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Mapping the research landscape of behavioural finance and artificial intelligence in retail stock market investment: A bibliometric and thematic review (2020–2026)

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***Abstract*---**Retail investors' decisions increasingly reflect a complex interplay between psychological biases and technology-driven tools, particularly Artificial Intelligence (AI), in contemporary financial markets. This bibliometric and thematic review maps the evolving intellectual landscape at the intersection of behavioural biases, Artificial Intelligence (AI), and retail investment decision-making. Using 428 English-language, peer-reviewed articles indexed in Scopus and Web of Science from 2020 to 2026, the study applies the bibliometrix R package and the PRISMA framework to ensure systematic screening and analysis. The findings indicate a strong upward growth trajectory, with nearly 74% of publications appearing between 2024 and 2026, reflecting the rapid expansion of scholarly

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interest in this area. The publication landscape is concentrated in a limited number of influential journals, with IEEE Access and the Journal of Behavioral and Experimental Finance emerging as key sources and Author-level analysis also reveals a small group of highly influential researchers. Geographically, research output is dominated by China, India, and the United States, with limited international collaboration. The thematic structure identifies investments, financial markets, machine learning, and forecasting as core themes, while artificial intelligence, fintech, and behavioural finance are emerging areas. Overall, the study shows a clear shift from fintech-oriented research toward a more AI-driven agenda, with growing attention to investor sentiment, financial stability, algorithmic trading, and natural language processing.

***Keywords*---**Behavioural Biases, Artificial Intelligence, Retail Investors, Bibliometric Analysis, Thematic Review, Investment Decision-Making, Fintech, Machine Learning.

1.0 INTRODUCTION

The intersection of behavioural biases and artificial intelligence (AI) in stock market investment decision-making has emerged as an important area of inquiry in contemporary financial research, particularly as retail investors increasingly engage with technology-enabled financial ecosystems. Traditional finance assumes that investors are rational actors who process information efficiently and make decisions that maximize expected utility. However, this assumption has been widely challenged by behavioural finance research, which demonstrates that retail investors often deviate from rational decision-making because of systematic cognitive and emotional biases such as overconfidence, loss aversion, herding, and anchoring (Barberis & Thaler, 2003; Kahneman & Tversky, 1979; Sharma & Negi, 2025). These biases, extensively documented by Kahneman and Tversky's foundational work on prospect theory, continue to exert significant influence on retail investor behaviour, often leading to suboptimal investment outcomes, overtrading, disproportionate reactions to market noise, and inadequate portfolio diversification (Phan, Ninh & Nguyen 2026). In emerging and developed markets alike, the rapid expansion of retail participation has intensified academic interest in understanding these behavioural deviations and their consequences for individual welfare and market efficiency (Simonn, 2025).

The stock market inherited with volatility, transparency, and liquidity, become a natural laboratory for financial technology innovation, particularly for artificial intelligence (AI)-driven solutions (Grandhmal et al., 2019). These markets are characterized by non-stationary, chaotic, and dynamic data streams that pose significant challenges for accurate prediction and decision-making (Kumar et al., 2022). Stock prices are influenced not only by quantitative indicators derived from historical trading data but also by qualitative factors such as corporate announcements, media narratives, social media sentiment, and macroeconomic signals, all of which play a critical role in shaping investor behaviour and market dynamics (Atkins et al., 2018; Khan et al., 2022). The growing recognition that

financial news and social sentiment substantially affect market predictability underscores the imperative for advanced AI techniques capable of processing both structured and unstructured information to generate robust investment insights (Nassirtoussi et al., 2014).

The stock market sector is undergoing a rapid technological transformation through the adoption of AI-based systems such as robo-advisors, algorithmic trading platforms, machine learning models, and predictive analytics tools. Deep learning architectures such as **Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU),** and **Convolutional Neural Networks (CNN)** have become dominant, while hybrid and transformer-based models continue to show promise in integrating multi-modal data, including financial news and social media sentiment (Fischer & Krauss, 2018; Chen et al., 2021; Tao et al., 2024; Ma et al., 2024). These technologies are increasingly being used to support, augment, or automate investment decisions by generating personalized recommendations, identifying patterns in large datasets, and improving forecasting accuracy (Gupta & Rao, 2026; Yadav & Kant, 2026). Proponents argue that AI can enhance forecasting accuracy, improve risk management, and reduce human bias by relying on data-driven models rather than intuitive heuristics (Annu & Tripathi, 2025). Recent studies indicate that AI-driven tools can provide objective information, personalized recommendations, and disciplined portfolio strategies that may help investors partially overcome biases like confirmation, anchoring, and overconfidence (Kulkarni et al., 2025). Furthermore, AI systems enable real-time extraction of investor behavioural patterns from large-scale data sources including social media, news feeds, and trading records, offering unprecedented granularity in detecting cognitive biases and gauging market psychology (Phan, Ninh & Nguyen 2026).

At the same time, the "black box" nature of many AI systems generates heightened concerns related to algorithmic bias, data privacy, and ethical compliance, contributing to investor scepticism and resistance (Katenova et al., 2025). Emerging phenomena such as automation bias and digital overconfidence suggest that technology may not simply eliminate behavioural distortions but may also reshape them in new ways (Gupta & Rao, 2026; Yadav & Kant, 2026).

Despite the expanding literature on behavioral finance and the parallel growth of AI in investment research, the intersection of these two streams remains fragmented and insufficiently synthesized. Existing studies have largely examined behavioral biases and AI applications separately, with limited attention to how they interact in retail investment decision-making (Sharma & Negi, 2025; Yadav & Kant, 2026). Furthermore, prior reviews have primarily adopted narrative or systematic approaches, with comparatively little use of bibliometric techniques to map scientific production, collaboration networks, and conceptual structures in this emerging field (Annu & Tripathi, 2023). This fragmentation makes it difficult to identify dominant themes, research clusters, and knowledge gaps, especially in contexts where retail investors are increasingly exposed to AI-mediated investment interfaces. Consequently, there exists a pressing need for a comprehensive bibliometric and thematic review that systematically maps the intellectual structure of this interdisciplinary domain, elucidates emerging

research trajectories, and identifies opportunities for future inquiry at the confluence of behavioural finance and artificial intelligence.

1.1 Rationale of the Study

The rationale for this bibliometric and thematic review stems from the rapid proliferation and fragmentation of literature at the intersection of behavioural biases, artificial intelligence, and retail investor decision-making. Bibliometric analyses document a robust annual growth rate of 13.34% in publications addressing AI and financial behaviour, yet existing reviews predominantly focus on technical performance such as price prediction and portfolio management while overlooking investor perceived risk, leaving a distinct gap in understanding how investors perceive AI during investment processes (Katenova et al., 2025). Emerging phenomena such as automation bias have intensified behavioral distortions, necessitating updated bibliometric mapping (Katenova et al., 2025). The moderating role of financial and AI literacy remains underexplored, despite evidence that AI mitigates biases through pattern analysis (Annu & Tripathi, 2025). Critical gaps persist in ethical considerations and regional disparities (Katenova et al., 2025). The transformative impact of digital platforms demands updated synthesis, yet the specific intersection remains inadequately mapped (Simonn, 2025). This study addresses these gaps by mapping intellectual structure, thematic evolution, and research clusters from 2020–2026, offering insights for future research and policy frameworks. The analysis is guided by overarching research questions that seek to understand:

RQ1: What is trend of publications in the context of **Behavioural Biases** and Artificial Intelligence in **Retail** stock market investment**?**

RQ2: Which are the most influential countries, journals, articles and authors that have contributed towards this domain?

RQ3: What are the most frequently used keywords and emerging research themes in this domain?

RQ4: What is the future research agenda on **Behavioural Biases** and Artificial Intelligence in **Retail** stock market investment**?**

2.0 RESEARCH METHODOLOGY

2.1 Tools and Techniques

Bibliometric analysis serves as a quantitative approach to assess different aspects of publications within a particular field (Broadus, 1987; Pritchard, 1969). This method is considered more objective than subjective alternatives (Lim and Zhang, 2022) and is crucial for analysing publication data to reveal significant trends, highly cited papers, prominent authors, and the most influential institutions and countries (Glänzel et al., 2019; Donthu et al., 2021). By providing insights into the historical evolution of a field, current research trends, and potential future directions, bibliometric analysis enhances the understanding of the research landscape and has recently gained prominence in business research (Donthu et al., 2021; Khan et al., 2022).

