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Abstract: Currently, the emphasis in digital finance research is on financial behaviour and market risk. The literature remains fragmented in the areas of FinTech, computational forecasting, behavioural finance and financial risk. This study examines the evolution, knowledge structure, and emerging themes of the digital finance literature on financial behaviour and market risk. Data were obtained from 967 documents from Scopus and Web of Science and subjected to co-citation, keyword co-occurrence, and thematic analysis. The number of publications increased considerably after 2019, with the upward trend continuing into 2025. The co-citation network suggests three knowledge foundations involving behavioural finance and technology acceptance; market theory and computational forecasting; and FinTech and robo-advisory. The keyword analysis identifies four streams covering FinTech and behaviour, AI-based investment, market prediction, and automated trading and risk management. Motor themes include FinTech, market volatility and machine learning, while the niche quadrant contains behavioural finance. Digital transformation, stock markets, and cryptocurrency are some of the themes that are emerging or declining. Ecosystem attributes, regulatory oversight and investor protections can be guided by evidence from the FinTech and risk themes. The results also inform investor education and additional research on the linkage between behavioural and computational approaches.

Keywords: digital finance; FinTech; behavioural finance; investor behaviour; market risk.

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1 Introduction

In recent years, digital finance has changed the ways investors access information and make financial decisions across digital platforms and market settings (Liu and Hou, 2023). FinTech platforms, investment apps, robo-advisors, and real-time data can accelerate the decision-making process (Mukthar et al., 2025). Therefore, technological factors, investor psychology and market structure influence the investment environment. However, related research is often scattered across disciplines and tends to focus on specific topics (Del Sarto and Ozili, 2025). Thus, a systematic synthesis of this literature is needed to identify its main knowledge areas and the relationships among them.

Additionally, the behavioural finance is also closely related to investor psychology, which affects trading through the risk perceptions, the sentiment, and the herding (Almansour et al., 2025). Digital finance enables a wider and quicker spread of market signals, while emotional responses can be magnified more easily (Wilkie et al., 2025). Therefore, sources of information can help boost short-term trading and enhance the feeling of scarcity. However, many studies focus on a specific tool or are based on a single psychological theory, and integration remains limited across formation processes (de Oliveira Santini et al., 2025; Akhtar et al., 2025). For the purpose of this study, digital finance is defined as the use of digital technologies in financial services, financial transactions, and investment decisions. Digital transformation refers to the restructuring and adaptation of organisations and service systems to digital technologies (Cheng et al., 2025; Wirtz and Langer, 2025). Digital finance can be placed within a perspective of digital transformation, for the two concepts should not be confused.

There are several related areas covered by existing reviews, but their research scopes remain quite separate across digital finance and investor behaviour (Gomber et al., 2018). Previous reviews have also examined the adoption of digital financial transactions and the overall framework of behavioural finance (Kajol et al., 2022; Hachicha et al., 2024). Other recent research has examined FinTech in relation to financial inclusion and the use of robo-advisory services (Del Sarto and Ozili, 2025). Numerous publications focus on platform efficiency but show limited links with financial behaviour and market risk across different market settings. At the same time, the research on the investor's sentiment often reports aggregate effects, with little attention paid to the heterogeneity across markets and the differences in market states (Zhou, 2025; Cui et al., 2025). These reviews and topic-specific studies provide only partial integration of digital financial technologies, financial-market contexts and behavioural mechanisms within a common analytical structure. Consequently, the field does not have a common frame of reference in terms of central themes, influential authors, and key clusters of research. Additionally, new directions such as robo-advisors and sentiment data must be placed further into the larger knowledge structure. Thus, additional bibliometric analysis is required to identify common intellectual roots and thematic linkages, as well as emerging research directions. It should not summarise publication trends, but should clarify how the research streams are related.

Therefore, this study uses bibliometric analysis to examine the evolution and knowledge structure of the digital finance literature on financial behaviour and market risk. The data covers research on financial technologies, market activities, and investor psychology in Scopus and Web of Science. These layers represent the technological setting, market setting, and behavioural process, respectively. However, the combination of the three layers limits the corpus to studies that connect these dimensions. The analysis is then conducted using co-citation to determine intellectual grounds and powerful knowledge groups. Moreover, the co-occurrence analysis of keywords and thematic mapping can be used to determine new and emerging research directions (Van Eck and Waltman, 2022). Accordingly, the study addresses the following research questions: RQ1. What are the trends in publication counts, geographic coverage, and scholarly impact of research on digital finance, financial behaviours and market risks? RQ2. Which cited works and clusters of keywords structure the intellectual and conceptual framework of this research area? RQ3. What is the distribution of the themes in the thematic map, and what are the directions for future research?.

2 Literature review

2.1 Digital finance in financial market contexts

Digital finance is the use of digital technologies across financial services, investment and market transactions. In this context, stock markets represent a particular context, while digital transformation constitutes the technological context. The process involves online trading, mobile investment applications, data analytics, and robo-advisors (Kajol et al., 2022). The technology-organisation-environment (TOE) perspective offers a way to consider these applications in light of the technological, organisational, and environmental context of digital transformation (Tornatzky et al., 1990). Investors can therefore access financial markets more quickly, while facing lower transaction costs (Qi, 2026). At the individual investor level, these factors can enhance perceived usefulness and ease of use, which are associated with platform acceptance in TAM and UTAUT (Venkatesh et al., 2003; Nair et al., 2023). Meanwhile, these tools can help reduce the information gap between retail and institutional investors. This change can encourage greater participation by retail investors in the stock market. These perspectives are complementary because the TOE perspective covers broader conditions and the TAM and UTAUT perspectives offer explanations for individual acceptance.

Furthermore, digital finance contributes to restructuring financial market operations. Adoption barriers may be reduced as real-time information and decision support algorithms enable faster transactions (Ferreira et al., 2021). However, while these technologies may enhance market liquidity, they can also put pressure on short-term reactions. From a bounded-rationality point of view, faster information cycles shift the focus from fundamentals to heuristics and short horizon cues (Tversky and Kahneman, 1974). In this regard, fundamental analysis as a basis for investment behaviour may be less dominant in the long term (Amin et al., 2025). This could instead include more emphasis on price signals and real-time data in investment decision-making. These changes can reshape financial market dynamics towards technological speed and short-horizon signals (Khan et al., 2022).

Meanwhile, the development of FinTech is changing the relationship between information and investment decisions (Abdeldayem and Aldulaimi, 2025). Previously, there was unequal and asymmetric access to information among investor groups. For instance, financial information is communicated and delivered almost simultaneously in the present digital environment. This can decrease information advantages and increase cognitive competition among investors (Bin-Nashwan et al., 2025). Behavioural finance suggests that an overload of market signals may encourage herd behaviour and emotional responses, with higher perceived risk and volatility. When many investors react to the same signal, these reactions can also cause greater price fluctuations. While digital finance can help markets function more smoothly, it may also increase investors' exposure to behavioural and trading risks (Jiang et al., 2018).

However, previous studies have focussed on market efficiency and behavioural risk separately, although these are linked. Other studies have focused on the performance of trading platforms and the effectiveness of robo-advisors (Yang et al., 2025). Existing studies, on the other hand, consider how technology affects liquidity and price volatility. These approaches are disjointed and are often not integrated within the same analytical context. Consequently, the relationship among digital finance, financial behaviour, and market risk remains unclear (Jin et al., 2025). This gap shows the need to synthesise these perspectives and identify major research lines and future directions in the field.

