decision support to information systems (Astor et al., TC = 110; 7.86/year; normalized TC = 2.26) and for early empirical work connecting fear and financial judgment (Journal of Marketing Research; Lee & Andrade, TC = 91; 5.69/year; normalized TC = 2.70). More recent influential studies include Kartini and Nahda's behavioral-bias evidence in an emerging-market context (TC = 73; 12.17/year; normalized TC = 3.36) and the finance psychology reference text by Baker (TC = 68; 5.23/year; normalized TC = 2.58), while methodological advances—such as scale development for behavioral biases (Ritika, TC = 39; 7.80/year; normalized TC = 3.49) and computational emotion/sentiment research (Zhou, TC = 31; 2.82/year; normalized TC = 2.58; Shen, TC = 28; 2.80/year; normalized TC = 1.00)—highlight the growing importance of measurement and analytics. Overall, the ranking shows that high normalized citation scores are achieved both by theoretical syntheses and by methods-oriented studies (psychometrics, digital emotion, and computational modeling), suggesting that the field's intellectual structure is shaped by convergence between behavioral finance theory and data-driven approaches.

Table-2: Most cited documents.

Paper	DOI	Total Citations	TC per Year	Normalized TC
ZAHERA SA, 2018, QUAL RES FINANC MARKETS	10.1108/QRFM-04-2017-0028	203	22.56	5.51
ASTOR PJ, 2013, J MANAGE INF SYST	10.2753/MIS0742-1222300309	110	7.86	2.26
LEE CJ, 2011, J MARK RES	10.1509/jmkr.48.SPL.S121	91	5.69	2.70
KARTINI K, 2021, J ASIAN FINANC ECON BUS	10.13106/jafeb.2021.vol8.no3.1231	73	12.17	3.36
KENT BAKER HK, 2014, INVEST BEHAVIOR: THE PSYCHOLOGY OF FINANCIAL PLAN AND INVEST	10.1002/9781118813454	68	5.23	2.58
JERČIĆ P, 2012, ECIS - PROC EUR CONF INF SYST		42	2.80	2.00
RITIKA, 2022, REV BEHAV FINANC	10.1108/RBF-05-2020-0087	39	7.80	3.49
KRET ME, 2019, J EXP PSYCHOL GEN	10.1037/xge0000508	33	4.13	3.14
ZHOU Z, 2016, LECT NOTES COMPUT SCI	10.1007/978-3-319-48740-3_24	31	2.82	2.58
SHEN J, 2017, REV BEHAV FINANC	10.1108/RBF-09-2016-0060	28	2.80	1.00

Source: Researcher own compilation using Bibliometrix R

4.2 Science Mapping and Network Analyses

4.2.1. Co-citation network

The co-citation network (Figure-3), reveals a clearly clustered intellectual structure underpinning research on investor emotions and financial decision-making, with each cluster representing a distinct but interconnected knowledge base. One prominent cluster centres on behavioral finance and investor psychology, anchored by highly co-cited works associated with Baker and core behavioral foundations such as Barberis and related Journal of Finance contributions, indicating that bias-based explanations remain a primary theoretical pillar. A second cluster reflects information and sentiment in financial markets, linking influential studies on online attention and mood signals (e.g., Bollen on Twitter mood) and internet-based information effects (e.g., Antweiler & Frank), highlighting the rise of computational and media-driven sentiment approaches as a major intellectual stream. A third cluster connects neuroeconomic and affective-decision foundations, visible through co-citation ties to emotion–reason frameworks (e.g., Damasio's Descartes' Error) and decision neuroscience work (e.g., Bechara), suggesting that parts of the literature draw directly on affective science to explain risk-taking and judgment under uncertainty. Importantly, the cross-links between clusters indicate that the field is not siloed: behavioral finance theory, digital sentiment analytics, and neuro-affective decision theory increasingly co-inform one another, supporting the conclusion that investor emotion research is evolving as an interdisciplinary domain with multiple foundational "schools" that converge around market behavior and decision outcomes.