Biblioshiny was selected for this bibliometric analysis due to its accessibility, comprehensive functionality, and compatibility with merged datasets. As the graphical interface of the Bibliometrix R-package, Biblioshiny enables researchers without programming expertise to conduct sophisticated science mapping

through an intuitive, interactive environment (Aria & Cuccurullo, 2017). It provides comprehensive analytical capabilities, including performance analysis, keyword co-occurrence networks, thematic maps, thematic evolution, co-citation, and collaboration analysis (Aria & Cuccurullo, 2017). The tool supports the SAAS(Software as a Service) workflow ensuring transparent, auditable, and reproducible research (Aria & Cuccurullo, 2026). Furthermore, Biblioshiny processes data from multiple sources including Web of Science and Scopus (Biblioshiny, 2026), enabling seamless integration of merged datasets. Its compatibility with specialized merging tools like BiblioMerge (Diez-Junguitu & Peña-Cerezo, 2026) and BibexPy (Kara et al., 2025) further enhances analytical efficiency and rigor.

2.2 Data Collection

This study adopts a **bibliometric approach** to systematically examine global research trends in **Behavioural Biases** and Artificial Intelligence in investment decision making **among Retail Investors**. Bibliometric analysis applies quantitative methods to evaluate scientific output, identify influential contributions, and map intellectual structures within a given field (Cobo et al., 2011; Aria & Cuccurullo, 2017; Zupic & Čater, 2015). The bibliometric dataset was retrieved from the **Scopus database and Web of Science database on June 3,** 2026. **Scopus database** is widely recognized for its comprehensive coverage, rigorous indexing standards, and high-quality metadata (Baas et al., 2020; Aksnes & Sivertsen, 2019) and Web of Science is the most known scientific database in the world, covering an extensive range of disciplines and allowing comparisons across scientific areas (Archambault et al., 2006; Wang et al., 2016). The data extracted from them were merged and duplicates were removed.

The decision to merge Web of Science and Scopus data enhances comprehensiveness and analytical robustness, as relying on a single database can limit coverage and introduce bias (Dagli et al., 2025). Merging expands coverage and reduces disciplinary bias—WoS excels in natural sciences and engineering, while Scopus offers broader social sciences coverage—critical given the interdisciplinary nature of behavioral biases and AI research spanning finance, economics, and computer science (Mongeon & Paul-Hus, 2016). Furthermore, merging enhances reliability, as studies show single databases fail to provide complete intellectual structures (Echchakoui, 2020). Established methodologies address challenges like duplicate records through DOI-based deduplication and data wrangling (Kumpulainen & Seppänen, 2022). Tools including Bibliometrix, VOSviewer, BibexPy, and KKU-BiblioMerge automate preprocessing and harmonization, minimizing manual effort (Kara et al., 2025; Chansanam & Li, 2025). To enhance transparency and replicability, the study used the PRISMA 2020 framework to document each screening and eligibility decision applied to the Scopus and Web of Science dataset (Page et al., 2021; Haddaway et al., 2022).

Table 1: Bibliometric research steps

Step	Description / Criterion	Details and Outcomes
Step 1. Scope of Investigation	Definition of research domain and time frame	*Mapping the Research Landscape of Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment:* ***A Bibliometric and Thematic Review***
Step 2. Database Selection	Primary source of bibliometric data	**Scopus**: Selected for its comprehensive multidisciplinary coverage, rigorous indexing standards, and enriched metadata suitable for large-scale bibliometric and citation analysis. And **Web of Science**: Selected for scientific database in the world, covering an extensive range of disciplines and allowing comparisons across scientific areas
Step 3. Document Selection	First Selection Criterion: Search String and Time Interval	TITLE-ABS-KEY (("behavioural finance" OR "behavioural finance" OR "behavioural bias" OR "behavioural bias" OR "investor psychology" OR "investor sentiment" OR heuristics OR overconfidence OR herding OR "loss aversion" OR anchoring OR "mental accounting" OR "confirmation bias" OR "self-attribution bias" OR "disposition effect" OR "representativeness bias" OR "availability bias" OR "regret aversion" OR "familiarity bias" OR "optimism bias" OR "conservatism bias" OR "risk perception" OR "cognitive bias") AND ("retail investors" OR investors OR traders OR "individual investors") AND ("stock market" OR trading OR "equity market" OR investment OR "financial market") AND ("artificial intelligence" OR AI OR fintech OR "algorithmic trading" OR "AI trading" OR "machine learning" OR robo-advisor OR "automated trading" OR "quantitative trading")) **Result:** Scopus: 634, Web of Science: 226 **Time Interval:** 2020–2026 **Subject Categories:** Business, Management and Accounting; Computer Science; Decision Sciences; and Economics, Econometrics and Finance; Psychology; Social Sciences; Engineering

Step	Description / Criterion	Details and Outcomes
		Result: Scopus: 518 documents, Web of Science: 219
	Second Selection Criterion: Document Type	Only Journal Articles considered (excluding conference papers, book chapters, etc.) **Result:** Scopus:276 documents, Web of Science: 215
	Third Selection Criterion: Language and Publication Stage	Only English-language and final published journal articles included **Result:** Scopus: 253 documents, Web of Science: 186 (final dataset)
Step 4. Processing of Selected Documents	Data export and preparation for analysis	Data exported from Scopus in CSV and Plain-Text formats and from Web of Science in Bib TeX and Plain-Text; The data extracted from Scopus and Web of Science merged, 11 duplicates were removed, synonymous terms merged, and author/institution names standardized to ensure dataset consistency. **Result:** Finally, 428 documents were selected for Bibliometric analysis.
Step 5. Analysis and Inference of Results	Analytical software and techniques	Bibliometric analysis performed using Biblioshiney in R software for visualization and mapping.

3.0 RESULTS

This section presents the findings of the bibliometric analysis, offering a comprehensive overview of the research landscape in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment. The results are organized across multiple dimensions to capture the breadth of academic contributions and the intellectual evolution of this domain.

3.1 Annual Publication

Figure 1, **forecast the annual scientific publications** based on past publication data. The blue dots represent actual publication counts, the blue line shows the fitted/forecasted trend, and the red dashed vertical line marks the **peak year (2025).**

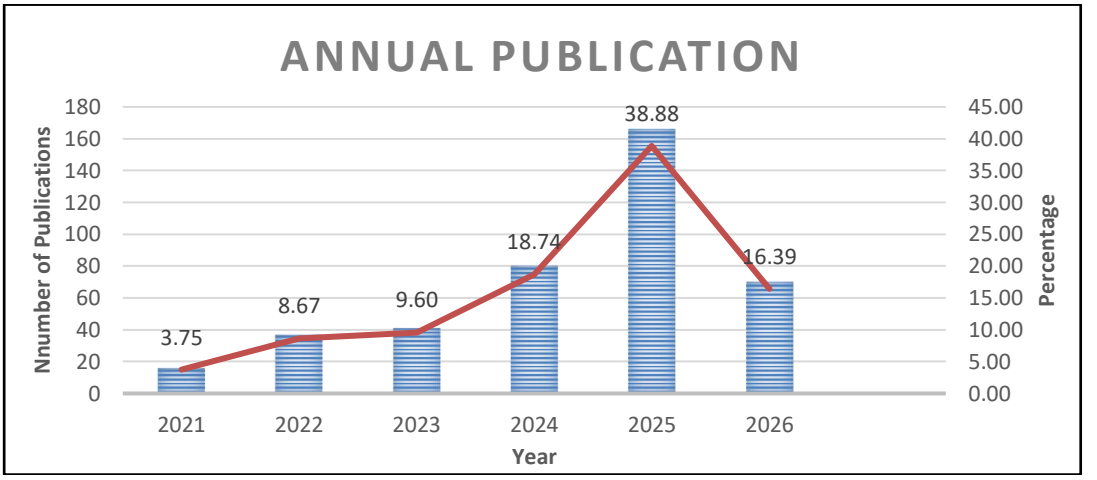


Figure 1. Year-wise publication trend on Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

The Annual Publication trend demonstrates a rapid expansion in research output on behavioural finance, artificial intelligence, retail investor behaviour and financial markets during the study period (2021–2026). The number of publications increased consistently from 16 publications (3.75%) in 2021 to 36 publications (8.67%) in 2022 and 40 publications (9.60%) in 2023, indicating the gradual emergence of the research field. This steady growth suggests increasing scholarly recognition of the importance of AI-driven financial technologies and behavioural finance in investment research.

A substantial acceleration is observed in 2024, when publications nearly doubled to 78 articles (18.74%), reflecting a significant expansion of research activity. This upward trajectory reached its peak in 2025, with 162 publications (38.88%), representing the highest annual scientific output during the study period. The sharp increase in publications during 2024–2025 indicates that the field entered a phase of rapid development, likely driven by growing academic and industry interest in artificial intelligence, machine learning, investor behaviour, fintech innovations, and predictive analytics in financial markets.