2.2 *Financial behaviour and market risks in the digital world*

Beliefs and responses of investors to information are often linked to decision patterns that differ from rational expectations (Shiller, 2003; Dastjerdi et al., 2025). In behavioural finance, there is a focus on emotions, subjective beliefs, and how risk is perceived (Tversky and Kahneman, 1974; Altman, 2011). These factors may influence trading decisions (Robalinho et al., 2023). These influences can become more pronounced when investors conduct investment and trading activities through digital platforms. Digital platforms facilitate quick reactions and shorten deliberation time (Choi and Choi, 2019). Time pressure may lead to using simpler cues instead of more information from a bounded-rationality perspective. Thus, trading can be more responsive to the immediate psychological signals.

Additionally, the digital financial landscape influences the development and flow of market sentiment (Khan et al., 2022; Çakërri et al., 2025). The information cascade theory can be used to explain the development of collective behaviour from widely visible signals (Bikhchandani et al., 1992). Digital platform investors are constantly shown price information, trading signals, and investment return-based rankings. These signals may facilitate social comparison and promote contagion among investors. In some cases, buy or sell decisions are not grounded in the asset's intrinsic value (Artikis and Kampouris, 2022). Instead, investors may make decisions by anticipating how most other participants are likely to act in the market. Digital trading platforms can support higher levels of herding behaviour because traders can observe and respond to the same trading signals in the market (Amin et al., 2025).

Simultaneously, short-term risk perception provides a different way of understanding how investors respond to uncertainty and price fluctuations (Kulkarni et al., 2025). Investors often focus on immediate price changes, paying less attention to long-term prospects (Xu and Yang, 2025). Investors could become more stressed with repeated market exposure, which may lead to more emotion-driven investing (Ren et al., 2025). In

this context, trading decisions could be more responsive and strategic thinking less attended to. The relation shows that technological infrastructure does not directly produce investment behaviour, but instead is a context that influences investment behaviour.

Still, the literature on investor psychology, spans several areas, while market sentiment, risk perception, and herd behaviour are usually treated independently (Tahvildaria, 2025; Jain et al., 2025). Few studies consider these factors together within the digital finance environment. The three perspectives are correlated and provide different levels of explanations of behaviour. Bounded rationality is related to the cognitive limits of an individual, and risk perception is linked to uncertainty and potential losses. The information cascade theory shows how collective responses can result from observed decisions and collective signals. When combined, they offer lenses through which to assess technology, information, behaviour in financial markets, and market risks. In this study, these perspectives support interpretation of the bibliometric patterns instead of being theories tested by the analysis. Their incorporation helps interpret the research clusters and gaps to be discussed later in the analysis.

3 Methods

3.1 Research design

This study uses bibliometric analysis to explore the development and knowledge landscape of digital finance research on financial behaviours and market risks. The keyword structure indicates the scope of the coverage of topics. Layer 1 focuses on the digital financial technologies and related innovations, including digital finance, FinTech, robo-advisors, and digital transformation. Layer 2 refers to the market and investment, including stock market, capital market, financial markets, and investment. Meanwhile, Layer 3 covers the financial behaviours and the psychology of the investor regarding the perceived risk in the market.

The relationship among the three layers follows a technology-market-behaviour mechanism. Digital financial technologies can change the speed, cost, and availability of market information and investment services (Gomber et al., 2018). In the context of financial markets, bounded rationality influences investors' interpretation of digital signals, depending on risk perception or heuristics (Simon, 2000; Tversky and Kahneman, 1974). Shared information may also encourage herding when investors follow the decisions of others (Bikhchandani et al., 1992). These responses may relate to investment decisions and patterns of market risk. Accordingly, the three layers are technological input, market context and behavioural or risk responses.

The three layers are linked with the AND operator, while OR is used within each layer to cover conceptual variations. Thus, the retrieved records that meet all three keyword layers can be included in the initial search corpus. This structure aims to focus the search scope in relation to the research questions, and limit irrelevant records.

3.2 Data collection

Data were collected from Web of Science Core Collection and Scopus. After the exclusion criteria were applied, 225 records remained from Web of Science and 784 from Scopus. The search used KEYWORD in Scopus and Topic TS in Web of Science. The

purpose of these fields is to capture the core research content and reduce irrelevant records (Salehpour and Samadzamini, 2024).

The same keyword groups and Boolean logic were applied using the field codes of each database. The data was successfully downloaded from Web of Science and Scopus on 25th July 2026. The final query was ('digital transformation' OR 'digital finance' OR FinTech OR 'financial technology' OR 'robo-advisor' OR 'robo-advisors' OR 'robo-advisory' OR 'online trading' OR 'mobile trading' OR 'electronic trading' OR 'online investing' OR 'online brokerage') AND ('stock market' OR 'stock markets' OR 'capital market' OR 'capital markets' OR 'financial market' OR 'financial markets' OR 'equity market' OR 'equity markets' OR 'securities market' OR 'securities markets' OR 'stock trading' OR investment OR investments OR 'retail investor' OR 'retail investors') AND ('behavioural finance' OR 'behavioural finance' OR 'investor behaviour' OR 'investor behaviour' OR 'trading behaviour' OR 'trading behaviour' OR 'investment behaviour' OR 'investment behaviour' OR 'behavioural intention' OR 'behavioural intention' OR 'trading intention' OR 'investment decision' OR 'investment decisions' OR 'investor psychology' OR 'risk perception' OR 'perceived risk' OR 'investor sentiment' OR 'market sentiment' OR 'market uncertainty' OR 'market volatility' OR herding OR overconfidence OR 'bounded rationality' OR 'information cascade').

There was no restriction on the year the research started and the retained records spanned 1991 to 2025. In the initial screening, documents from 2026 and those that were identified as retracted in publications were excluded from the retrieved documents. The document types and language information are reported in Appendix B.

The database files were merged in bibliometrix 5.2.1 using mergeDbSources (scopus, wos, remove.duplicated = TRUE). In total, 40 duplicate records and two retracted records were removed, leaving 967 records in the final analysis dataset. The titles and abstracts of these were compared to the three layers of key words. The screening process is presented in the PRISMA diagram in Appendix C.

3.3 Analytical techniques

The analysis was conducted using bibliometrix 5.2.1 and VOSviewer 1.6.20. Based on this dataset, bibliometric and thematic techniques were applied to examine the knowledge structure (Klarin, 2024; Boodai and Boodai, 2025). First, the descriptive indicators were employed to provide a broad overview of publication trends, sources and academic contributions over time.

Second, co-citation analysis of the cited references was carried out to determine knowledge clusters using a threshold of eight citations per reference. Author-provided keywords were analysed using keyword co-occurrence at a minimum threshold of five. Full counting, association-strength normalisation, and the default clustering settings of VOSviewer 1.6.20 were applied (Van Eck and Waltman, 2022). VOSviewer's thesaurus function was used to group synonymous labels, normalise spelling variants and remove general terms from the labels.

Finally, a thematic map was built in which clusters were classified in terms of centrality and density (Hachicha et al., 2024). The map was generated from author keywords using the default settings of bibliometrix 5.2.1 for term selection, minimum frequency, stemming, clustering, and seed. This map contributes to the identification of foundational themes, dynamic themes, and emerging research directions, providing a basis for the results and discussion.