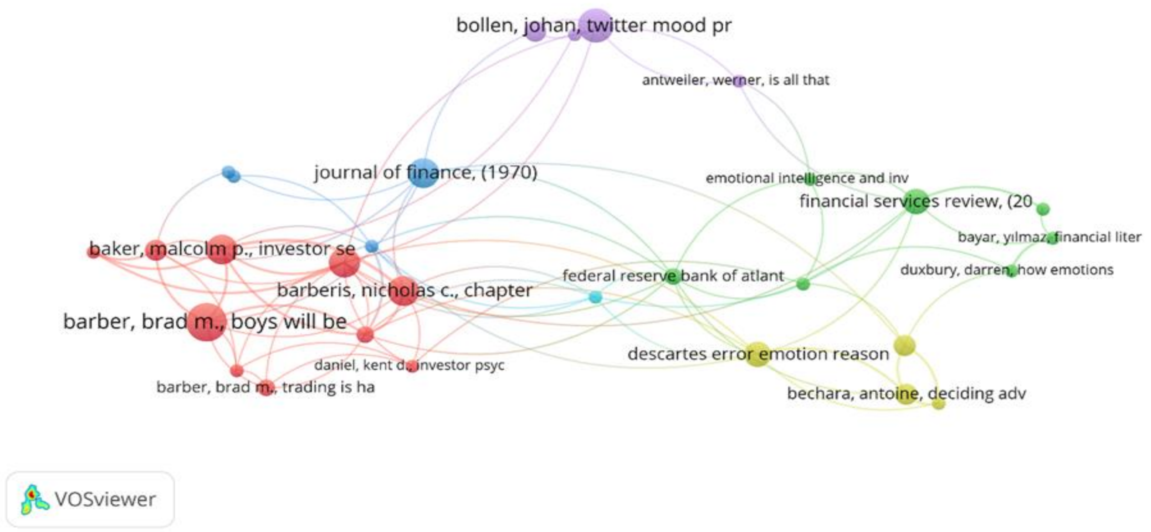

Figure-3: Co-citation network

Source: Researcher own compilation using VOSViewer

4.2.2. Bibliographic coupling

The bibliographic coupling network (Figure-4), highlights the current research fronts in investor emotion and financial decision-making by linking documents that share similar reference bases. The most dominant hub is Zahera (2018) (largest node), indicating that later studies converge strongly around this work as a common theoretical and review foundation, which is typical in maturing fields where a highly cited synthesis anchors subsequent empirical extensions. A second major hub is Kartini (2021), forming a distinct but strongly connected cluster with recent studies (e.g., Brooks 2023; Spytska 2024; Verma 2026), suggesting an active stream focused on behavioral biases and investment decision outcomes—often in applied or emerging-market contexts—built on shared behavioral finance references. In parallel, Astor (2013) appears as a substantial node positioned within a technology-oriented cluster, reflecting a coupling structure tied to information systems and decision-support foundations (e.g., emotion regulation and NeuroIS), which connects to finance-oriented work through shared psychological and decision-science references.

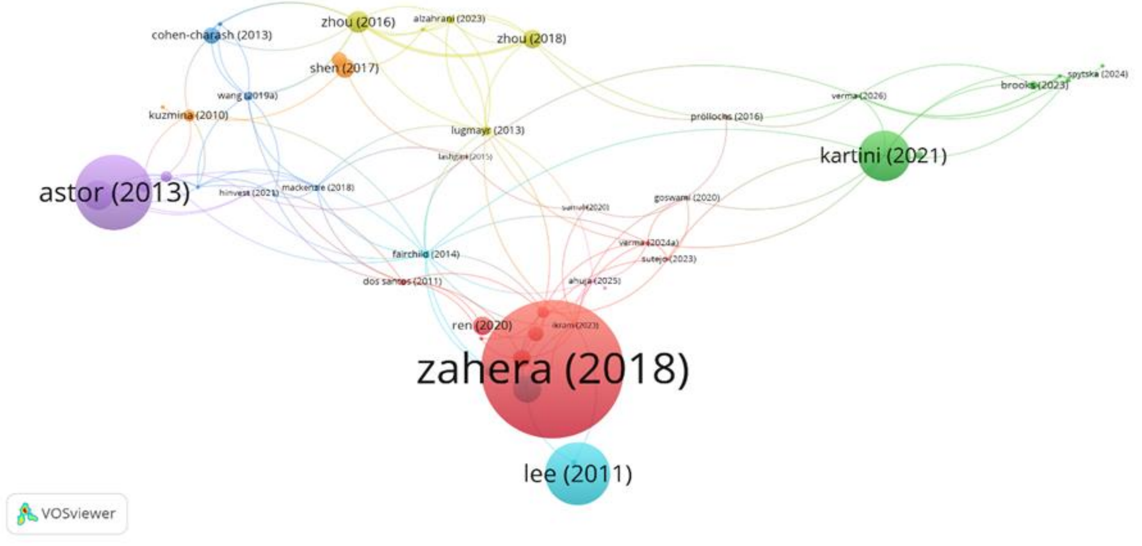

Figure-4: Bibliographic coupling network

Source: Researcher own compilation using VOSViewer

A further coupled stream is visible around digital sentiment and online emotion analytics, where Zhou (2016; 2018) and Shen (2017) function as key connectors, linking studies that employ computational extraction of emotions from online platforms, news, or social media and relate these signals to market behavior. Notably, the network shows multiple cross-cluster links (e.g., between Zahera 2018 and sentiment nodes), indicating that recent scholarship increasingly integrates behavioral-bias explanations with data-driven sentiment measurement. From a Scopus-standard interpretation, this coupling pattern suggests that the field's contemporary development is shaped by three interacting fronts: (i) behavioral-bias and investor decision research anchored by synthesis work, (ii) technology-mediated emotion regulation and decision-support perspectives, and (iii) computational sentiment analytics as an expanding methodological frontier.