Although the number of publications declined to 68 articles (16.39%) in 2026, this reduction should be interpreted cautiously. Bibliometric analyses often include incomplete publication years because many articles remain in press or have not yet been indexed at the time of data extraction. Consequently, the apparent decline is more likely attributable to partial indexing of the current publication year rather than a genuine reduction in research activity.

Overall, the publication trend reveals a strong upward growth trajectory, with nearly 74% of all publications appearing during the 2024–2026 period. This concentration of recent publications highlights the rapidly evolving and emerging nature of the research domain. The findings indicate that the convergence of behavioural finance, artificial intelligence, machine learning, and retail investor behaviour research has become a major area of scholarly interest, with continued

growth expected as AI-enabled financial decision-making, algorithmic trading, investor sentiment analysis, and digital financial ecosystems continue to evolve.

3.2 Most Relevant Sources

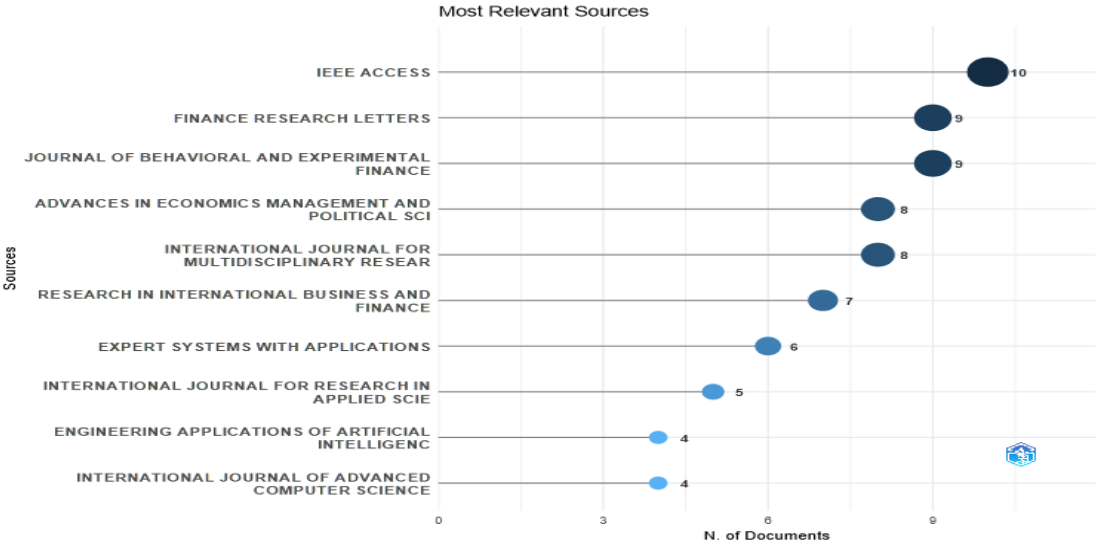


Figure 2 Most relevant sources/journals in the Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment, ranked by the number of documents published

Figure 2, shows the **most relevant journals/sources** in a document set of the Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment, ranked by the **number of documents** associated with each source.

- **IEEE Access** is the top source with **10 documents.**
- **Finance Research Letters** and **Journal of Behavioral and Experimental Finance** follow with **9 documents each.**
- **Advances in Economics, Management and Political Science** and **International Journal for Multidisciplinary Research** each have **8 documents.**

The distribution suggests the document collection is **centered on finance and interdisciplinary research,** with some presence in computer science and AI-related journals. The larger bubbles indicate higher relevance or frequency, so **IEEE Access** appears to be the strongest recurring source in this set.

3.3 Prolific Journal

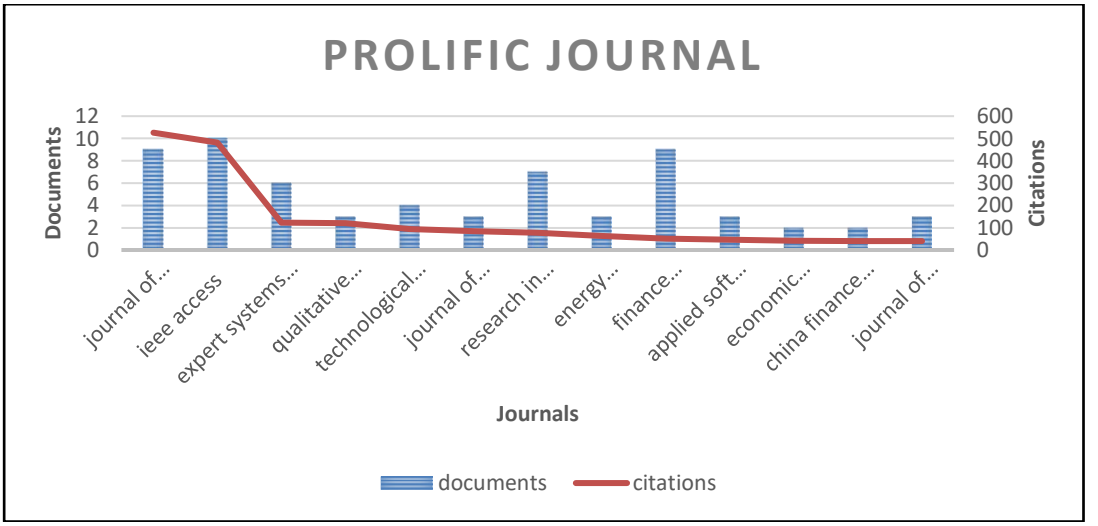


Figure 3. Most prolific journals in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 3, presents the relationship between the **number of published documents** (bars, left axis) and the **total citations received** (line, right axis) across the most prolific journals in the field. This dual-axis representation provides insights into both publication productivity and scholarly impact. The analysis of prolific journals reveals that scholarly output is concentrated within a relatively small number of publication outlets. IEEE Access and the Journal of Behavioral and Experimental Finance emerge as the most influential journals, combining high publication productivity with exceptional citation impact. **Journal of Behavioral and Experimental Finance** appears to achieve the highest citation impact, exceeding 500 citations, closely followed by **IEEE Access** with a similarly high citation level. While several journals contribute substantially to the volume of research, citation influence remains concentrated among a limited group of sources. The coexistence of finance-focused and technology-focused journals among the leading outlets underscores the interdisciplinary character of the field and highlights the growing convergence of artificial intelligence, machine learning, and financial research.

3.4 Prolific Author

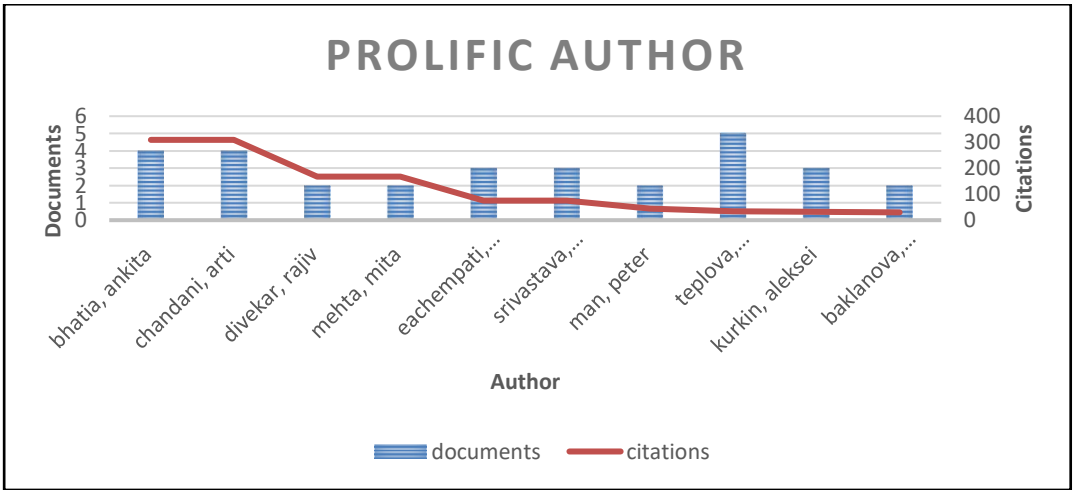


Figure 4 Most prolific authors in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 4, presents the productivity and citation performance of the most prolific authors in the field. The blue bars represent the number of published documents, while the orange line indicates the total citations received by each author. This dual-axis visualization enables the simultaneous assessment of research productivity and scholarly influence.