4 Results

4.1 Overview of research development

In the dataset, publication patterns explain the growth of the field over time and the sharing of academic contributions among key actors. Detailed indicators are summarised during Tables A1–A4 in Appendix A.

Figure 1 illustrates the development of the field using four descriptive cross-sections. Publication output was low for a long time, after which it turned into a clear growth phase following 2019. In 2025, the number of publications increased to 368, indicating a fast growth of this study domain. The surge is partly due to the composition of the 2025 publications, which comprised 171 conference papers and 55 book chapters in addition to 131 journal articles (Kasaraneni and Rosaline, 2024).

Authorship of the research was widely spread and there was no single group that controlled the data. The fractionalised publication counts varied from 4.25 to 4.74, with the highest being for Wang followed by Liu and Li. Thus, the contribution structure is consistent with a growing area in which many groups engage in knowledge building (Klarin, 2024).

Next, academic influence is concentrated in a small set of highly cited papers. The best three works have obtained 702, 496 and 258 citations, respectively, and many papers are published in 2019–2023 with more than 175 citations. Thus, the data set contains both continuity in main reference sources and recognition of new research in a short period (Padilla-Ospina et al., 2018).

Finally, the country distribution shows a concentration of research contributions from a few countries. China leads with 220 papers, followed by India (103) and the USA (49). This is perhaps partly because of the country's developed digital finance landscape and its leading role in digital financial inclusion (Shen et al., 2025). China also has a high domestic publication ratio (203 SCPs versus 17 MCPs). The fact that MCP shares are larger in a number of other nations indicates that there is greater international collaboration (Aria et al., 2023).

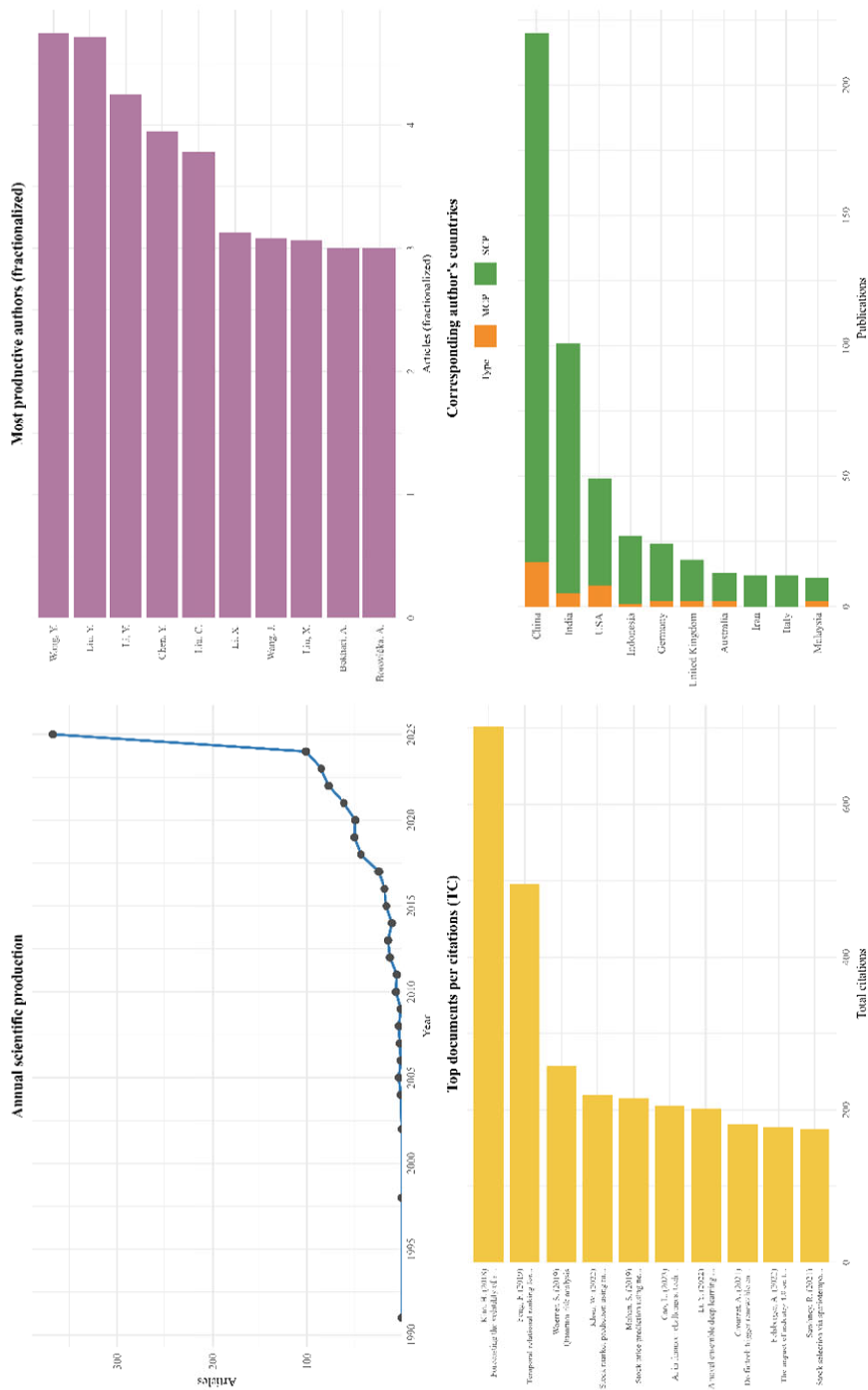
4.2 Document co-citation analysis

In the research orientation, the development process of the co-citation network shows the linked works and the formation of knowledge flows, as presented in Table A5, Appendix A.

Figure 2 shows the process of creating a network for the development of published citations with documents grouped according to co-citation frequency and total link strength (TLS). The recommended indicators measure the level of knowledge cohesion and identify academic background in the research field.

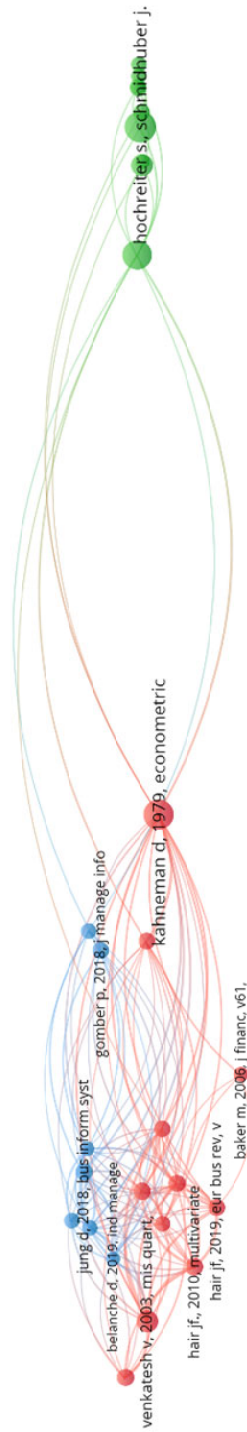
Cluster 1 refers to behavioural finance, technology acceptance and empirical measurement methods. The reference 'user acceptance of information technology' (17, 52) indicates that technology acceptance is relevant for the investigation of digital investment behaviour (Venkatesh et al., 2003). In addition, 'prospect theory' (33, 42) extends the interpretation to investor decisions under risk and uncertainty (Kahneman and Tversky, 1979). In this cluster, structural equation measurement (12, 49) remains a common approach for assessing relationships among research constructs (Fornell and Larcker, 1981).