4.2.3. Keyword co-occurrence analysis

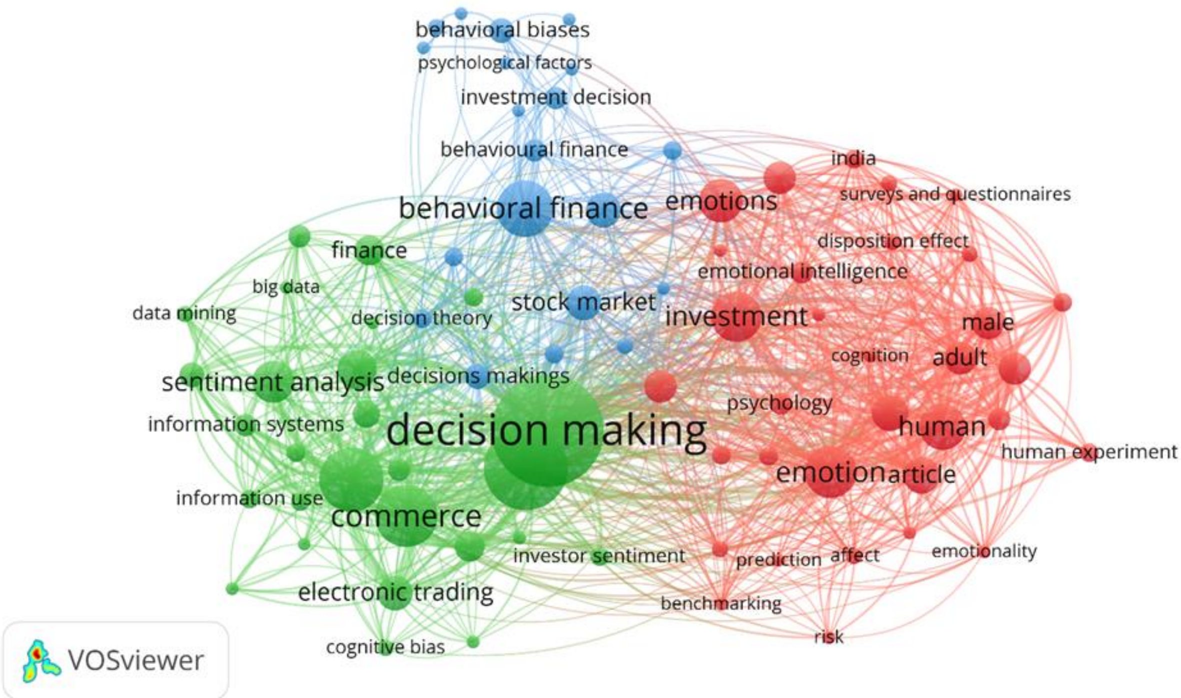

Figure-5: Keyword co-occurrence network

Source: Researcher own compilation using VOSViewer

The keyword co-occurrence network (Figure-5), reveals three dominant thematic clusters that structure research on investor emotions and financial decision-making. The largest, centrally positioned cluster (green) is organized around "decision making" and connects strongly with sentiment analysis, information systems, commerce, electronic trading, big data, and data mining, indicating a technology- and analytics-driven stream where investor emotion is operationalized through digital traces and computational methods. A second cluster (blue) is anchored by "behavioral finance," "stock market," "investment decision," and behavioral biases/psychological factors, representing the core behavioral finance tradition that explains deviations from rationality through bias-based mechanisms and decision theory. The third cluster (red) centres on "emotions," "investment," "human," "adult," "male," and methodological terms such as surveys and questionnaires and human experiment, reflecting a psychologically oriented stream that emphasizes individual-level affect, cognition, and empirical measurement through primary data and experimental designs; within this cluster, the presence of terms such as disposition effect, emotional intelligence, risk, and prediction suggests a focus on how affective traits and emotional responses shape risk-taking and trading outcomes. Importantly, the dense interconnections among clusters—particularly through bridging terms like investment, stock market, and investor sentiment—indicate increasing integration between traditional behavioral finance explanations and emerging computational sentiment/FinTech approaches, supporting the conclusion that the field is evolving toward an interdisciplinary synthesis rather than remaining siloed within a single methodological or theoretical tradition.

5. Discussion

5.1. Intellectual Structure Interpretation

The bibliometric evidence indicates that research on investor emotions and financial decision-making is organised around a set of stable intellectual pillars, but is simultaneously undergoing methodological and thematic reconfiguration. The co-citation structure suggests three dominant paradigms. First, a behavioral finance and investor psychology paradigm remains central, reflecting continued reliance on bias-based explanations of investment behavior and decision anomalies (Zahera & Bansal, 2018). The prominence of foundational emotion–decision studies (e.g., fear and judgment in financial contexts) further supports the view that affect is treated as a core driver of risk perceptions and preference formation (Lee & Andrade, 2011). Second, the network indicates a neuro-affective and decision-science foundation—represented through emotion–reason and neuroeconomic lines of work—suggesting that parts of the field draw on psychological and neuroscientific explanations to clarify why emotion influences choice under uncertainty (Astor et al., 2013). Third, the bibliographic coupling results reveal an expanding digital sentiment and computational market analytics paradigm in which investor emotions are increasingly operationalised through online and media-derived signals rather than only via self-report constructs (Shen et al., 2017; Zhou et al., 2016; Zhou et al., 2018).

