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Technology and automation in financial trading: A bibliometric review

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ABSTRACT

In this bibliometric study, the significant transformations in the financial sector brought about by automation and technological advancements from 1984 to 2022 are explored. A total of 863 articles is analyzed, and a consistent upward trajectory in research focused on fast trading technologies and algorithmic strategies is identified. The key findings reveal that the research is grouped into five thematic clusters, ranging from algorithmic trading and machine learning to systemic risks associated with high-frequency trading and the impacts of algorithmic trading on market quality. This study encapsulates the evolving landscape of financial markets, emphasizing emerging trends in cryptocurrencies and machine learning, which will continue to shape future research directions. In conclusion, five macroareas and ten specific future research areas are proposed.

1. Introduction

The financial sector has undergone a substantial transformation in recent decades that has been driven by automation and technological advancements (Aquilina et al., 2022; Zaharudin et al., 2022; Clapham et al., 2023). The practice of rapidly executing transactions in financial markets, often using sophisticated computer algorithms, is commonly known as fast trading. In fast trading, the speed of signal transmission is crucial (Shkilko and Sokolov, 2020). Fast trading encompasses a range of strategies that leverage cutting-edge technologies, such as high-speed networks, colocation facilities, and powerful computer systems, to enable traders to respond to market changes in real time and quickly execute orders and trades. According to Clapham et al. (2023), the automation of the buy side has specifically led to changes in trading technology and the development of related trading strategies, such as algorithmic trading (AT) and high-frequency trading (HFT). HFT is a type of automated algorithmic trading that has become the dominant trading strategy in financial markets due to its ability to operate at extremely rapid speeds (Arifovic et al., 2022). According to the European Parliament, HFT is a subset of AT that is distinguished by infrastructure that is intended to minimize latency, such as colocation, the absence of human intervention in the generation, routing, and execution of orders, and high intraday message volumes, which include order, quote, and cancellation messages (European Parliament and Council, 2014). The Netherlands Authority of Financial Markets

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(NAFM) defines HFT as "a form of automated trading based on mathematical algorithms" (Netherlands Authority of Financial Markets, 2010, p.8). The Australian Securities and Investments Commission (ASIC) defines HFT as "a subset of high-speed algorithmic trading" (Australian Securities and Investments Commission, 2010, p.30). HFT is regarded as a subset of AT and exhibits many of its traits. High-frequency traders are different from other AT investors in that they can process fresh information, locate profitable trading opportunities, and analyze news flow considerably more quickly than human traders can (Zaharudin et al., 2022). HFT outperforms human traders in terms of speed partly because it uses sophisticated machines (Menkveld, 2013).

High-frequency traders thus differ significantly from conventional market players by combining speed and information processing (Bongaerts and Van Achter, 2016). The U.S. Securities and Exchange Commission has observed that there is no precise definition of HFT (U.S. Securities and Exchange Commission (SEC), 2010, 2014). As a result, authorities, researchers, and market participants have described HFT differently. Computer technology, electronic trading, electronic markets, and automated trading are all strongly related to HFT, although they are not interchangeable and provide only a partial picture of HFT (Hossain, 2022; Zaharudin et al., 2022). HFT and other trading activities, such as AT, are sometimes confused due to the absence of a clear definition (Hossain, 2022). Therefore, HFT has been falsely linked to problems such as the 2010 flash crash (Moosa and Ramiah, 2015; Zaharudin et al., 2022). Investors, regulators, and researchers are paying increasing attention to the impact of automation and technology on financial trading (Dubey et al., 2021; Myklebust, 2021). These studies have extensively considered issues such as liquidity (Hendershott et al., 2011; Bongaerts et al., 2016), price discovery (Brogaard et al., 2014a; Manahov and Hudson, 2014), latency arbitrage (Manahov, 2016a; Wah and Wellman, 2016), and transaction costs, among others (Brogaard et al., 2014a; Stoikov and Waeber, 2016).