Figure 1 Annual growth of publications on digital finance and stock markets (see online version for colours)



Source: Authors' elaboration (2026)

Figure 2 Document co-citation network (see online version for colours)



Source: Authors' elaboration (2026)

Building on these foundations, Cluster 2 further explores market theory, portfolio risk and computational forecasting. ‘Long short-term memory’ (35, 8) shows the role of neural networks in analysing sequential financial data (Hochreiter and Schmidhuber, 1997). Meanwhile, ‘portfolio selection’ (31, 16) is an analysis of diversification and asset allocation in conditions of uncertainty (Markowitz, 1952). Theoretically, the efficient market theory (11, 6) and GARCH (11, 5) offer well-established frameworks for explaining returns and modeling volatility respectively (Fama, 1970; Bollerslev, 1986).

Building on this discussion, Cluster 3 shapes an axis between FinTech and robo-advisory, in which technology is reshaping financial advice and investment services. “Robo-Advisory: Digitalization and Automation of Financial Advisory” (11, 39) shows the connection between automation, financial advice, and investor needs (Jung et al., 2018). Simultaneously, ‘artificial intelligence in FinTech’ (8, 35) clarifies the factors associated with customer adoption of robo-advisors (Belanche et al., 2019). FinTech transformation and robo-advising outcomes provide an interpretation of digital services, portfolio diversification and investor biases (Gomber et al., 2018; D’Acunto et al., 2019).

A relatively consistent intellectual structure is formed within these clusters. The groups follow a roadmap from behavioural decisions and technology adoption to market risk and forecasting, to FinTech and robo-advisory. These references are aligned and relate behaviour, market analysis and technology but do not identify causal relationships between these dimensions.

4.3 *Keyword co-occurrence analysis*

The study identified a combination of terms from conceptual axes of interest in the field. Information on thematic clusters is summarised in Table A6 in Appendix A.

Figure 3 shows the structure of the keyword concurrency, with concepts grouped according to the frequency of occurrence and sum of link strength. This clustering method assists in identifying axes of research and relationships among technology, behaviour and financial markets.

Cluster 1 focuses on FinTech, stock markets, and behavioural factors in digital finance (Arenas et al., 2024). Representative keywords include ‘FinTech’ (84, 117), ‘stock market’ (71, 101), and ‘behavioural finance’ (52, 90). At the same time, ‘investor sentiment’ (31, 34) and ‘investor behaviour’ (23, 36) indicate a close connection between digital finance and market behaviour (Kim and Lee, 2022).

In Cluster 2, the focus is on AI-driven investment decisions and digital investment services (Bhatia et al., 2022). The keywords ‘investment decision’ (57, 82), ‘artificial intelligence’ (46, 108), and ‘neural network’ (43, 82) form the centre of this group (Snihovyi et al., 2019). In addition, ‘robo-advisor’ (31, 47) and ‘digital transformation’ (24, 16) connect these methods with investment and portfolio applications.

On the other side, Cluster 3 refers to sentiment analysis or market prediction using machine learning (Khan et al., 2022; Mohan et al., 2019). The keywords ‘machine learning’ (92, 221), ‘sentiment analysis’ (52, 117), and ‘deep learning’ (50, 101) have the strongest positions in this group. Additionally, ‘stock market prediction’ (43, 87) and ‘market volatility’ (29, 79) reflect the use of computational methods to study prices and market changes.

Source: Authors' elaboration (2026)



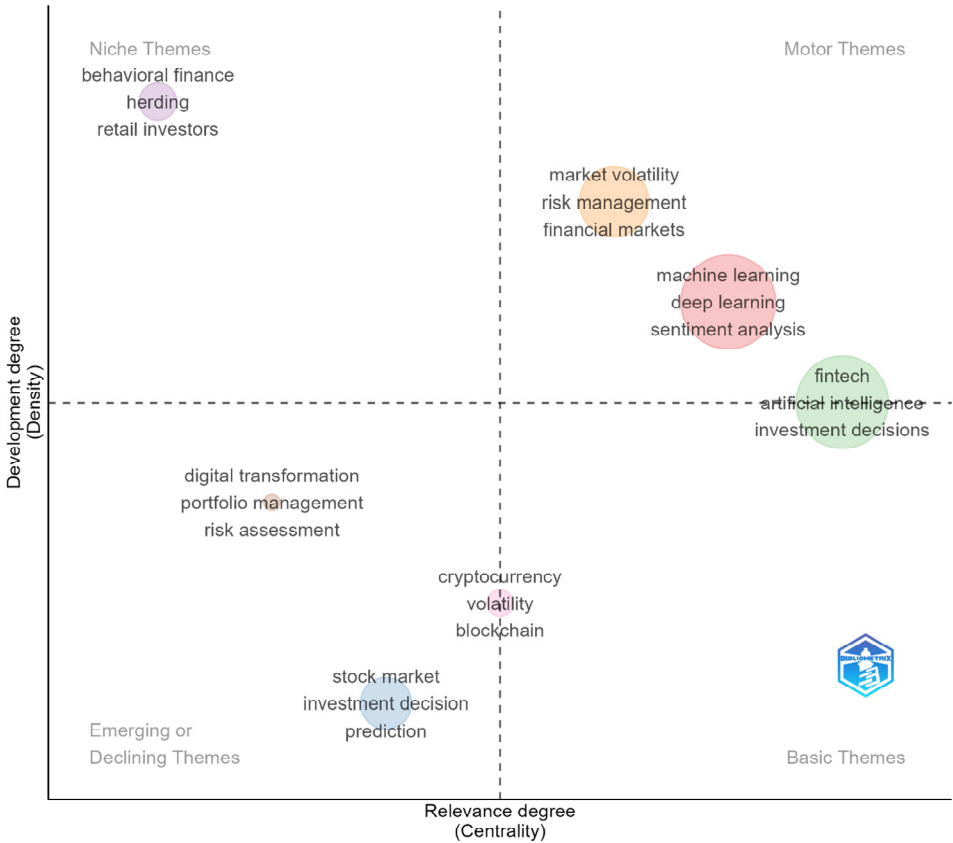
Lastly, Cluster 4 relates to financial markets, risk management, and automated trading (He et al., 2022). The keywords ‘financial market’ (33, 68) and ‘risk management’ (24, 61) establish the financial and risk context (Park et al., 2024). Simultaneously, the related terms ‘algorithmic trading’ (16, 51), ‘reinforcement learning’ (12, 18), and ‘natural language processing’ (10, 16) link this context to data-driven trading strategies (Takenaga and Li, 2023).

Overall, the clusters are not independent, but connected via FinTech, stock markets, investment decisions, and computational approaches. This research area is related to digital finance, investor behaviour, market risk, and financial analysis based on data.

4.4 Thematic analysis

The purpose of this study is to propose potential topics and analyse the distribution of topic groups according to their structure. The classification results are presented in Table A7, Appendix A.