A key interpretive finding is the evident shift toward data-driven sentiment approaches without replacing the behavioral finance core. The keyword co-occurrence map places “decision making” at the centre but shows strong connectivity to “sentiment analysis,” “big data,” “data mining,” “information systems,” and “electronic trading,” indicating that affect is now frequently measured through digital traces and computational pipelines rather than only through surveys and experiments. This trend aligns with the rising publication surge after 2023 and with the clustering patterns where computational sentiment research bridges traditional behavioral constructs (biases, disposition effect, risk) with technology-mediated investing contexts. Importantly, citation patterns are consistent with an intellectual architecture in which synthesis work anchors the field while empirical and methodological diversification accelerates: the highly cited systematic review (Zahera & Bansal, 2018) appears as a dominant coupling hub, supporting its role as a shared reference base for newer studies extending measurement, context, and analytics.

5.2. Interdisciplinary Integration

Across the results, interdisciplinarity is not incidental—it is structurally embedded. First, the integration of finance + psychology is evident in both the co-citation foundations and the keyword cluster emphasising “emotions,” “psychology,” “cognition,” and behavioral outcomes such as the disposition effect. These patterns reflect a continuing theoretical dependence on psychological constructs and mechanisms to explain deviations from rational choice, consistent with behavioral finance syntheses and empirical affect research (Lee & Andrade, 2011; Richards et al., 2018; Zahera & Bansal, 2018). Second, the integration of finance + data science is increasingly salient, visible in the decision-making and sentiment analysis cluster connecting to big data, data mining, and information systems, and reinforced by key coupling nodes in online emotion and prediction studies (Shen et al., 2017; Zhou et al., 2018). In practical terms, this indicates a methodological convergence: psychological theory provides interpretive mechanisms (why emotions matter), while data-driven methods provide scalable measurement (how emotions can be observed and modelled in real time).

The source analysis further supports this integration, as influential outputs are distributed across finance journals (e.g., Qualitative Research in Financial Markets), psychology outlets (e.g., Acta Psychologica), and computational venues (e.g., IEEE Access), suggesting that the field’s knowledge production is shaped by multiple scholarly ecosystems rather than a single discipline. This dispersion is typical of domains that evolve at the intersection of theory-rich behavioral explanations and tool-rich computational methodologies.

5.3. Emerging Research Frontiers

Three emerging frontiers are indicated by the coupling and keyword structures. First, social media-driven investing is increasingly visible, with digital emotion and online sentiment studies functioning as connectors between behavioral theory and market analytics, reinforcing evidence that news and social media emotions can be associated with market movements and volatility (Shen et al., 2017; Zhou et al., 2016). Second, retail investor psychology is rising as an applied stream, reflected by the strong coupling around applied behavioral-bias research and the rapid recent increase in publications—consistent with the global expansion of retail participation via mobile trading and platform-based investing (Kartini & Nahda, 2021). Third, the clustering of sentiment analytics with predictive and computational terms suggests the emergence of "emotional AI"—models that infer, forecast, or respond to affective signals in financial contexts—aligning with the growing presence of AI/ML-oriented studies in the domain's methodological space (Sarode et al., 2019). Collectively, these frontiers point to a field that is increasingly concerned with (a) scalable emotion measurement, (b) platform-mediated investor behavior, and (c) algorithmic utilisation of emotion as an explanatory and predictive feature.

5.4. Practical Implications

For investors, the results reinforce the need for systematic bias awareness and structured decision hygiene. Because behavioral biases and affective states remain central in the intellectual structure, investor education should address emotional triggers (fear, regret, overconfidence) and implement practical debiasing mechanisms such as pre-commitment rules, diversified rebalancing schedules, and decision checklists (Zahera & Bansal, 2018). Risk management practices should also incorporate emotion-aware strategies, including volatility-sensitive position sizing and avoidance of impulsive trading during emotionally salient news cycles, consistent with evidence that emotion signals can correlate with market movement and instability (Shen et al., 2017; Zhou et al., 2018).

For policymakers, the dispersion of the literature across psychology, finance, and computational methods suggests that regulation and investor protection frameworks should incorporate behavioral insights alongside market microstructure considerations. Policy instruments can focus on market stability by mitigating channels of emotional contagion, including misinformation and rumor-driven trading environments, and by strengthening disclosure practices to reduce ambiguity-related panic. Behavioral regulation can also target choice architecture in trading platforms (e.g., friction design, warning labels for high-frequency trading behavior), thereby reducing impulsive decision-making under affective pressure.