The analysis of prolific authors reveals notable differences between research productivity and scholarly influence. Teplova, Tamara emerges as the most productive author in terms of publication output with approximately five publications, whereas Bhatia, Ankita and Chandani, Arti achieve the highest citation impact, each receiving more than 300 citations. The findings indicate that intellectual influence within the field is concentrated among a small group of highly cited researchers, while publication activity is distributed across a broader community of contributors. This pattern suggests that the field's development is driven by a limited number of seminal works that serve as key reference points for subsequent research, highlighting the importance of research quality and visibility in shaping scholarly impact.

3.5 Most Influential Documents Based on Citation Impact

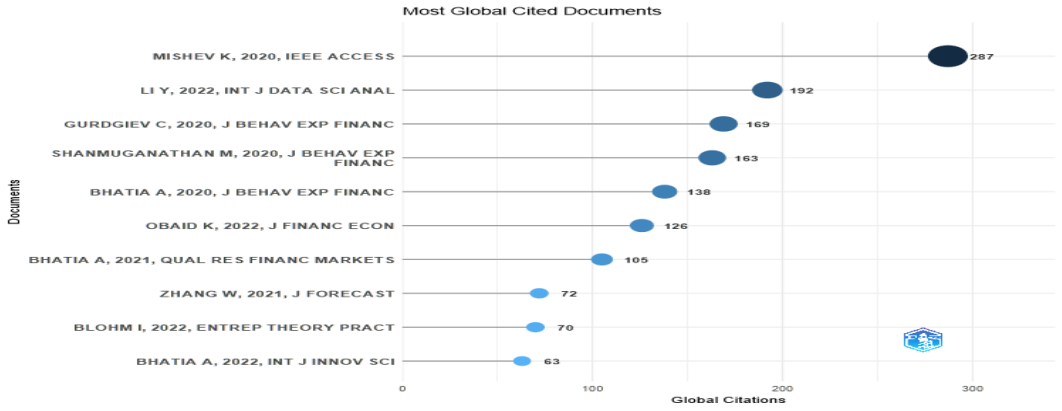


Figure 5 Most **globally cited documents** in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 5, presents the **most globally cited documents in the field,** where the **y-axis represents the cited publications (author, year, and source)** and the **x-axis represents the total number of citations received**. Bubble size is proportional to citation count, enabling a visual comparison of each publication's scholarly influence.

The citation analysis identifies a set of highly influential publications that have shaped the intellectual trajectory of the field. Mishev (2020) in *IEEE Access* emerges as the most impactful study, receiving nearly 300 citations and serving as a foundational reference for subsequent research. Several publications from the *Journal of Behavioral and Experimental Finance* also exhibit strong citation performance, underscoring the journal's pivotal role in advancing scholarly discourse. The dominance of articles published between 2020 and 2022 highlights the recent and rapidly evolving nature of the research area. Overall, the findings reveal a concentrated intellectual structure in which a limited number of seminal publications exert substantial influence on the development and dissemination of knowledge.

3.6 Keyword co-occurrence Map

A keyword co-occurrence network is a core technique in bibliometric science mapping that reveals the conceptual and intellectual structure of a research field. It analyses how frequently keywords appear together in the same publications, identifying thematic clusters, emerging trends, and knowledge gaps. (Cobo et al., 2011a; 2011b)

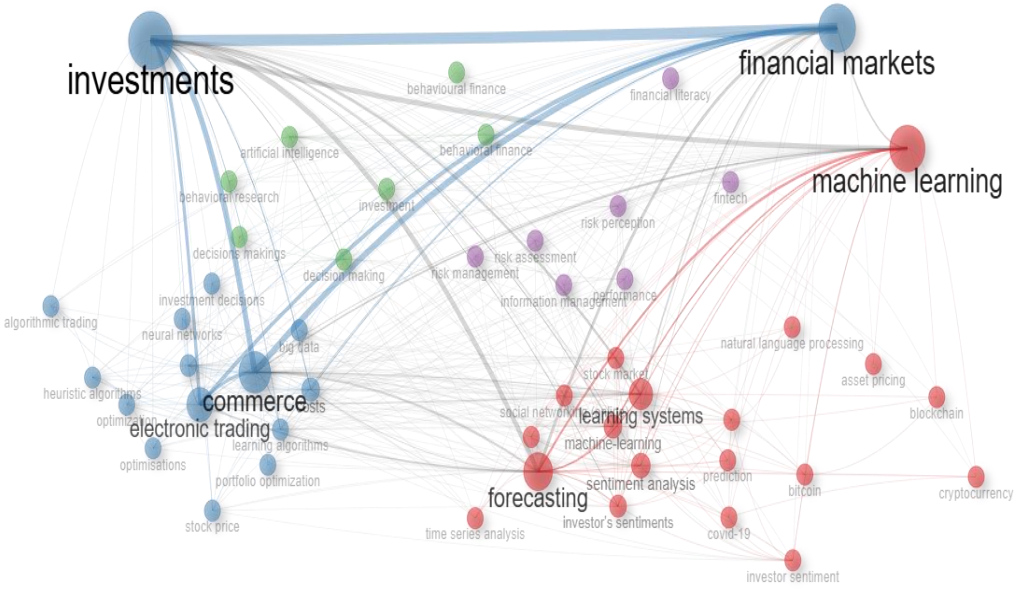


Figure 6 Keyword co-occurrence network in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 6, is a keyword co-occurrence network map generated using Biblioshiny. The nodes represent keywords, node size indicates keyword frequency, colours indicate thematic clusters, and links show co-occurrence relationships. The network reveals four major thematic clusters connected through numerous cross-links, indicating that the research field is highly interdisciplinary.

Table 2: Keyword co-occurrence network map interpretation

Cluster	**Dominant Keywords**	**Research Focus**	**Interpretation**
Blue Cluster – E-commerce and Consumer Behaviour	Commerce, Consumer Behaviour, Trust, Technology Adoption	Consumer purchasing decisions, trust in online platforms, adoption of digital technologies, customer satisfaction, and online shopping behaviour	This cluster represents the traditional foundations of e-commerce research. The prominence of Commerce indicates that it is the most frequently investigated concept, serving as a central node that links consumer behaviour, trust, and technology adoption within the online retail ecosystem.
Red Cluster – Social Media and Digital	Social Media, Social Networking, Marketing,	Social media as a marketing channel, influencer	This cluster highlights the growing importance of social media in digital marketing. The strong

Cluster	Dominant Keywords	Research Focus	Interpretation
Marketing	Consumer Engagement, Purchase Intention	marketing, digital marketing strategies, customer engagement, and social commerce purchasing behaviour	interconnections among the keywords suggest that consumer engagement, purchase intention, and marketing activities are closely integrated within social networking platforms.
Green Cluster – Technology Acceptance and Innovation	Innovation, Technology Adoption, Perceived Usefulness, User Acceptance	Technology Acceptance Model (TAM), Innovation Diffusion Theory, user adoption of emerging digital platforms, and technology acceptance behaviour	This cluster emphasizes the theoretical foundations explaining technology adoption and innovation. It primarily reflects studies employing established acceptance models to understand users' intentions and behaviours toward emerging digital technologies, thereby bridging consumer behaviour and social commerce research.
Purple Cluster – Social Commerce Ecosystem	Social Commerce, Information Sharing, Customer Interaction, Online Communities	Social commerce platforms, online communities, user-generated content, customer interaction, and information exchange	This cluster focuses on the social commerce ecosystem by examining how online communities, customer interactions, and information sharing facilitate commercial activities. Its strong connections with the e-commerce and social media clusters demonstrate that social commerce represents the convergence of these two research domains.

The extensive inter-cluster linkages indicate a highly integrated research landscape where consumer behaviour, social media, and technology adoption collectively shape contemporary digital commerce research. The largest nodes are: Commerce, Investments, Financial markets and Machine learning. These represent the most influential and frequently occurring concepts in the dataset.

3.7 Intellectual Structure of the Research Domain

Intellectual Structure (IS) is a bibliometric method widely applied in knowledge domain analysis and science mapping that reveals the **conceptual and theoretical foundations** of a research field by identifying relationships among

influential works, authors, and research themes. It represents the "**hidden connections**" and "**intellectual currents**" within a discipline, mapping how knowledge is organized, transmitted, and evolves over time. (White, H. D., & Griffith, B. C. ,1981; Cheng., & T. Tsung., 2016).