Figure 4 Strategic thematic map based on centrality and density (see online version for colours)



Source: Authors' elaboration (2026)

Figure 4 is a two dimensional topic map, where Callon centrality is a measure of relevance and Callon density is a measure of development status. Clusters are classified into sub-regions and propose the connectivity of clusters in the structure of knowledge.

In the Motor themes area, 'FinTech' (2.003; 22.773) occupies a significant place with its central character and internal development (Cao et al., 2021; Abdeldayem and Aldulaimi, 2025). At the same time, 'market volatility' (1.609; 22.935) reflects the importance of market risk and risk management in financial markets (Kim and Won, 2018). Another motor theme is 'machine learning' (1.661; 22.897), which covers deep learning, sentiment analysis, and market prediction (Khan et al., 2022). These themes suggest that there are strong relationships between financial technologies, investment decisions, and market risk.

Among the niche themes, 'behavioural finance' (0.480; 27.170) is well developed internally but remains weakly connected to other themes. This cluster was related to herding and retail investors, indicating that this is a specialised behavioural stream in financial market research (Almansour et al., 2025). These themes give analytical depth and help to explain differences in investor behaviour in digital markets.

In the Emerging or declining themes, 'digital transformation' (0.575; 22.178) is relatively peripheral but related to portfolio management and risk assessment (Ding et al., 2024). Likewise, the term 'stock market' (0.701; 17.763) refers to investment decisions and predictions, and thematic development remains low (Li and Pan, 2022). Furthermore, the theme of 'cryptocurrency' (0.728; 20.845) has a peripheral position, and the area of research is defined by volatility and blockchain (D'Amato et al., 2022).

Thus, the map suggests there might be an association between FinTech, computational analysis, financial behaviour, and market risk. In particular, the themes of FinTech, machine learning, and market volatility are more developed and established, while behavioural finance is still a niche research area. In contrast, digital transformation, stock market prediction, and cryptocurrency are less developed themes whose rankings could vary as connections with the primary research axes grow.

5 Discussion

The academic study of digital finance and investment behaviour in financial markets has been gaining momentum since 2019. The resulting knowledge structure is a connection between technology, behaviour, and market risk, but these are not even. The co-citation network shows three knowledge bases: behavioural finance and technology acceptance, market risk and forecasting, and FinTech and robo-advisory. There are also four streams identified through keyword co-occurrence. They concern FinTech and behaviour, AI-driven investment services, machine learning and market prediction, and risk management and automated trading. The thematic map also differentiates between motor themes and niche and emerging or declining themes. The relationships described below are discussed without assuming that these bibliometric associations represent causal effects.

5.1 FinTech and financial behaviour in stock markets

FinTech appears as a motor theme connected with stock markets, investor sentiment, and investor behaviour. This position brings together research interests concerning digital

access, market information and financial decisions within a common research stream. Past studies indicate that market signals could show differences in speed and transparency as FinTech platform adoption increases (Di Pietro et al., 2021). Bounded rationality can serve as a basis for explaining why investors may rely on simplified signals when processing a large amount of information (Simon, 2000). The emerging trend indicates a close thematic relationship between FinTech, financial behaviour and market risk, but does not reveal any behavioural mechanism.

Meanwhile, AI analytics and robo-advisors are linked in the investment sector and digital services. Past research suggests that these tools are often associated with portfolio rebalancing and decreases in execution costs (Cao et al., 2021; Shanmuganathan, 2020). Investors might also respond to similar recommendations and converge on common signals, although the network does not establish reactive trading. Evidence also indicates that FinTech may be related to leverage decisions and the risk outcomes of the market (Lai et al., 2023). The result suggests that FinTech has a wider presence in the theme, and behavioural finance is prominent in the context of herding and retail investing. The present structure contrasts with past reviews which considered technology adoption and streams of behavioural finance separately (Kajol et al., 2022; Hachicha et al., 2024).

5.2 Digital transformation and technology adoption for investment services

Digital transformation is not among the motor themes, but on the emerging or declining quadrant. Its position indicates relatively low links with the primary research fields, and its uses span data infrastructure, portfolio management and risk assessment. The dispersed pattern may help explain why the theme has yet to develop a clearly defined central position within the research field. Its placement beside artificial intelligence, neural networks, robo-advisors and investment decisions suggests that it mainly provides a technological setting for financial services (Bounfour et al., 2025). Research into FinTech also highlights that digital change involves innovation and transformation across financial activities (Gomber et al., 2018).

In this context, robo-advisory serves as an example of how digital transformation is reflected in automated financial advice (Jung et al., 2018). It is also linked to investment decisions, such as research into behavioural biases and the use of robo-advisors (Bhatia et al., 2022). TOE provides a framework with which to examine the organisational resources and market environment of these services (Tornatzky et al., 1990; Yewei et al., 2025). At the user level, TAM shows how perceived usefulness and ease of use play a role in technology acceptance (Davis, 1989). UTAUT extends this view by considering social influence and facilitating conditions in the adoption process (Venkatesh et al., 2003). These views are located on various analytical levels, and the links between them are not directly assessed through bibliometric results.

Thus, it could be argued that its peripheral location is more a result of the existing configuration of the field than of the academic irrelevance of research into digital transformation. It indicates that its association with financial behaviour and market risk is still inconsistent in the literature. The evidence of robo-advisor adoption suggests that the concept of user acceptance is relevant in this evolving space (Belanche et al., 2019). However, these links are thematic and do not necessarily imply a causal relationship.

5.3 Behavioural finance and herding in digital markets

The niche quadrant is for behavioural finance, where there are stronger connections within the field than to the broader themes. There is more attention on herding and retail investors, with FinTech, machine learning and volatility being central themes. Behavioural finance was recognised as a wider knowledge field in past scientometric studies (Hachicha et al., 2024). The narrower position might be due to a combination of behavioural studies and digital finance and market-risk research within the current corpus. This is related to this narrower internal orientation, as evidenced by behavioural biases, risk perception, and financial literacy (Almansour et al., 2025; Alhumaidhi et al., 2025). Risk perception is therefore an associated concept and does not appear to define the theme of this quadrant.

In addition, the bounded rationality and heuristic judgment perspectives provide mutually reinforcing views of this particular stream. The concept of bounded rationality can explain the influence of limited cognitive capacity on decision-making in complex information environments (Simon, 2000). In situations where market conditions are not well known, heuristic judgment can be used to interpret reliance on salient signals (Tversky and Kahneman, 1974). Information cascade theory offers another perspective on herding when the choices made by others act as signals for subsequent investors (Bikhchandani et al., 1992). Platform attributes and regulations have been associated with herding in digital investment settings (Jiang et al., 2018). Internet postings may also influence the trading choices of individual investors (Ammann and Schaub, 2021). The proposed mechanisms are not tested with the bibliometric results but are interpreted with reference to these sources.

Investor-level behaviour remains mostly confined to the niche cluster, and there are only limited connections to the computational mainstream. It puts the analysis into perspective by placing herding, retail investor participation and risk perception in the wider context of the knowledge structure. Even when automated advice is integrated into investment decisions, behavioural biases remain a role (Bhatia et al., 2021). However, the network shows thematic affiliation and not necessarily a common effect that exists for all digital investors.