For financial institutions, the integration of sentiment analytics into decision-making clusters indicates practical opportunity for sentiment-based strategies and early-warning systems. Institutions can combine traditional risk signals with structured sentiment indicators from news and online sources to detect shifts in market mood that precede volatility regimes (Shen et al., 2017; Zhou et al., 2016). However, implementation should be paired with governance controls to avoid overfitting and to ensure ethical use, particularly as emotion-driven predictive models become more prevalent within AI-enabled finance (Sarode et al., 2019).

6. Research Agenda and Future Directions

6.1 Theoretical Directions

Future theory development should prioritise integration rather than parallel advancement. One important direction is the integration of emotional finance with ESG and sustainability-related decision contexts, where moral emotions, climate anxiety, and ethical preferences may influence risk perceptions and long-horizon investing. Although ESG is not yet a dominant node in the current keyword structure, the field's increasing attention to real-world decision environments suggests that incorporating ESG-related affective drivers can expand explanatory power beyond traditional risk–return framing. A second theoretical direction concerns cross-cultural emotional behavior. The presence of country markers (e.g., "India") in the keyword map indicates active regional research streams, but comparative theory remains limited. Systematic cross-cultural theory building is needed to explain how social norms, financial literacy, market institutions, and culturally shaped emotion regulation influence investment choices and susceptibility to biases (Kartini & Nahda, 2021; Zahera & Bansal, 2018). A refined theoretical agenda should therefore move toward culturally sensitive models of emotional investing that account for institutional context and social influence.

6.2 Methodological Directions

Methodologically, the results suggest value in combining depth and scale. First, mixed-method designs (e.g., qualitative insights + quantitative bibliometrics + computational sentiment) can bridge construct clarity with predictive analytics, aligning with the field's dispersion across sources and methods. Second, experimental finance remains essential for isolating causal pathways (emotion → cognition → decision), particularly for biases such as the disposition effect and emotion regulation mechanisms (Richards et al., 2018). Third, there is growing opportunity for neuroimaging and physiological approaches to validate emotion mechanisms and reduce reliance on indirect proxies. NeuroIS-oriented work demonstrates how biosignals can support emotion regulation in decision contexts (Astor et al., 2013), but broader adoption in finance remains limited. Progress would benefit from stronger measurement triangulation—linking self-report emotion, behavioral outcomes, and physiological indicators—alongside transparent replication and cross-market validation.

6.3 Contextual Directions

Three contexts merit particular attention. First, cryptocurrency markets provide a high-volatility, narrative-driven environment where emotional contagion and attention shocks may have outsized effects, making them a natural laboratory for emotional finance and sentiment analytics. Second, emerging economies deserve sustained focus given differences in investor sophistication, institutional trust, and market microstructure; applied bias studies in such contexts have already demonstrated relevance and may benefit from larger comparative designs (Kartini & Nahda, 2021). Third, crisis periods remain crucial for theory testing because uncertainty heightens affective processing and shifts reliance toward intuitive decision systems; given the field's historical publication accelerations around uncertainty windows, longitudinal crisis-focused designs can clarify when emotion mechanisms amplify volatility versus when regulation dampens it (Lee & Andrade, 2011; Shen et al., 2017).

7. Conclusion

This bibliometric investigation mapped the evolving research landscape on investor emotions and financial decision-making using Scopus-indexed literature (2010–2026). The findings show a rapidly expanding publication trajectory, particularly after 2023, alongside a citation structure in which mature cohorts (2013–2021) currently exhibit stronger annualised impact due to longer citation windows. Science mapping results reveal a multi-pillar intellectual architecture: (i) a dominant behavioral finance and bias-based paradigm, (ii) affective and neuro-decision foundations that explain emotion–reason interactions, and (iii) a fast-growing computational sentiment paradigm connecting digital traces (news, social media, online mood) with market outcomes. Keyword co-occurrence indicates that "decision making" sits at the field's core while bridging behavioral finance constructs with sentiment analytics and technology-mediated investing.

The study contributes by consolidating fragmented evidence into an interpretable knowledge map, identifying dominant themes, key sources, and emerging frontiers—particularly social media-driven investing, retail investor psychology, and emotion-aware AI. Nevertheless, results should be interpreted with awareness of dataset boundaries and bibliometric constraints. Overall, the evidence suggests that emotional finance is moving toward an interdisciplinary synthesis in which psychological mechanisms and computational measurement increasingly reinforce one another, providing a strong platform for future theory refinement and methodological innovation.

Limitations

This study has several limitations consistent with bibliometric research practice. First, reliance on a single database (Scopus) may exclude relevant publications indexed elsewhere or in non-indexed outlets, which can influence network structures and source rankings. Second, a degree of language bias is likely because Scopus coverage is predominantly English and may underrepresent regionally significant work published in other languages. Third, citation-based indicators are subject to citation lag, particularly for recent publications (e.g., 2024–2026), meaning lower average citations in recent years primarily reflect shorter citable windows rather than reduced scholarly relevance. Finally, bibliometric mapping relies on metadata quality; variations in author names, keyword standardisation, and indexing practices can affect clustering results, even when the underlying intellectual connections are robust.