Although information technology (IT)-based trading may have some advantages, it has also given rise to questions about the fairness and stability of the market. Critics of HFT claim that HFT can lead to increased volatility and extreme events such as flash crashes (U.S. Securities and Exchange Commission (SEC), 2010; Kirilenko and Lo, 2013) and can give large institutional investors unfair advantages, potentially resulting in market manipulation (Dalko and Wang, 2020; Hao et al., 2023).

Additionally, Breckenfelder (2019) discovered that HFT competition can boost speculative trading, resulting in a decline in market liquidity and an increase in short-term volatility. Financial authorities worldwide have recently enacted new laws and regulations to address these concerns and promote openness and fairness in IT-based trade. Through specific controls, the Markets in Financial Instruments Directive II (MiFID II) recognizes the dangers associated with AT and HFT. Despite the advantages of new trading technologies, there are directives aimed at addressing the potential risks associated with the increased use of AT and HFT. According to Recital (63) of MiFID II, to mitigate the abovementioned risks, firms that use high-frequency algorithmic trading techniques or engage in AT are required to implement a combination of specific risk controls directed at them, as well as direct electronic access providers and trading venues that these firms use (European Parliament and Council, 2014). Similarly, the "Supervisory Statement on Algorithmic Trading" published in 2021 by the Bank of England contains regulations for HFT. For companies that engage in HFT, this document includes rules and regulations that address issues such as risk management, governance, cybersecurity, compliance, and trading activity oversight (Bank of England, 2021).

Despite the rapid advancements in technology and automation within financial trading, a comprehensive academic literature review on this topic is lacking. This paper aims to fill this gap by summarizing research developments in this area through a bibliometric approach. Previous research that aligns most closely with our study includes works by Ruiz Roque da Silva et al. (2022), Anas et al. (2023), and Hussain et al. (2023). Ruiz Roque da Silva et al. (2022) focused on the significant research concerning trading algorithms in the cryptocurrency market from 2008 to 2021. Anas et al. (2023) scrutinized the literature on cryptocurrencies that utilize high-frequency data. On the other hand, Hussain et al. (2023) explored the applications of high-frequency data in broader financial trading, centering their analysis on the 100 most influential HFT papers. Diverging from these works, the current study significantly broadens this perspective. While the importance of HFT is acknowledge, this study encompasses a broader spectrum, examining 'automated' or 'technologically driven' trading in a comprehensive manner, thereby offering deeper insight into the various ways in which technology is reshaping financial trading.

This paper aims to offer a more reliable and unbiased analysis that can quantitatively generate key research clusters or themes and thereby review the current state-of-the-art and valuable avenues for future research in the field of technology and automation in financial trading. To do this, we apply bibliometric techniques. As Ali et al. (2021) argued, formulating research questions is essential for conducting a review in a more structured and logical order. Therefore, we derive the following six research questions for our review:

1. *#RQ1: What is the publication trend in this research topic?*
2. *#RQ2: Which countries, authors, journals, and institutions contribute to this research field?*
3. *#RQ3: Which are the most influential publications in this field of study?*
4. *#RQ4: What is the intellectual structure of this research field?*
5. *#RQ5: Which are the research fronts of this research field?*
6. *#RQ6: What are the future research directions?*

The above research questions will help in understanding the "what," "how," and "where" of research on this specific topic. This paper presents a study of 863 papers on technology and automation-driven financial trading from 1984 to 2022. The Scopus database and VOS Viewer software are used.

The remainder of the paper is organized as follows. Section 2 provides an overview of the methodology used to identify the research articles that are reviewed and analyzed in Section 3. Sections 4 and 5 provide a detailed analysis. Section 6 discusses the direction of current research and potential future research opportunities based on bibliometric analysis. Finally, Section 7 presents the conclusions