5.4 Market risk and directions for computational research

Motor themes of market volatility and machine learning appear, highlighting closer links between market risk and computation. This relationship may arise because financial markets produce large volumes of price, news and social-media data. These sources are employed in machine-learning research to classify market moves and aid stock prediction (Khan et al., 2022). News sentiment has also been incorporated into models of stock-price changes (Mohan et al., 2019). These findings suggest a strong development of this region, but do not prove that computational models have a positive impact on market outcomes.

Furthermore, the fourth keyword cluster connects financial markets and risk management with algorithmic trading, reinforcement learning and natural language processing. Their grouping has a common theme of data-driven decision-making, portfolio management and automated trading systems. Reinforcement learning has been applied to automatic stock-trading systems (He et al., 2022). Multiagent networks with risk sensitivity have been designed to support a portfolio in uncertain environments (Park

et al., 2024). Natural language processing provides another route for examining emotions in stock-market information (Takenaga and Li, 2023). There is little evidence of a common financial mechanism in these studies, which have a similar methodological background.

Meanwhile, the stock market and cryptocurrency are in the emerging or declining quadrant with lower development than the motor themes. The stock market is widely used in prediction and investment studies, which can have an influence on the internal thematic coherence. Cryptocurrency is more narrowly connected with blockchain and volatility, including ambiguity and return risk (D'Amato et al., 2022). The thematic map is static and thus does not indicate whether these themes are developing or declining. However, the peripheral nature of their location suggests that they remain less closely linked with risk management and behaviour research. Together, these results could further the analysis beyond publication trends and provide a distinction of the more established streams of computation from less connected market themes.

6 Conclusions and implications

6.1 Conclusion and theoretical contribution

This study examined the knowledge structure of digital finance literature on financial behaviour and market risk. The data included 967 documents from 1991 to 2025 that were indexed in Scopus and Web of Science. The number of publications surpassed the 2019 level, and the analysis showed that there were connected research areas with different levels of development. Three knowledge foundations were revealed by the co-citation analysis. They covered behavioural finance and technology acceptance, market theory and computational forecasting, and FinTech and robo-advisory. Keyword analysis revealed four streams related to FinTech and behaviour, AI-driven investment decisions, market prediction, and automated risk management. FinTech, market volatility and machine learning were among the motor themes in the thematic map. The thematic map separated behavioural finance into the niche quadrant from digital transformation, the stock market and cryptocurrency in the emerging or declining area.

Theoretically, the outcome is a systematically organised bibliometric synthesis instead of an explanatory model of digital investing. The findings provide insights into the points of intersection and the limits of the relationship between technology adoption, investor behaviour and market risk. Organisational adoption and user acceptance of digital investment services can be interpreted with the lenses of TOE, TAM and UTAUT. There are related perspectives on individual judgment and herding, including bounded rationality and information cascade theory. The perspectives are not confirmed and are not to be considered as mechanisms supported by the bibliometric results. The discovery could serve as a basis for further comparative studies in the future, given the ongoing evolution of digital finance research with new developments.

6.2 Practical and social implications

The practical implications vary depending upon the research streams identified. The first keyword cluster includes FinTech, alongside closely related themes of stock markets, investor sentiment and investor behaviour. Therefore, platform developers should select

ways to display alerts, recommendations, and risk information that are comprehensible to users. The second group involves AI and neural networks in relation to investment choices and robo-advisors. The findings could assist FinTech developers and financial institutions in improving transparency and balanced human–AI interaction for automated advice (Abasaheb and Rajagopal, 2025).

Meanwhile, the motor theme of market volatility and the fourth keyword cluster provide a sense for regulatory implications. The regulators might keep track of model risk, algorithmic strategies, and common signals applied in automated trading. Financial institutions should also consider their social responsibilities and the processes used to produce recommendations and deliver them to retail investors (Salloum et al., 2015). These directions are based on the thematic connections, but do not suggest that digital tools cause instability in the market.

Socially, the niche position of behavioural finance is related to investor education, herding, and retail involvement. Social information, real-time alerts, and market sentiment could all affect judgment when uncertainty arises and should be discussed through education programmes. Digital literacy should also include the limits of automated advice, and distinctions among predictive signals and fundamentals of finance. Disclosures of risk and easy complaint process could provide additional support for less experienced investors. In this direction, investor protection is associated with the behavioural themes observed in the results.

6.3 Limitations and future research

This study has several methodological limitations. First, the data rely on the coverage and quality of the metadata from Scopus and Web of Science. The data was in English only, and the research published in other languages may be underrepresented. The three-layer query helped to control the scope but remains sensitive to the choice of terms and Boolean combinations. Therefore, studies using newer or less common labels might not have been captured by the search. Additionally, the network structure and the membership of the clusters may change with the threshold values, complete counting, normalisation, clustering parameters and thesaurus choices.

Beyond these methodological issues, the interpretation of the knowledge structure also has several limits. Digital transformation and digital finance overlap in part, and this may lead to concept contamination across technology-adoption and corporate-performance studies (Manigandan and Raghuram, 2025; Dankwah and Nnindini, 2025). The corpus also brings together financial behaviour, investment services and computational forecasting, with their representation varying across research areas. The scale of the computational stream may be more a product of publication and keyword trends than the practical significance of the individual topics. The measurement of influence from recent studies may be underestimated because of citation lag, which is more noticeable during the increase in growth seen since 2019. Digital transformation, the stock market, and cryptocurrency were in the emerging or declining quadrant on the thematic map. Since the map presents a static view, it cannot determine which direction these themes are taking. Bibliometric association has suggested that the topics and references are common, but that neither behavioural nor market effects can be determined.

Future studies could consider repeating the analysis with other sets of keywords and other bibliographic sources to address such limitations. Longitudinal analysis is required

in order to differentiate between themes that are growing in significance from those that are becoming less relevant over time. By comparing the four keyword clusters across countries and markets, their stability under different institutional and international environments can be tested (Tokaji et al., 2025). Empirical studies might examine the relationships proposed in the network, such as sentiment, herding around platform signals, automated advice and market volatility. Future studies can link the niche behavioural stream with computational approaches and risk management, without the assumption of a common causal mechanism.

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Declarations

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Appendix A

Tables of bibliometric analysis results

Table A1 Annual scientific production

No.	Year	Articles
1	1991	1
2	1998	1
3	2002	1
4	2004	2
5	2005	4
6	2006	2
7	2007	3
8	2008	4
9	2009	2
10	2010	7
11	2011	6
12	2012	13
13	2013	15
14	2014	11
15	2015	17
16	2016	19
17	2017	25
18	2018	43
19	2019	50
20	2020	49
21	2021	61
22	2022	77
23	2023	85
24	2024	101
25	2025	368

Source: Authors' analysis (2026)

Table A2 Most influential authors

<i>Author</i>	<i>Articles fractionalised</i>
Wang, Y.	4.744
Liu, Y.	4.712
Li, Y.	4.251
Chen, Y.	3.950
Liu, C.	3.783
Li, X.	3.128
Wang, J.	3.083
Liu, X.	3.067
Bokhari, A.	3.000
Borovicka, A.	3.000

Source: Authors' analysis (2026)