References

(1) Abrahamson, M., & Grant, M. (2025). Judgments and decisions by expert fund managers. Contributions to Finance and Accounting, Part F4970, 47–64. https://doi.org/10.1007/978-3-032-08545-0_4

(2) Ahuja, S., & Kumar, B. (2025). An elicitation study to understand the equity investment motivation and decisions among indian millennials. Qualitative Research in Financial Markets, 17(1), 66–86. https://doi.org/10.1108/QRFM-04-2023-0081

(3) Alzahrani, A. I., Sarsam, S. M., Al-Samarraie, H., & others. (2023). Exploring the sentimental features of rumor media to predict stock market reactions. International Review of Economics & Finance, 87, 433–444. https://doi.org/10.1016/j.iref.2023.05.006

(4) Alzahrani, A., Sarsam, S., Al-Samarraie, H., & Alblehai, F. (2023). Exploring the sentimental features of rumor messages and investors' intentions to invest. International Review of Economics and Finance, 87, 433–444. https://doi.org/10.1016/j.iref.2023.05.006

(5) Ang, L., Hellmann, A., Kanbaty, M., & Sood, S. (2020). Emotional and attentional influences of photographs on impression management and financial decision making. Journal of Behavioral and Experimental Finance, 27, Article 100348. https://doi.org/10.1016/j.jbef.2020.100348

(6) Annapurna, R., & Basri, S. (2024). The influence of emotional intelligence and behavioural biases on mutual fund churning frequency: Evidence from india. Acta Psychologica, 248, Article 104426. https://doi.org/10.1016/j.actpsy.2024.104426

(7) Aryadevi, M., Vincent, G., & Challa, V. (2025). Emotional intelligence, financial literacy, and attitudes toward risk: Determining investment choices towards investment decision. International Research Journal of Multidisciplinary Scope, 6(2), 504–515. https://doi.org/10.47857/irjms.2025.v06i02.03127

(8) AsleBagh, P., Bonyadi-Naeini, A., & Moeeni, M. (2024). Investigating the effect of three different factors including experience, personality and color on the decision-making process in stock markets using EEG. Journal of Behavioral and Experimental Economics, 109, Article 102163. https://doi.org/10.1016/j.socec.2024.102163

(9) Astor, P., Adam, M., Jerčić, P., Schaaff, K., & Weinhardt, C. (2013). Integrating biosignals into information systems: A neurois tool for improving emotion regulation. Journal of Management Information Systems, 30(3), 247–278. https://doi.org/10.2753/MIS0742-1222300309

(10) Badlani, B., Yadav, R., & Kumar, A. (2023). Psychological impact of cryptocurrency volatility on investor emotions and decision making. Journal for ReAttach Therapy and Developmental Diversities, 6(7), 204–214.

(11) Bari, A., Peidaee, P., Khera, A., Zhu, J., & Chen, H. (2019). Predicting financial markets using the wisdom of crowds. 2019 4th IEEE International Conference on Big Data Analytics, ICBDA 2019, 334–340. https://doi.org/10.1109/ICBDA.2019.8713246

(12) Bikas, E., & Kavaliauskas, A. (2010). Lithuanian investors' behaviour during financial crisis; lietuvos inverstuotojų elgsena finansų krizė. Business: Theory and Practice, 11(4), 370–380. https://doi.org/10.3846/btp.2010.40

(13) Brooks, C., & Williams, L. (2022). When it comes to the crunch: Retail investor decision-making during periods of market volatility. International Review of Financial Analysis, 80, Article 102038. https://doi.org/10.1016/j.irfa.2022.102038

(14) Brooks, C., Sangiorgi, I., Saraeva, A., Hillenbrand, C., & Money, K. (2023). The importance of staying positive: The impact of emotions on attitude to risk. International Journal of Finance and Economics, 28(3), 3232–3261. https://doi.org/10.1002/ijfe.2591

(15) Cabrera-Paniagua, D., Cubillos, C., Cubillos, A., Urra, E., & Mellado, R. (2018). Affective algorithm for controlling emotional fluctuation of artificial investors in stock markets. IEEE Access, 6, 7610–7624. https://doi.org/10.1109/ACCESS.2018.2802781

(16) Charles, C., Tong, W., Li, L., & Allen, A. (2025). Enhancing stock price prediction through fine-tuned cardiffnlp twitter-roberta: A web application approach using financial news articles. Conference Proceedings - IEEE SOUTHEASTCON, 995–1000. https://doi.org/10.1109/SoutheastCon56624.2025.10971641

(17) Cheng, J., Fu, J., Kang, Y., Zhu, H., & Dai, W. (2019). Sentiment analysis of social networks' comments to predict stock return. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 11956 LNCS, 67–74. https://doi.org/10.1007/978-3-030-37429-7_7

(18) Chhabra, A., Hasan, N., Ansari, M., & Alam, M. (2025). Algorithmic trading and AI: A synergy for risk management. AI-Driven Finance in the VUCA World, 27–45. https://doi.org/10.1201/9781003482154-3

(19) Chidambaram, N., & Vikkraman, P. (2016). Does the propensity of overconfidence bias hinge on demographics and personality traits?. International Journal of Applied Business and Economic Research, 14(3), 1515–1529.