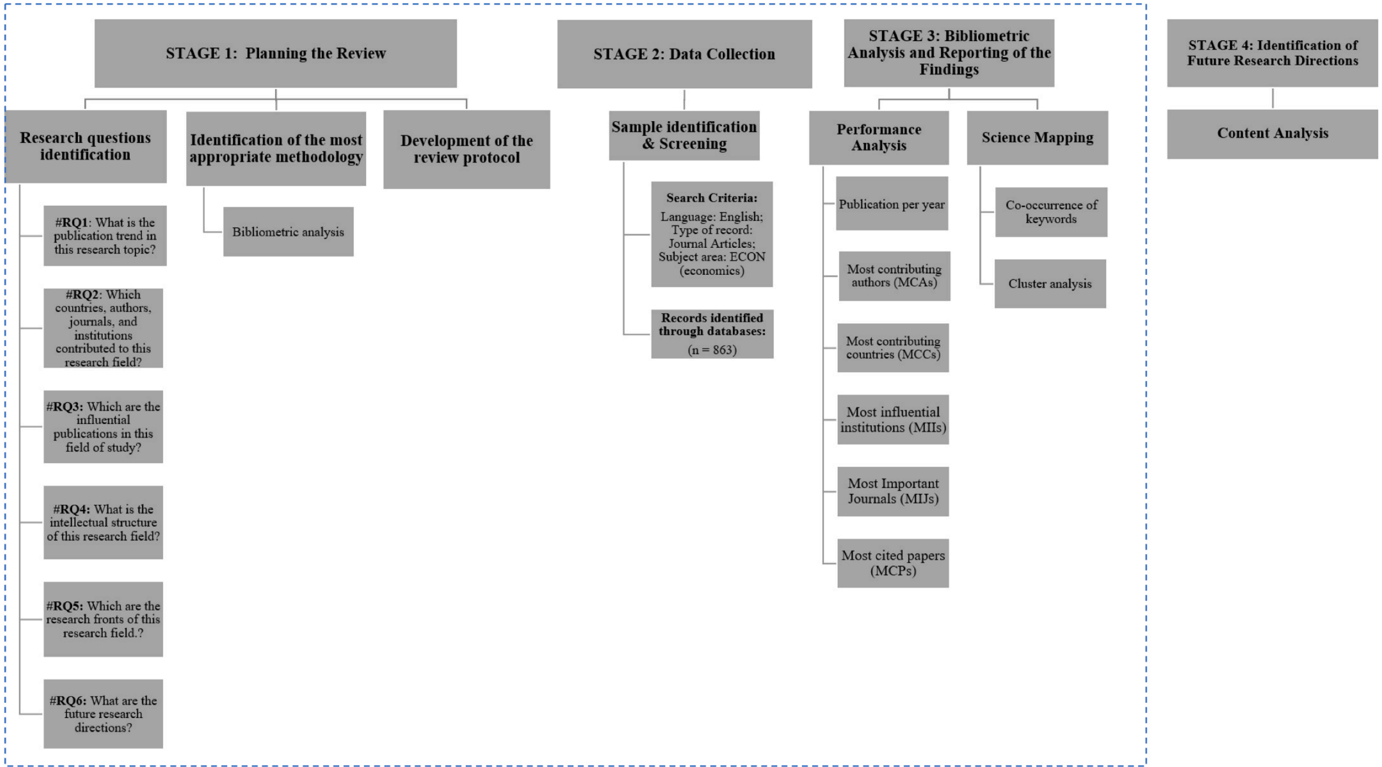

Fig. 1. Methodological flowchart.

Table 1
Research questions.

Bibliometric analysis		
Research question(s)	**Research objective(s)**	**Bibliometric tool(s)**
#RQ1: What is the publication trend in this research topic?	To understand how the research field has evolved.	Performance analysis (descriptive analysis; publication analysis)
#RQ2: Which countries, authors, journals, and institutions contributed to this research field?	To determine which countries, authors and institutions contributed the most to the field and were the most cited.	Performance analysis (descriptive analysis; citation analysis)
#RQ3: Which are the influential publications in this field of study?	To understand which research articles are the most influential in the field.	Performance analysis (descriptive analysis; citation analysis)
#RQ4: What is the intellectual structure of this research field?	To identify the research hotspots and their evolution.	Science mapping (coword analysis)
#RQ5: Which are the research fronts of this research field?	To determine the main subresearch fields in this research area.	Intellectual structure analysis (content analysis)
#RQ6: What are the future research direction?	To determine unexplored research gaps to be analyzed in future works.	Intellectual structure analysis (content analysis)

Source: Authors' elaboration

and limitations of the study.