Table A3 Most cited documents

<i>Paper</i>	<i>DOI</i>	<i>TC</i>	<i>TC per year</i>	<i>Normalised TC</i>
Kim (2018), <i>Expert Sys. Appl.</i>	10.1016/j.eswa.2018.03.002	702	78.00	21.44
Feng (2019). <i>ACM Trans Inf Syst</i>	10.1145/3309547	496	62.00	14.05
Woerner (2019), <i>Npj Quantum Inf.</i>	10.1038/s41534-019-0130-6	258	32.20	7.31
Khan (2022), <i>J. Ambient Intell. Humanized Comput.</i>	10.1007/s12652-020-01839-w	220	44.00	11.48
Mohan (2019), <i>Proc. – IEEE Int. Conf. Big Data Serv. Appl.</i>	10.1109/BigDataService.2019.00035	215	26.90	6.09
Cao (2023), <i>ACM Comput. Surv.</i>	10.1145/3502289	205	51.20	12.67
Li (2022), <i>Int. J. Data Sci Anal.</i>	10.1007/s41060-021-00279-9	202	40.40	10.54
Croutzet (2021), <i>Renew. Energ.</i>	10.1016/j.renene.2021.07.144	181	30.20	8.43
Felsberger (2022), <i>Prod. Plan. Control</i>	10.1080/09537287.2020.1810765	177	35.40	9.23
Sawhney (2021), <i>AAAI Conf. Artif. Intell., AAAI</i>	10.1609/aaai.v35i1.16127	175	29.20	8.15

Note: Total citations (TC)

Source: Authors' analysis (2026)

Table A4 Leading countries by publications

<i>Rank</i>	<i>Country</i>	<i>Articles</i>	<i>Articles (%)</i>	<i>SCP</i>	<i>MCP</i>	<i>MCP (%)</i>
1	China	220	22.75	203	17	7.73
2	India	103	10.65	98	5	4.85
3	USA	49	5.07	41	8	16.33
4	Indonesia	27	2.79	26	1	3.70
5	Germany	24	2.48	22	2	8.33
6	UK	18	1.86	16	2	11.11
7	Australia	13	1.34	11	2	15.38
8	Iran	12	1.24	12	0	0.00
9	Italy	12	1.24	12	0	0.00
10	Malaysia	11	1.14	9	2	18.18

Notes: Single country publications (SCP); multiple country publications (MCP)

Source: Authors' analysis (2026)

Table A5 Knowledge clusters identified through document co-citation analysis

<i>Cluster</i>	<i>Documents</i>	<i>Citations</i>	<i>TLS</i>
1	Baker, M. (2006) <i>J. Financ.</i> , Vol. 61, p.1645, DOI: 10.1111/j.1540-6261.2006.00885.x	8	5
1	Barber, B.M. (2001) <i>Q. J. Econ.</i> , Vol. 116, p.261, DOI: 10.1162/003355301556400	10	21
1	Davis, F.D. (1989), <i>Manage Sci.</i> , Vol. 35, p.982, DOI: 10.1287/mnsc.35.8.982	10	17
1	Fornell, C. (1981) <i>J. Marketing Res.</i> , Vol. 18, p.382, DOI: 10.1177/002224378101800104	12	49
1	Hair, J.F. (2019) <i>Eur. Bus. Rev.</i> , Vol. 31, p.2, DOI: 10.1108/EBR-11-2018-0203	10	31
1	Hair, J.F. (2010) <i>Multivariate Data Analysis</i> , 7th ed.	12	45
1	Henseler, J. (2015) <i>J. Acad. Market Sci.</i> , Vol. 43, p.115, DOI: 10.1007/s11747-014-0403-8	9	25
1	Kahneman, D. (1979) <i>Econometrica</i> , Vol. 47, p.263, DOI: 10.2307/1914185	33	42
1	Podsakoff, P.M. (2003) <i>J. Appl. Psychol.</i> , Vol. 88, p.879, DOI: 10.1037/0021-9010.88.5.879	11	44
1	Venkatesh, V. (2003) <i>MIS Quart.</i> , Vol. 27, p.425, DOI: 10.2307/30036540	17	52
1	Venkatesh, V. (2012) <i>MIS Quart.</i> , Vol. 36, p.157	10	33
2	Bollen, J., Mao, H. and Zeng, X. (2011) 'Twitter mood predicts the stock market', <i>Journal of Computational Science</i> , Vol. 2, pp.1–8	9	5
2	Bollerslev, T. (1986) 'Generalized autoregressive conditional heteroskedasticity', <i>Journal of Econometrics</i> , Vol. 31, pp.307–327	11	5

Note: TLS = total link strength

Source: Authors' analysis (2026)

Table A5 Knowledge clusters identified through document co-citation analysis (continued)

Cluster	Documents	Citations	TLS
2	Fama, E.F. (1970) 'Efficient capital markets: a review of theory and empirical work', <i>The Journal of Finance</i> , Vol. 25, pp.383–417	11	6
2	Fama, E.F. and French, K.R. (1993) 'Common risk factors in the returns on stocks and bonds', <i>Journal of Financial Economics</i> , Vol. 33, pp.3–56	9	2
2	Hochreiter, S. and Schmidhuber, J. (1997) 'Long short-term memory', <i>Neural Computation</i> , Vol. 9, pp.1735–1780	35	8
2	Markowitz, H. (1952) <i>J. Financ.</i> , Vol. 7, p.77, DOI: 10.1111/j.1540-6261.1952.tb01525.x	31	16
2	Markowitz, H. (1959) <i>Portfolio Selection: Efficient Diversification of Investments</i>	17	6
2	Murphy, J.J. (1999) <i>Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications</i>	8	4
2	Patel, J., Shah, S., Thakkar, P. and Kotecha, K. (2015) 'Predicting stock and stock price index movement using trend deterministic data preparation and machine learning techniques', <i>Expert Systems with Applications</i> , Vol. 42, pp.259–268	9	3
3	Belanche, D. (2019) <i>Ind. Manage Data Syst.</i> , Vol. 119, p.1411, DOI: 10.1108/IMDS-08-2018-0368	8	35
3	D'Acunto, F. (2019) <i>Rev. Financ. Stud.</i> , Vol. 32, p.1983, DOI: 10.1093/rfs/hhz014	9	22
3	Gomber, P. (2018) <i>J. Manage Inform. Syst.</i> , Vol. 35, p.220, DOI: 10.1080/07421222.2018.1440766	10	16
3	Jung, D. (2018) <i>Bus. Inform. Syst. Eng.</i> , Vol. 60, p.81, DOI: 10.1007/s12599-018-0521-9	11	39
3	Jung, D. (2018) <i>Electron. Mark.</i> , Vol. 28, p.367, DOI: 10.1007/s12525-017-0279-9	8	35
3	Lee, I. (2018) <i>Bus. Horizons</i> , Vol. 61, p.35, DOI: 10.1016/j.bushor.2017.09.003	9	12
3	Shanmuganathan, M. (2020) <i>J. Behav. Exp. Financ.</i> , Vol. 27, DOI: 10.1016/j.jbef.2020.100297	9	34

Note: TLS = total link strength

Source: Authors' analysis (2026)