(20) Chu, J., Liu, X., Wu, R., Zhang, L., Li, Y., & Cho, H. (2018). Relationship between negative emotion and investment behavior of enterprises. NeuroQuantology, 16(6), 213–218. https://doi.org/10.14704/nq.2018.16.6.1656

(21) Cohen-Charash, Y., Scherbaum, C., Kammeyer-Mueller, J., & Staw, B. (2013). Mood and the market: Can press reports of investors' mood predict stock prices?. PLoS ONE, 8(8), Article e72031. https://doi.org/10.1371/journal.pone.0072031

(22) Crosby, D. (2015). Investor emotions and financial decisions. Personal Benchmark: Integrating Behavioral Finance and Investment Management, 49–82. https://doi.org/10.1002/9781119204190.ch2

(23) Damayanti, (2019). The difference between fuzzy trace theory and heuristic theory in risk taking in the context of financial investment. International Journal of Engineering and Advanced Technology, 8(5), 170–177. https://doi.org/10.35940/ijeat.E1025.0585C19

(24) de Arriba-Pérez, F., García-Méndez, S., Regueiro-Janeiro, J., & Javier González-Castaño, F. (2020). Detection of financial opportunities in micro-blogging data with a stacked classification system. IEEE Access, 8, 215679–215690. https://doi.org/10.1109/ACCESS.2020.3041084

(25) de Arriba-Pérez, F., García-Méndez, S., Regueiro-Janeiro, J., & others. (2020). Detection of financial opportunities in micro-blogging social networks. IEEE Access, 8, 215679–215690. https://doi.org/10.1109/ACCESS.2020.3041084

(26) Dikshit, N., Srivastava, K., & Sav, S. (2026). The impact of real estate fraud on victims' wealth: Exploring emotional and social biases in decision-making. Acta Psychologica, 262, Article 106107. https://doi.org/10.1016/j.actpsy.2025.106107

(27) Divakara Reddy, N., Santosh, B., Ananda, S., & Desai, G. (2026). Behavioral biases and investment decision-making in the indian stock market: The moderating role of financial literacy and investor experience.. F1000Research, 14, Article 1283. https://doi.org/10.12688/f1000research.171289.2

(28) Dos Santos, J., & Barros, C. (2011). What determines the financial decision-making: Reason or emotion?; o que determina a tomada de decisão financeira: Razão ou emoção?. Revista Brasileira de Gestao de Negocios, 13(38), 7–20.

(29) Fairchild, R. (2014). Emotions in the financial markets. Investor Behavior: The Psychology of Financial Planning and Investing, 347–364. https://doi.org/10.1002/9781118813454.ch19

(30) Fareri, D., Hackett, K., Tepfer, L., Kelly, V., Henninger, N., Reeck, C., Giovannetti, T., & Smith, D. (2022). Age-related differences in ventral striatal and default mode network function during reciprocated trust. NeuroImage, 256, Article 119267. https://doi.org/10.1016/j.neuroimage.2022.119267

(31) Feng, Z., & Krishnen, K. (2024). The relationship between accounting information disclosure and decision-making among investors in china. Journal of Ecohumanism, 3(7), 4429–4439. https://doi.org/10.62754/joe.v3i7.4555

(32) Finet, A., Kristoforidis, K., & Viseur, R. (2022). The emergence of behavioral biases in trading situations: An exploratory study; l'émergence de biais comportementaux en situation de trading: Une étude exploratoire. Recherches en Sciences de Gestion, 146(5), 147–182. https://doi.org/10.3917/resg.146.0147

(33) Gadzinski, G., Schuller, M., & Mousavi, S. (2022). Long-lasting heuristics principles for efficient investment decisions. Qualitative Research in Financial Markets, 14(4), 570–583. https://doi.org/10.1108/QRFM-04-2021-0072

(34) Gaŕling, T., & Duxbury, D. (2025). Emotions in financial markets. Encyclopedia of Monetary Policy, Financial Markets and Banking, V3–373. https://doi.org/10.1016/B978-0-44-313776-1.00088-X

(35) Gautam, S., & Kumar, P. (2023). Behavioral biases of investors in the cryptocurrency market. AIP Conference Proceedings, 2782, Article 020105. https://doi.org/10.1063/5.0154194

(36) Giulia, P., Martina, V., Maria, S., Valeria, N., & Enrico, R. (2025). Past performance impacts financial judgments and willingness to sell more than types of fund, differences between professionals vs. lay people. Scientific Reports, 15(1), Article 35502. https://doi.org/10.1038/s41598-025-19313-y

(37) Gong, Y., Peng, Y., Xu, L., Chen, K., & Shi, W. (2025). Shipping news sentiment as a predictor of iron ore freight rates: Hybrid evidence from lexicon-based analysis and threshold autoregression modelling. Transport Policy, 169, 178–190. https://doi.org/10.1016/j.tranpol.2025.05.003

(38) Goswami, S., Goswami, B., Panicker, A., & Sharma, A. (2020). Exploring the role of emotions and psychology in financial investment decisions in indian securities market. International Journal of Advanced Science and Technology, 29(1), 532–547.