2. Methodological framework, design parameters, and techniques

The intellectual structure of scientific fields of study can be determined using bibliometric studies, which are objective and quantitative techniques (Garfield, 1979). These techniques have received increasing attention in management research areas such as entrepreneurship (e.g., Rey-Martí et al., 2016; Servantie et al., 2016; Xu et al., 2021), family business (e.g., López-Fernández et al., 2016; Caputo et al., 2018; Ratten et al., 2020), business ethics (e.g., Özmen Uysal, 2010), and human resource management (e.g., Fernandez-Alles and Ramos-Rodrigues, 2009; Mohammad Saif and Islam, 2022; Bahuguna et al., 2023). Surprisingly, bibliometric research on the subject of finance has received considerable attention (Bahoo, 2020; Bahoo et al., 2020; Baker et al., 2020; Baker et al., 2021; Khan et al., 2022). Recent bibliometric research articles in finance cover a wide range of topics, from reflective summaries of well-established themes that emphasize research stream identification to relatively new fields of study that present numerous potential future research questions (Khan et al., 2022). Overall, bibliometric analysis has grown in popularity over the past few years as a result of numerous variables, such as the accessibility of software tools and the enhanced ability to manage massive amounts of data (Donthu et al., 2021). The objective quantitativeness of the bibliometric technique, which helps prevent the sample selection bias inherent in systematic reviews, is one of its benefits. Additionally, bibliometric methods are useful for identifying trends in a particular field's conventional research topics, coauthorships, cocitations, and journal performance (Baker et al., 2020). To improve our understanding of the chosen issue and assess the growth of the study field in accordance with current trends, we used a bibliometric analysis with a quantitative approach (Zupic and Čater, 2015; Vallaster et al., 2019). We incorporated qualitative content analysis into our study to gain a deeper understanding and add context to the quantitative findings. As depicted in Fig. 1, we employed a four-step method. Alongside performance analysis and science mapping, content analysis, as supported by recent scholarly work (see, for example, Migliavacca et al., 2022; Khan et al., 2022; Carè et al., 2023; Carè et al., 2024), enabled us attain a more nuanced comprehension of the research landscape. This method is particularly suitable for uncovering prevalent themes, trends, and research gaps. By integrating content analysis, we improved our quantitative data from performance analysis and science mapping with qualitative insights, thereby providing a holistic view of the field. This comprehensive approach underlines not only the quantitative metrics of research impact and collaboration networks but also the thematic and contextual dimensions that shape scholarly discourse.

In Table 1, the research questions are presented together with their corresponding research objectives and analysis methods. As previously mentioned, a multistep methodology is applied to reveal the intellectual structure of the research field. This methodology mainly consists of performance analysis, science mapping, and content analysis.

Performance analysis is a popular bibliometric technique that can provide important insights into the output, influence, and productivity of a research community (see, e.g., Carè et al., 2023; Carè et al., 2024). The numbers of publications and citations are the most widely used metrics for determining an author's impact. In particular, an author's productivity is connected with the number of publications, and their influence on the scientific community is correlated with the number of citations (Merigó and Yang, 2017). The h-index, impact factor, and publication and citation counts are several common indicators used in performance analysis. Researchers can determine publishing patterns, the authors who are most frequently referenced, the nations that contribute the most to a research field, and the journals that are most active in that field by analyzing these indicators (Waltman and Van Eck, 2012). According to Cobo et al. (2011), performance analysis focuses on uncovering development trends and identifying the most productive authors and journals in a field, whereas science mapping attempts to study the conceptual structure of a research topic. On the other hand, science mapping aims to show how scientific fields are organized and develop, as mentioned by Zupic and Čater (2015). Science mapping is a visual representation of the relationships between various academic specialties, fields, materials, and authors. The visualization of similarities technique, as reported by van Eck and Waltman (2010, 2014), was used to facilitate the science mapping analysis. The open access bibliometric network analysis application VOSviewer was used to construct the knowledge maps (van Eck and Waltman, 2010). A content analysis of the literature data was also performed to uncover cognitive schemas, which are also known as emergent research

Table 2
Search protocol.