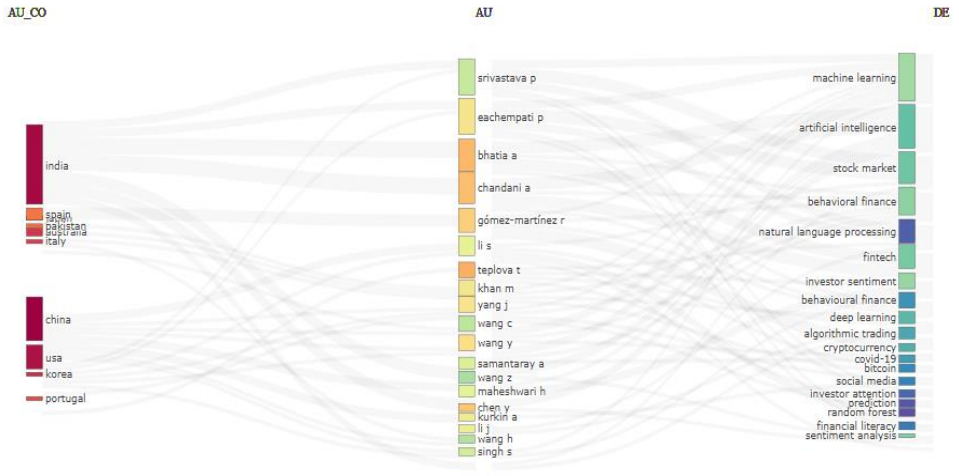


Figure 7 Intellectual Structure in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 7, is a **three-field Sankey diagram** (Country → Author → Keywords). It illustrates how countries, influential authors, and research themes are interconnected within the literature.

Table 3: Intellectual Structure of the Research Domain

Dimension	**Key Findings**	**Interpretation**
Leading Contributing Countries	India, China, USA, Portugal, Spain, Pakistan, Australia, Italy, and South Korea.	India is the leading contributor, exhibiting the largest node and the strongest collaborative links, indicating the highest research output within the dataset. China and the USA also make notable contributions, while European and Asia-Pacific countries demonstrate moderate participation, reflecting the global nature of AI-driven financial research.
Most Influential Authors	Srivastava P., Eachempati P., Bhatia A., Chandani A., Gómez-Martínez R., Li S., Teplova T., Khan M., Yang J.,	These authors represent the most productive contributors in the dataset. The strength of the connecting links indicates

Dimension	Key Findings	Interpretation
	and Wang C.	close associations between authors, their affiliated countries, and major research themes, highlighting their significant influence on the field.
Major Research Themes	Machine Learning, Artificial Intelligence, Stock Market, Behavioural Finance, Natural Language Processing, FinTech, Investor Sentiment, Deep Learning, Algorithmic Trading, and Cryptocurrency. Emerging topics include Bitcoin, Investor Attention, Prediction, Random Forest, Financial Literacy, Sentiment Analysis, and Social Media,	The dominant research themes emphasize the integration of artificial intelligence and machine learning in financial markets, particularly for stock market prediction, investor behaviour analysis, and financial decision-making. Emerging keywords indicate increasing interest in cryptocurrency markets, sentiment analytics, and the impact of social media and global events on financial systems.
Country–Author Relationships	Strongest associations are observed between Indian authors and major research themes, followed by contributions from China and the USA.	The country–author relationships demonstrate India's central role in advancing AI and finance research, with China and the USA serving as important secondary contributors. The network reflects concentrated research productivity within these leading countries.
Author–Keyword Relationships	Strong linkages exist between leading authors and topics such as AI-driven stock market prediction, machine learning, behavioural finance, natural language processing, FinTech, and cryptocurrency.	The author–keyword associations indicate that influential researchers primarily focus on applying advanced artificial intelligence techniques to financial forecasting, investor sentiment analysis, algorithmic trading, and digital financial innovations, thereby shaping the current research landscape.

The three-field plot reveals the intellectual structure of the research domain by linking countries, authors, and keywords. India emerges as the most influential contributor, followed by China and the USA. The most productive authors include Srivastava P, Eachempati P, Bhatia A, and Chandani A. The dominant research themes are Machine Learning, Artificial Intelligence, Stock Market, and

Behavioural Finance, highlighting the increasing application of advanced computational techniques in financial decision-making and market prediction. The presence of keywords such as Natural Language Processing, Investor Sentiment, Algorithmic Trading, and Cryptocurrency reflects the evolution of the field toward data-driven and technology-enabled financial analysis.

3.8 Corresponding Author's Countries

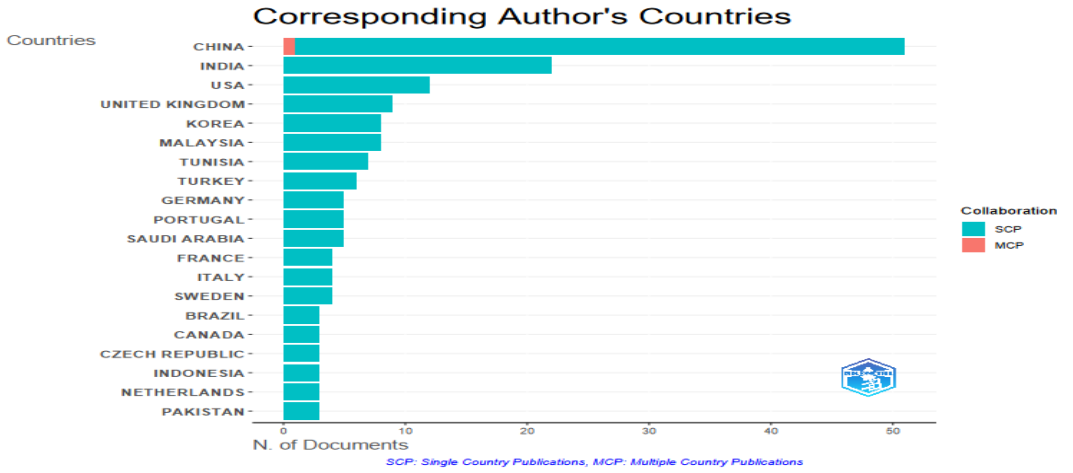


Figure 8, Distribution of publications by the country of the corresponding author in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

The figure 8, presents the distribution of publications by the country of the corresponding author. The x-axis represents the number of documents, while the y-axis lists the countries contributing corresponding authors. It reveals a strong concentration of scholarly output in Asia, with China emerging as the leading contributor, followed by India and the United States. The predominance of single-country publications indicates that research in this domain is largely conducted within national research ecosystems, whereas international collaboration remains limited. Although China exhibits some evidence of multinational cooperation, the overall scarcity of multiple-country publications suggests substantial opportunities for expanding global research partnerships and fostering greater international knowledge exchange.

3.9 Author Collaboration Network Analysis

Author Collaboration Network Analysis is a bibliometric method that visualizes co-authorship relationships to uncover the **social structure** of a research field. It identifies key researchers, collaborative clusters, and the extent of scholarly interaction using network metrics like degree centrality. This analysis reveals patterns of scientific cooperation and knowledge flow across institutions and countries. (Scientometrics., 2020; NOAA Library., 2019)

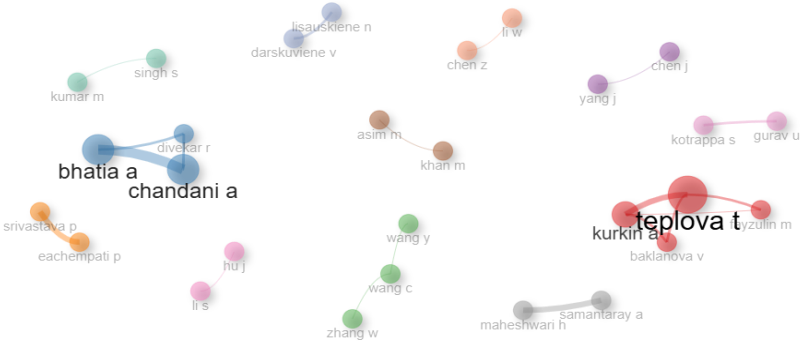


Figure 9 Author collaboration network in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 9, illustrates the **author collaboration network,** where nodes represent individual authors and links indicate co-authorship relationships. The size of each node reflects the relative contribution or influence of an author within the collaboration network, while different colours represent distinct collaboration clusters. The network structure provides insights into the social and intellectual organization of research activity within the field.

Table 4: Summary of the author collaboration network and its research implications

Network Component	**Observation**	**Interpretation**	**Research Implication**
Overall Network Structure	The network comprises several small, disconnected clusters alongside one dominant collaboration group. Most clusters include two to three closely connected authors.	Collaboration is fragmented, with research conducted primarily within localized teams rather than through a highly integrated global network.	Indicates opportunities to strengthen international and interdisciplinary collaborations to enhance knowledge exchange and research impact.
Dominant Collaboration Cluster	The largest (red) cluster contains the highest number of authors and collaboration links, with a central author serving as the primary collaboration hub.	Represents a mature and highly productive research group with strong internal collaboration and substantial influence on the field.	Suggests that a small number of leading researchers and research groups play a pivotal role in shaping the intellectual development of the domain.