(39) Hariharan, A., & Adam, M. (2015). Blended emotion detection for decision support. IEEE Transactions on Human-Machine Systems, 45(4), 510–517. https://doi.org/10.1109/THMS.2015.2418231

(40) Hariharan, A., Adam, M., Astor, P., & Weinhardt, C. (2015). Emotion regulation and behavior in an individual decision trading experiment: Insights from psychophysiology. Journal of Neuroscience, Psychology, and Economics, 8(3), 186–202. https://doi.org/10.1037/npe0000040

(41) Helleringer, G. (2015). Retail investors and disclosure requirements. European Perspectives on Behavioural Law and Economics, 193–209. https://doi.org/10.1007/978-3-319-11635-8_10

(42) Herathmenike, H. M. M. A., Dewasiri, N. J., Munasinghe, M., & others. (2025). Unpacking investor psychology: A systematic review. F1000Research, 14. https://doi.org/10.12688/f1000research.168166.1

(43) Herathmenike, H., Dewasiri, N., & Munasinghe, A. (2025). Unpacking investor psychology: A systematic review and meta-analysis of behavioural biases shaping investment decisions*. F1000Research, 14, Article 1146. https://doi.org/10.12688/f1000research.168166.1

(44) Hillenbrand, C., Saraeva, A., Money, K., & Brooks, C. (2020). To invest or not to invest?: The roles of product information, attitudes towards finance and life variables in retail investor propensity to engage with financial products. British Journal of Management, 31(4), 688–708. https://doi.org/10.1111/1467-8551.12348

(45) Hinvest, N., Alsharman, M., Roell, M., & Fairchild, R. (2021). Do emotions benefit investment decisions? anticipatory emotion and investment decisions in non-professional investors. Frontiers in Psychology, 12, Article 705476. https://doi.org/10.3389/fpsyg.2021.705476

(46) Hsu, H., & Lobo Marques, J. (2023). Neurofinance: Exploratory analysis of stock trader's decision-making process by real-time monitoring of emotional reactions. Proceedings of the European Conference on Management, Leadership and Governance, 2023-November, 147–155.

(47) Huang, J., Jiménez-Zarco, J., & Jin, X. (2024). Direct interaction in digital interactive media and stock performance: Evidence from panorama. PLoS ONE, 19(5 May), Article e0302448. https://doi.org/10.1371/journal.pone.0302448

(48) Ikram, B., Fouad, B., & Sara, C. (2023). An exploration of overconfidence and the disposition effect in the stock market. International Journal of Financial Studies, 11(2), Article 78. https://doi.org/10.3390/ijfs11020078

(49) Kartini, K., & Nahda, K. (2021). Behavioral biases on investment decision: A case study in Indonesia. Journal of Asian Finance, Economics and Business, 8(3), 1231–1240. https://doi.org/10.13106/jafeb.2021.vol8.no3.1231

(50) Kaur, D., & Badola, S. (2026). Uncovering the dynamics between digitalisation and investor-related outcomes. Qualitative Research in Financial Markets, 18(2), 379–407. https://doi.org/10.1108/QRFM-10-2023-0230

(51) Lee, C. J., & Andrade, E. B. (2011). Fear, social projection, and financial decision making. Journal of Marketing Research, 48(Special Issue), S121–S129. https://doi.org/10.1509/jmkr.48.SPL.S121

(52) Lugmayr, A. (2013). Predicting the future of investor sentiment with social media. In Handbook of Social Media Management: Value Chain and Business Models in Changing Media Markets (pp. 565–589). Springer. https://doi.org/10.1007/978-3-642-28897-5_33
(53) Ren, R., & Wu, D. (2020). An innovative sentiment analysis to measure herd behavior. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 50(10), 3841–3851. https://doi.org/10.1109/TSMC.2018.2864942
(54) Richards, D. W., Fenton-O'Creevy, M., Rutterford, J., & Kodwani, D. G. (2018). Is the disposition effect related to investors' reliance on System 1 and System 2 processes or their strategy of emotion regulation? Journal of Economic Psychology, 66, 79–92. https://doi.org/10.1016/j.joep.2018.01.003
(55) Ritika, & Kishor, N. (2022). Development and validation of behavioral biases scale: A SEM approach. Review of Behavioral Finance, 14(2), 237–259. https://doi.org/10.1108/RBF-05-2020-0087