Task	Description
Sample collection: Keyword identification according to the objective of the study	Before conducting the review, the search strings were tested to identify inconsistencies.
Sample collection: Document type	The search was limited only to journal articles (ar), short surveys (sh), and reviews (re).
Sample collection: Language	Only peer-reviewed articles published in English
Sample collection: Time span	Excluded 2023
Sample collection: Subject area	"ECON"
Sample collection: Main keyword identification	1. Algorithmic trading 2. Electronic trading 3. Automated trading 4. Trading algorithm* 5. High-frequency trading 6. Computerized trading 7. Quantitative trading 8. Colocation trading 9. Machine trading 10. Nonhuman trading 11. Low-latency trading 12. Robotic trading 13. Black box trading 14. Program trading

Source: Authors' elaboration

themes or categories. This method was also used to comprehend the subthemes more deeply.

2.1. Database curation

To conduct this study, we utilized a double-tiered procedure for identifying and reviewing articles. First, we defined relevant search terms for Scopus database mining. Scopus was chosen due to its wide coverage of peer-reviewed research in reputable journals and its widespread use in the academic community (Alshater et al., 2020; Baker et al., 2020; Donthu et al., 2020). Second, we applied specific criteria to determine which articles to include in our database for the bibliometric and content analyses. This process ensured that only the most relevant and high-quality articles were included in our study, aiding in ensuring the accuracy and validity of our findings. By utilizing this rigorous approach, we aimed to provide a comprehensive and reliable analysis of our research topic.

2.2. Keyword extraction for database searching

The selection of keywords for this study was based on a preliminary review of the literature. We conducted a search on Google Scholar using the keyword "high-frequency trading" and briefly reviewed the first 50 studies to identify any other terms that have been frequently or synonymously used in the literature. In addition, we examined previously published articles that appeared in journals ranked ABS3 or higher to identify potential keywords for the database search. Based on this review, we considered all the terms listed in Table 2 as potential keywords for our study. We ensured that these terms were relevant and commonly used in the literature to accurately capture the scope of our study. This approach allowed us to comprehensively identify and select the most relevant and appropriate keywords.

To ensure the relevance and suitability of the chosen keywords, the initial list was refined by the authors through discussion and careful consideration. Before proceeding with the review, we conducted a test search of the search strings to identify any inconsistencies or errors. We also removed any keywords that did not yield any results during the test search. After refining the list of keywords, we selected the search strings summarized in Table 2 to conduct the database search in March 2023. This approach allowed us to accurately and comprehensively scan the chosen database for articles relevant to our study.

2.3. Article selection

To ensure a high level of quality, we selected only peer-reviewed articles written in English in the categories of economics, econometrics, and finance (ECON). To ensure the integrity and completeness of our analysis, we limited our dataset to studies published up to the end of 2022, excluding 2023 to avoid including partial data. In more detail, we used an evaluation approach based on the methodology proposed by Liao et al. (2017) and divided it into three phases. In the first phase, we established precise criteria for inclusion and exclusion (see Appendix 1). All research articles that passed the initial screening underwent a thorough review of their abstracts and full texts during the eligibility phase. In the subsequent phase, two examiners conducted an independent and rigorous review and decided whether to include each article. Next, we integrated the retrieved references into a Microsoft Excel spreadsheet for screening. The first examiner reviewed the references based on predetermined inclusion and exclusion criteria. To maintain consistency, the second examiner independently checked 5 % of the references based on established practices. We selected research articles that mainly focused on discussing, examining, or analyzing our research topic as the main content based on the inclusion criteria outlined in Appendix 1.

Using these article selection criteria and search strings, we created a comprehensive database of 863 documents. We saved the results in the research information system (RIS) and comma-separated value (CSV) formats with appropriate citation and bibliographic information for further analysis.