Network Component	Observation	Interpretation	Research Implication
Secondary Collaboration Clusters	Medium-sized clusters (e.g., blue and green) exhibit moderate collaboration intensity, while several smaller clusters (orange, purple, pink, turquoise, grey, and brown) consist of two-author collaborations.	Reflects specialized research teams focusing on specific subtopics, with limited collaboration across groups.	Highlights the existence of niche research communities and underscores the need for greater cross-cluster collaboration to promote thematic integration and innovation.

The author collaboration network reveals a moderately fragmented research community composed of several independent collaboration clusters and one dominant research group. The largest cluster exhibits a hub-and-spoke structure, indicating the presence of influential authors who coordinate extensive collaborative activities and contribute substantially to scientific production. Although multiple research teams are actively engaged in the field, cross-cluster collaboration remains limited, suggesting opportunities for strengthening scholarly integration. Overall, the findings indicate that knowledge production is concentrated within a small number of collaborative networks, with a few key authors playing a pivotal role in advancing the field's intellectual development.

3.10 Country Scientific Production:

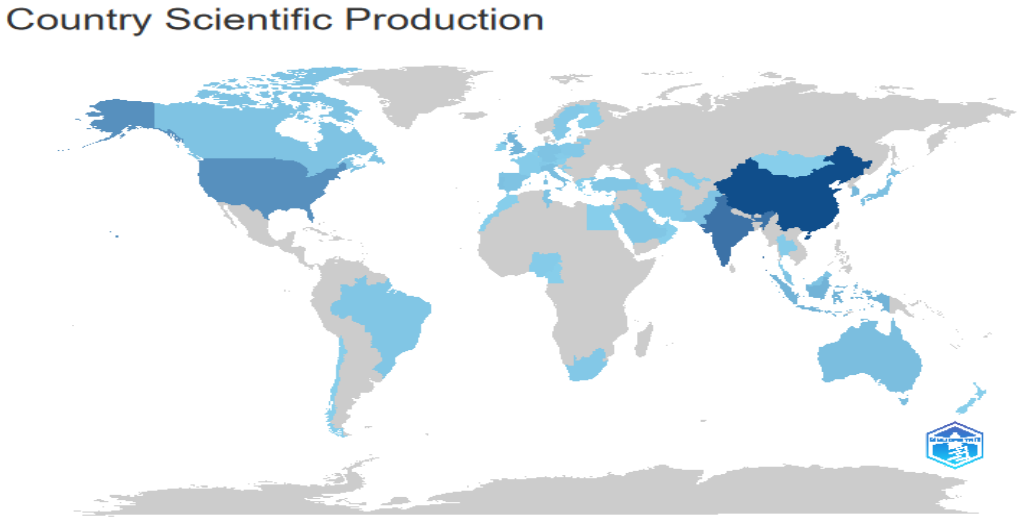


Figure 10 Country Scientific Production in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Country Scientific Production Analysis measures the volume of scholarly output by nation, typically counting publications with at least one author affiliated with that country. It reveals geographic research distribution and identifies leading contributors globally (Hensel, 2025). Figure 10, illustrates the geographical distribution of scientific production across countries. The intensity of the blue shading represents the relative volume of publications, with darker shades indicating greater research output. The map reveals a highly uneven global distribution of scientific contributions, with research activity concentrated in a limited number of countries.

The country scientific production map reveals a geographically concentrated pattern of research activity, with China and India emerging as the dominant contributors to the literature. The most prominent contributor is **China**, which exhibits the darkest shading on the map, confirming its position as the leading source of scientific output in the field, followed by **India, which** emerges as the second most productive country. The strong representation of Asian countries underscores the region's growing influence in shaping the field's intellectual development. Contributions from North America, Europe, the Middle East, and Oceania demonstrate the global reach of the research area; however, substantial disparities remain across regions.

3.11 Country Citation Impact Analysis

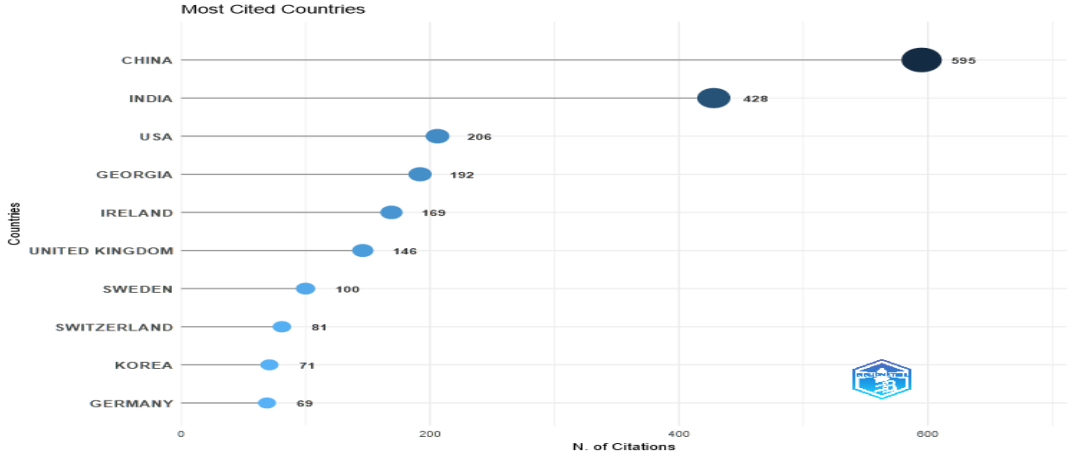


Figure 11. Country citation impact analysis in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Country Citation Impact Analysis evaluates the scholarly influence of a nation's research by measuring total citations received and per-article citation rates. These metrics assess research quality, visibility, and global recognition (Gzoyan et al., 2026).

Figure 11, presents the citation impact of the most influential countries in the research field. The **y-axis represents countries,** while the **x-axis represents the total number of citations received.** Bubble sizes are proportional to citation

counts, allowing a visual comparison of the relative scholarly influence of each country.

The country citation analysis reveals a highly concentrated pattern of scholarly influence, with China and India emerging as the most impactful contributors to the field. China dominates the citation landscape with 595 citations, reflecting both high research productivity and strong academic visibility. **India** ranks second with approximately **428 citations**, demonstrating a strong research influence. The United States remains an influential contributor, while countries such as Georgia and Ireland demonstrate notable citation performance despite smaller research outputs. Overall, the results suggest that research impact is concentrated among a limited number of countries, with Asian nations playing a leading role in shaping the intellectual development and global dissemination of knowledge within the field.

3.12 Thematic Map Analysis

Thematic Map Analysis is a bibliometric technique that visualizes research themes based on two dimensions: **centrality** (relevance/integration) and **density** (development/internal strength). It categorizes themes into four quadrants: motor themes (well-developed and central), basic themes (important but underdeveloped), niche themes (developed but peripheral), and emerging/declining themes. This strategic diagram helps identify research priorities and gaps. (Cobo et al., 2011; 2015)

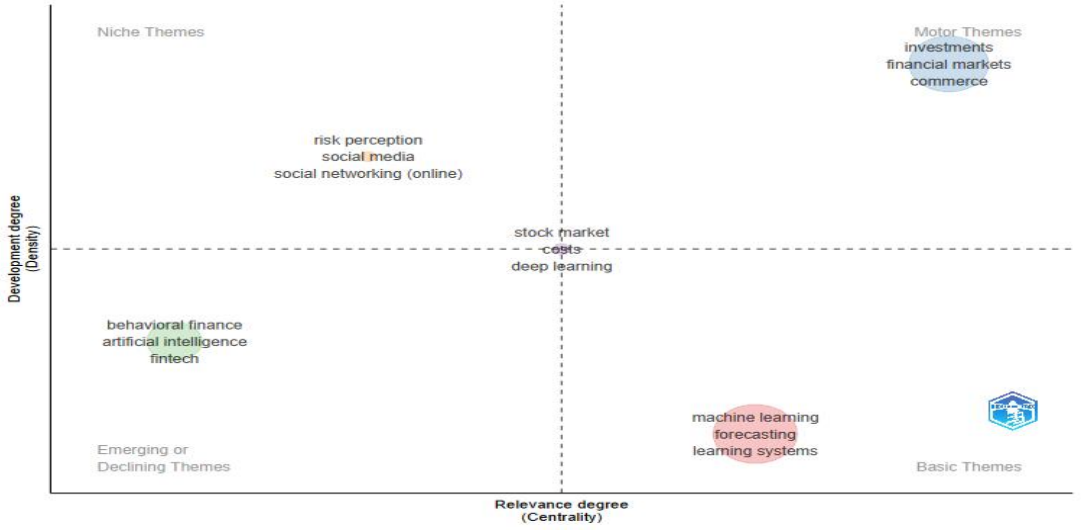


Figure 12 Thematic map analysis in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 12, presents the thematic map of the research field, which classifies themes according to two dimensions: centrality (x-axis) and density (y-axis). Centrality reflects the importance and relevance of a theme within the overall research network, while density indicates the degree of internal development and maturity of a theme. Based on these dimensions, themes are categorized into four

quadrants: Motor Themes, Niche Themes, Basic Themes, and Emerging or Declining Themes.