Table A6 Major keyword clusters and their characteristics

<i>Cluster</i>	<i>Keyword</i>	<i>Occurrences</i>	<i>TLS</i>
1	Fintech	84	117
1	Stock market	71	101
1	Behavioral finance	52	90
1	Investor sentiment	31	34
1	Investor behavior	23	36
1	Cryptocurrency	21	40
1	Agent-based model	16	22
1	Volatility	16	23
1	Social media	12	15
1	Blockchain	11	22
1	Financial forecasting	10	21
1	Herding	10	13
1	Digital finance	9	10
1	GARCH	9	14
1	Financial literacy	8	18
1	Big data	7	15
1	Bitcoin	7	12
1	Bounded rationality	7	6
1	Market efficiency	6	8
1	Retail investors	6	10
1	Trading behavior	6	9
1	Trust	6	9
1	Value at risk	6	4
1	Capital asset pricing model	5	4
1	Crowdfunding	5	7
1	Fintech adoption	5	9
1	Peer-to-peer lending	5	6
1	Perceived risk	5	4
1	Systemic risk	5	8
2	Investment decision	57	82
2	Artificial intelligence	46	108
2	Neural network	43	82
2	Robo-advisor	31	47
2	Digital transformation	24	16
2	Portfolio optimization	24	32
2	Investment	21	42
2	Technical analysis	12	26

Source: Authors' analysis (2026)

Table A6 Major keyword clusters and their characteristics (continued)

<i>Cluster</i>	<i>Keyword</i>	<i>Occurrences</i>	<i>TLS</i>
2	Portfolio management	10	26
2	Portfolio selection	9	2
2	COVID-19	8	9
2	Genetic algorithm	8	4
2	Market sentiment	7	15
2	Asset allocation	6	8
2	Corporate governance	6	5
2	ESG	6	10
2	Financial risk	6	12
2	Financial risk management	6	10
2	Data science	5	16
2	Digitalization	5	9
2	Emerging markets	5	13
2	Financial instruments	5	7
2	Financial management	5	7
2	Financial services	5	8
2	Fuzzy logic	5	6
2	Risk	5	12
2	Technology adoption	5	8
3	Machine learning	92	221
3	Sentiment analysis	52	117
3	Deep learning	50	101
3	Stock market prediction	43	87
3	Market volatility	29	79
3	LSTM	28	59
3	Stock price prediction	18	34
3	Stock market volatility	13	22
3	Technical indicators	10	20
3	Time series	9	26
3	Random forest	8	22
3	Time series forecasting	7	19
3	ARIMA	6	15
3	Ensemble learning	6	10
3	Convolutional neural network	5	6
3	XGBoost	5	8
4	Financial market	33	68
4	Risk management	24	61

Source: Authors' analysis (2026)

Table A6 Major keyword clusters and their characteristics (continued)

<i>Cluster</i>	<i>Keyword</i>	<i>Occurrences</i>	<i>TLS</i>
4	Algorithmic trading	16	51
4	Reinforcement learning	12	18
4	Natural language processing	10	16
4	Deep reinforcement learning	8	25
4	Predictive analytics	7	28
4	Financial time series	6	18
4	Risk assessment	6	13
4	Fraud detection	5	15
4	High-frequency trading	5	30
4	Large language models	5	9
4	Trading strategies	5	19

Source: Authors’ analysis (2026)

Table A7 Top thematic map of research themes

<i>Themes</i>	<i>Callon centrality</i>	<i>Callon density</i>	<i>Rank centrality</i>	<i>Rank density</i>	<i>Cluster frequency</i>
Machine learning	1.661	22.897	6	5	474
Stock market	0.701	17.763	3	1	171
Fintech	2.003	22.773	7	4	448
Behavioral finance	0.480	27.170	1	7	125
Market volatility	1.609	22.935	5	6	261
Digital transformation	0.575	22.178	2	3	76
Cryptocurrency	0.728	20.845	4	2	96

Source: Authors’ analysis (2026)

Appendix B

Main information about data

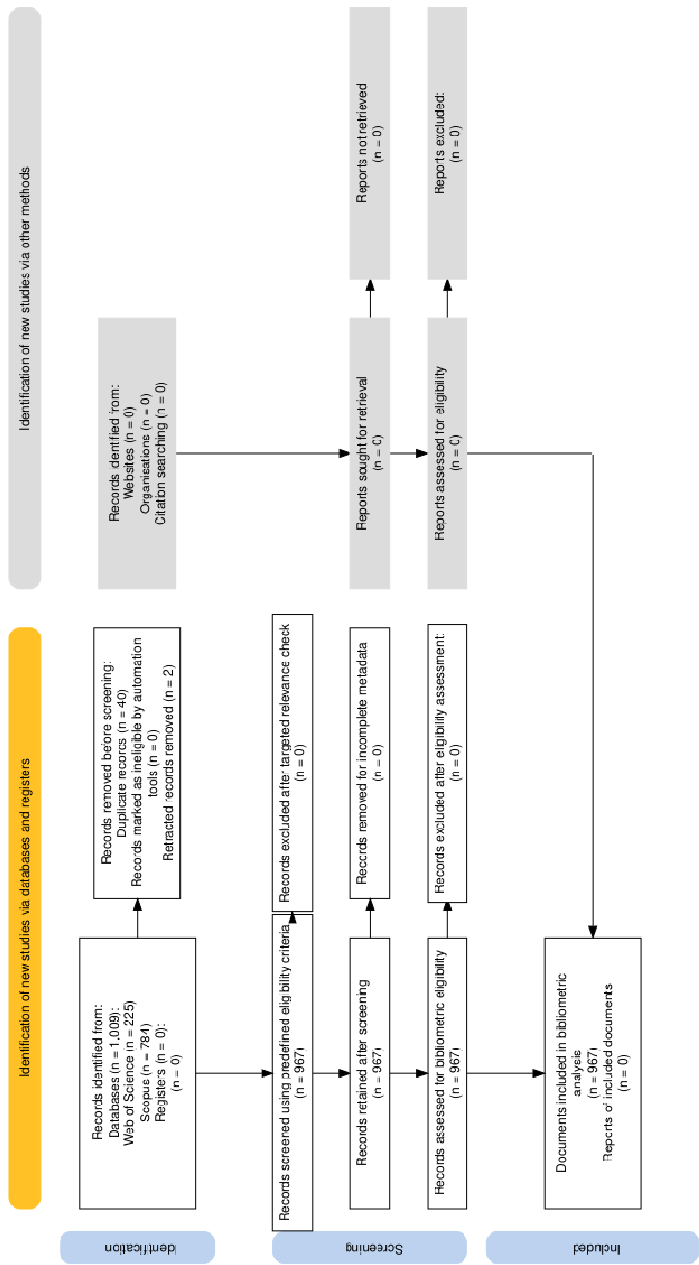
<i>Description</i>	<i>Results</i>
Timespan	1991:2025
Sources (Journals, Books, etc.)	627
Documents	967
Annual Growth Rate %	18.98
Document Average Age	4.3
Average citations per doc	11.76
References	33791
Document contents	
Keywords Plus (ID)	4683
Author's Keywords (DE)	2769
Authors	
Authors	2429
Authors of single-authored docs	115
Authors collaboration	
Single-authored docs	127
Co-Authors per Doc	3.12
International co-authorships %	6.929
Document types	
Article	396
Article; book chapter	3
Article; early access	9
Article; proceedings paper	1
Book	18
Book chapter	101
Conference paper	383
Editorial material	1
Proceedings paper	44
Review	10
Short survey	1

Source: Authors' analysis (2026)

Appendix C

Flow diagram of data identification and screening

Figure A1 Study selection process based on the PRISMA 2020 flow diagram (see online version for colours)



Source: Haddaway et al. (2022)