Table 5: Summary of thematic map quadrants and their research implications in behavioural finance, artificial intelligence in Retail Stock Market Investment

Thematic Quadrant	**Representative Cluster**	**Interpretation**	**Research Implication**
Motor Themes (High Centrality, High Density)	Investments – Financial Markets – Commerce	Well-developed and highly interconnected themes forming the intellectual core of the field. These topics demonstrate strong theoretical and empirical maturity and are closely linked with multiple research streams.	Represents the dominant research focus, emphasizing investment behaviour, financial market dynamics, and commercial applications of AI and analytical approaches.
Niche Themes (Low Centrality, High Density)	Risk Perception – Social Media – Social Networking (Online)	Mature and internally cohesive research area with specialized methodologies but limited interaction with the broader research landscape.	Indicates a specialized stream examining the influence of social media and online platforms on investor behaviour and financial decision-making, with opportunities for greater integration.
Basic Themes (High Centrality, Low Density)	Machine Learning – Forecasting – Learning Systems	Fundamental and highly connected topics that are still evolving conceptually despite their increasing importance across the literature.	Reflects the growing adoption of AI-based predictive analytics in finance. Continued development is expected to strengthen these themes, potentially transforming them into future motor themes.
Emerging Themes (Low Centrality, Low Density)	Behavioural Finance – Artificial Intelligence – Fintech	Emerging research area characterized by limited thematic integration and relatively low conceptual maturity.	Suggests increasing scholarly interest in AI-driven fintech and behavioural finance, with significant potential for expansion and

Thematic Quadrant	Representative Cluster	Interpretation	Research Implication
			future integration into the mainstream research agenda.
Transitional Themes (Near the Origin)	Stock Market – Costs – Deep Learning	Moderately developed themes that connect multiple research areas but have not yet achieved strong specialization or influence.	Highlights the growing application of deep learning in stock market analysis and indicates considerable scope for future theoretical and empirical development.

The thematic map reveals a multidimensional intellectual structure characterized by established research on investments, financial markets, and commerce, which function as the principal motor themes driving the field. Machine learning, forecasting, and learning systems emerge as highly relevant foundational themes with strong growth potential, reflecting the increasing integration of advanced analytical techniques into financial research. Meanwhile, artificial intelligence, fintech, and behavioural finance appear as emerging themes that are gaining scholarly attention but remain insufficiently integrated into the broader research network. Overall, the thematic evolution suggests a transition toward data-driven and technology-oriented approaches, indicating that future research will likely be shaped by the convergence of financial analytics, artificial intelligence, and digital innovation.

3.13 Thematic Evolution Analysis

Thematic Evolution Analysis is a bibliometric technique that tracks how research themes emerge, transform, or merge across different time periods. It uses overlapping maps and Sankey diagrams to visualize thematic changes, revealing the dynamic progression of a field's intellectual structure (Cobo et al., 2011a; 2011b). This analysis identifies emerging topics and declining themes, providing insights into the evolution of research trajectories.

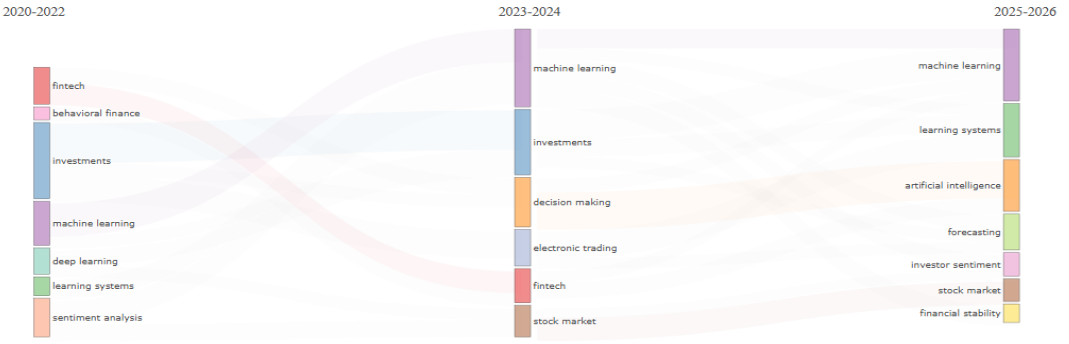


Figure 13 Thematic evolution analysis in Behavioural Finance and Artificial Intelligence in Retail Stock Market Investment

Figure 13, presents the **thematic evolution of the research field across three time periods (2020–2022, 2023–2024, and 2025–2026).** The Sankey diagram illustrates how major research themes have evolved, merged, and diversified over time. The width of each thematic node reflects its relative importance, while the connecting flows indicate the continuity and transformation of research topics across successive periods.

Table 6: Thematic evolution of research on behavioural finance, artificial intelligence, in Retail Stock Market Investment (2020–2026)

Period	**Dominant Themes**	**Key Developments**	**Research Implications**
Early Development (2020–2022)	Investments, Machine Learning, Fintech, Behavioural Finance, Deep Learning, Learning Systems, Sentiment Analysis	Research focused on integrating AI techniques with financial decision-making. Machine learning and investments emerged as the dominant themes, while fintech and behavioural finance gained prominence. Deep learning and sentiment analysis were increasingly adopted for financial forecasting and market prediction.	Established the technological and behavioural foundations of the field, highlighting the initial adoption of AI-driven analytical approaches in finance.
Expansion and Diversification (2023–2024)	Decision Making, Electronic Trading, Stock	Thematic structure expanded toward practical financial applications. Machine	Demonstrates the transition from methodological development to

Period	Dominant Themes	Key Developments	Research Implications
	Market, Fintech, Machine Learning, Investments	learning evolved into a core analytical framework, while decision making, electronic trading, and stock market research gained increasing importance.	application-oriented research, emphasizing AI-supported investment decisions and digital trading systems.
Maturity and Future Orientation (2025–2026)	Machine Learning, Learning Systems, Artificial Intelligence, Forecasting, Investor Sentiment, Stock Market, Financial Stability	Artificial intelligence emerged as a distinct research domain, while machine learning remained the most stable and influential theme. Forecasting, investor sentiment, and financial stability gained prominence, reflecting greater integration of AI, behavioural finance, and systemic risk considerations.	Indicates a mature research landscape characterized by advanced predictive analytics, behavioural insights, and increasing attention to financial resilience and regulatory challenges.

Table 7: Major thematic evolution trends on behavioural finance, artificial intelligence, in Retail Stock Market Investment (2020–2026)

Evolutionary Trend	Description	Implication
Transition from Fintech to Artificial Intelligence	Research shifted from broad fintech applications toward specialized AI and machine learning techniques.	Reflects increasing conceptual maturity and technological specialization within financial research.
Growth of Predictive Analytics	Deep learning and sentiment analysis evolved into forecasting and investor sentiment research.	Highlights the growing reliance on AI-driven predictive models for investment analysis and market forecasting.
Sustained Centrality of Investment Research	Investments, decision making, and stock market themes remained prominent throughout all periods.	Confirms investment decision-making as the principal application domain of AI and behavioural finance research.
Emergence of Financial Stability	Financial stability appeared as a key theme in the latest period.	Demonstrates increasing scholarly attention to systemic risk, market resilience, governance, and regulatory

Evolutionary Trend	Description	Implication
		implications of AI adoption in financial markets.

The thematic evolution analysis reveals a dynamic transition from fintech-oriented research toward a more mature and AI-driven research agenda. While investments and machine learning have remained central themes throughout the study period, recent years have witnessed the emergence of artificial intelligence, forecasting, investor sentiment, and financial stability as key areas of investigation. The persistence of machine learning across all periods highlights its foundational role in the field, whereas the growing prominence of artificial intelligence reflects the increasing sophistication of computational approaches in finance. Overall, the thematic trajectory suggests an ongoing convergence of financial analytics, behavioural finance, and artificial intelligence, positioning AI-enabled decision-making and market forecasting as major directions for future research.

4.0 CONCLUSION

This bibliometric and thematic review provides a comprehensive mapping of the intellectual landscape at the intersection of behavioural biases, artificial intelligence, and investment decision-making among retail investors. Through systematic analysis of publication trends, citation patterns, collaborative networks, and thematic evolution, the study reveals several significant findings that advance understanding of this rapidly evolving field. This bibliometric study provides a comprehensive overview of the evolving intellectual landscape at the intersection of behavioural finance, artificial intelligence (AI), machine learning, retail investors and stock market research.

4.1 Publication Landscape and Source Influence

The findings demonstrate that the field has experienced rapid growth since 2020, with nearly 74% of all publications appearing during the 2024–2026 period, reflecting increasing scholarly interest in integrating advanced computational techniques with financial decision-making and investor behaviour. The analysis reveals that scholarly output in this domain is concentrated within a relatively small number of publication outlets. This coexistence of technology-focused and finance-focused journals among the leading outlets underscores the interdisciplinary character of the field, highlighting the growing convergence of artificial intelligence, machine learning, and financial research (Annu & Tripathi, 2025). The publication landscape is highly concentrated, with citation influence remaining concentrated among a limited group of sources while several journals contribute substantially to research volume.

4.2 Author Productivity and Influence

The analysis of prolific authors reveals notable differences between research productivity and scholarly influence. Teplova, Tamara emerges as the most productive author in terms of publication output, whereas Bhatia, Ankita and Chandani, Arti achieve the highest citation impact, each receiving more than 300 citations (Mishra & Tripathi, 2025). The findings indicate that intellectual

influence within the field is concentrated among a small group of highly cited researchers, while publication activity is distributed across a broader community of contributors.

4.3 Geographic Distribution and Collaboration

The geographic analysis reveals a strong concentration of scholarly output in Asia, with China emerging as the leading contributor followed by India and the United States (Mind over machine, 2026). China dominates the citation landscape with 595 citations, while India ranks second with approximately 428 citations. The predominance of single-country publications indicates that research is largely conducted within national research ecosystems, whereas international collaboration remains limited (Simonn, 2025). The author collaboration network reveals a moderately fragmented research community composed of several independent collaboration clusters and one dominant research group with a hub-and-spoke structure. While cross-cluster collaboration remains limited, the presence of multiple research teams actively engaged in the field suggests substantial opportunities for strengthening scholarly integration.

4.4 Thematic Structure and Evolution

The thematic analyses reveal a clear evolution toward an AI-driven financial research landscape. The thematic map identifies **investments, financial markets, and commerce** as the principal motor themes, while **machine learning, forecasting, and learning systems** emerge as foundational themes with strong growth potential, reflecting the increasing adoption of advanced analytical techniques in finance (Annu & Tripathi, 2025). In contrast, **artificial intelligence, fintech, and behavioural finance** remain emerging themes that are gaining scholarly attention but have yet to achieve full integration within the broader research network (Katenova et al., 2025). The thematic evolution further demonstrates a shift from fintech-oriented research to a more mature AI-centric agenda, with **artificial intelligence, investor sentiment, forecasting, and financial stability** emerging as key research areas alongside the enduring prominence of **investments** and **machine learning** (Phan, Ninh & Nguyen 2026). Consistent with these findings, the three-field plot highlights **machine learning, artificial intelligence, stock market, and behavioural finance** as dominant themes, alongside growing interest in **natural language processing, algorithmic trading, cryptocurrency, and investor sentiment,** reflecting the increasing emphasis on data-driven financial analytics (Mishra & Tripathi, 2025).

5.0 FUTURE RESEARCH DIRECTIONS

Based on the findings of this bibliometric and thematic review, several directions for future research emerge that can advance scholarly understanding and practical applications at the intersection of behavioural biases, artificial intelligence, and retail investor decision-making.

Table 8: Future Research Directions

Research Direction	Future Research Agenda	Potential Contribution
Enhancing International Research Collaboration	Foster cross-cultural comparative studies examining behavioural biases and AI adoption patterns across diverse socioeconomic contexts; establish international research consortia to facilitate knowledge exchange	Enriched understanding of cultural, regulatory, and institutional factors shaping AI-retail investor relationships; development of globally relevant theoretical frameworks; enhanced scholarly integration
Deepening Integration of Behavioural Finance and AI	Develop comprehensive theoretical frameworks bridging psychological insights with computational approaches; conduct empirical investigations on automation bias and its impact on decision-making quality and market dynamics	Robust theoretical foundations integrating behavioural finance and AI; improved understanding of investor over-reliance on AI recommendations; enhanced decision-making frameworks
Addressing Ethical Considerations and Algorithmic Bias	Develop transparent and explainable AI systems; investigate data privacy, algorithmic transparency, and consumer protection implications; establish ethical guidelines for AI deployment in financial services.	Fair and accountable AI systems; enhanced investor trust; informed regulatory frameworks; protection of vulnerable investor populations
Investigating Financial and AI Literacy as Moderating Factors	Systematically examine how varying literacy levels influence AI adoption and susceptibility to biases; conduct longitudinal studies tracking literacy evolution alongside AI adoption patterns	Evidence-based educational interventions; user-centered financial technologies; enhanced investor protection through literacy programs
Examining Emerging Digital Platforms	Investigate AI-powered recommendation systems and social trading platforms; study generative AI's influence on investment advice and decision-making; examine technology-behaviour interactions	Comprehensive understanding of digital platform impacts; evidence-based guidelines for platform design; identification of emerging risk factors
Strengthening Methodological	Leverage advanced bibliometric techniques,	Novel insights from diverse data sources; robust

Research Direction	Future Research Agenda	Potential Contribution
Rigor and Data Diversity	machine learning, and natural language processing; adopt cross-disciplinary approaches combining finance, computer science, psychology, and behavioural economics	analytical frameworks; comprehensive understanding of human-AI interaction in financial contexts
Informing Policy and Regulatory Frameworks	Develop evidence-based regulatory frameworks promoting innovation while ensuring investor protection; conduct cross-jurisdictional studies examining regulatory effectiveness	Harmonized global standards; balanced innovation-investor protection frameworks; enhanced market integrity
Evaluating Long-Term Impact of AI on Market Dynamics	Conduct longitudinal studies examining AI adoption consequences; investigate algorithmic trading, sentiment analysis, and predictive modeling impacts on systemic risk	Comprehensive risk management strategies; enhanced financial stability; evidence-based policy development

As the field continues to mature, future research should address the identified gaps in ethical considerations, international collaboration, and theoretical integration to advance both scholarly knowledge and practical applications in AI-enabled financial decision-making.

6.0 LIMITATIONS

The findings of this study should be interpreted in the context of several limitations inherent to bibliometric research. First, the analysis is database-dependent, as it is based exclusively on journal articles indexed in **Scopus** and **Web of Science** published between **2020 and 2026**. Although these databases are widely recognized for their comprehensive coverage and high-quality indexing, they may not capture the full spectrum of scholarly output, potentially excluding relevant studies indexed in other databases or repositories.

Second, bibliometric outcomes are influenced by the quality and completeness of bibliographic metadata, the design of the search strategy, and the accuracy of database records. Variations in indexing practices, author names, keywords, or citation information may affect publication counts, citation metrics, and the construction of collaboration and thematic networks.

Third, citation-based indicators should be interpreted with caution, as citation performance may be influenced by factors such as publication age, journal visibility, disciplinary citation practices, and accessibility, rather than solely reflecting the theoretical significance or scientific quality of a publication.

Fourth, bibliometric techniques such as co-occurrence analysis, thematic mapping, and network visualization are effective for identifying intellectual structures, conceptual relationships, and research trends. However, these methods reveal patterns of association rather than causal relationships among research themes or constructs and should therefore be interpreted as descriptive rather than explanatory.

Finally, the study was limited to **English-language, peer-reviewed journal articles,** thereby enhancing methodological consistency and ensuring the inclusion of high-quality scholarly literature. Nevertheless, this criterion may have excluded valuable contributions published in conference proceedings, books, book chapters, dissertations, and non-English sources. In addition, the analysis focused primarily on empirical studies within the subject areas of **Business, Management and Accounting, Computer Science, Decision Sciences, Economics, Econometrics and Finance, Psychology, and Engineering,** while conceptual, theoretical, and interdisciplinary works outside these domains were excluded. Consequently, the findings may not fully capture the broader theoretical and multidisciplinary perspectives that contribute to the evolving literature on behavioural finance, artificial intelligence, and retail stock markets investors.

STATEMENTS AND DECLARATIONS

'Funding' and/or 'Competing interests'

- No funding was received to assist with the preparation of this manuscript.
- The authors have no competing interests to declare that are relevant to the content of this article.
- All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.

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