2.4. Standardization procedures

Typographical mistakes and ambiguities in bibliographic data occasionally need to be fixed (Ruiz-Parrado et al., 2022). Franceschini et al. (2016) focused on the potential for inaccuracies in bibliometric databases regarding author names, issue years, titles, journal names, and keywords. The dataset was manually checked for errors to prevent such problems. In addition, our analysis is based on a bibliometric method that uses keyword processing. Unfortunately, neither the majority of journals need a set of standard keywords nor do writers choose their keywords according to standardized criteria (e.g., acronyms, plural and singular forms). The rules outlined in Appendix 2 were manually applied to the keywords before the science mapping analysis began.

2.5. Mapping techniques

After completing the keyword standardization steps, the articles were exported to VOSviewer software, a freely available computer program developed for constructing and viewing bibliometric maps, for bibliometric analysis. VOSviewer generates a map using a cooccurrence matrix, which is based on a three-step process. The first step involves calculating a similarity matrix based on the cooccurrence matrix. In the second step, the VOS mapping technique is applied to the similarity matrix to create a map. In particular, the VOSviewer software utilizes the similarity matrix to create a two-dimensional map, where the distance between items reflects their similarity, denoted as Sij. The fundamental concept of the VOS mapping technique is that items with higher similarity are positioned closer together, while dissimilar items are placed farther apart. As a result, the program minimizes the weighted sum of the squared Euclidean distances between all pairs of items.

We utilized the "cooccurrence" feature in VOSviewer to generate clusters of frequently occurring keywords. These clusters are formed by the association strength of the keywords (Van Eck et al., 2006; Van Eck and Waltman, 2007; Ali et al., 2021) and group together articles with similar characteristics. The software applies a specific equation to calculate the association strength:

$$AS_{ij} = \frac{C_{ij}}{w_i w_j} \quad (1)$$

In Eq. (1), cij represents "the number of cooccurrences of items i and j," while wi and wj refer to "either the total number of occurrences of items i and j or the total number of cooccurrences of these items." It has been demonstrated that the similarity between items i and j, as calculated by Eq. (1), is proportional to the ratio between the observed number of cooccurrences of i and j and the expected number of cooccurrences of i and j, assuming that their cooccurrences are statistically independent (van Eck and Waltman, 2010, p. 531). The weight of the squared distance in the summation increases with the greater similarity between the two items (van Eck and Waltman, 2010; Barnett et al., 2020).

To prevent the creation of trivial maps, where all items are located at the same position, a constraint was applied to ensure that the average distance between any two items was equal to 1. Let us denote the number of items to be mapped as 'n'. The VOS mapping technique aims to create a two-dimensional map where the positions of items 1 to n accurately reflect the similarity 'sij' between any pair of items i and j. The goal is to position items with high similarity closer together and items with low similarity farther apart. The VOS mapping technique achieves this goal by minimizing the weighted sum of the squared Euclidean distances between all pairs of items. The weight assigned to the squared distance is determined by the similarity between two items. To ensure that all items do not end up at the same location, a constraint is applied to enforce an average distance of 1 between any two items. Mathematically, the objective function to be minimized can be expressed as follows:

$$V(x_1, \ldots, x_n) = \sum_{i<j} S_{ij} \|x_i - x_j\|^2 \quad (2)$$

where the vector $x_i = (x_{i1}, x_{i2})$ represents the position of item i on a two-dimensional map and ||•|| represents the Euclidean norm. The objective function is minimized while adhering to the given constraint

$$\frac{2}{n(n-1)} \sum_{i<j} \|x_i - x_j\| = 1 \quad (3)$$

The optimization problem of minimizing Eq. (2) while satisfying Eq. (3) is addressed through a numerical solution in two stages. First, the constrained optimization problem is transformed into an unconstrained problem. Then, a majorization algorithm, specifically a variant of the stress majorization of a complicated function (SMACOF) algorithm developed by Borg and Groenen (1997), is used to solve the unconstrained problem (van Eck and Waltman, 2010; Markscheffel and Schröter, 2021). To improve the probability of discovering a globally optimal solution, the majorization algorithm can be executed multiple times, each with a distinct randomly generated initial solution (Van Eck, Waltman, 2010); Barnett et al., (2020)).

Moreover, the determination of the number of clusters in VOSviewer is based on a resolution parameter. By adjusting this

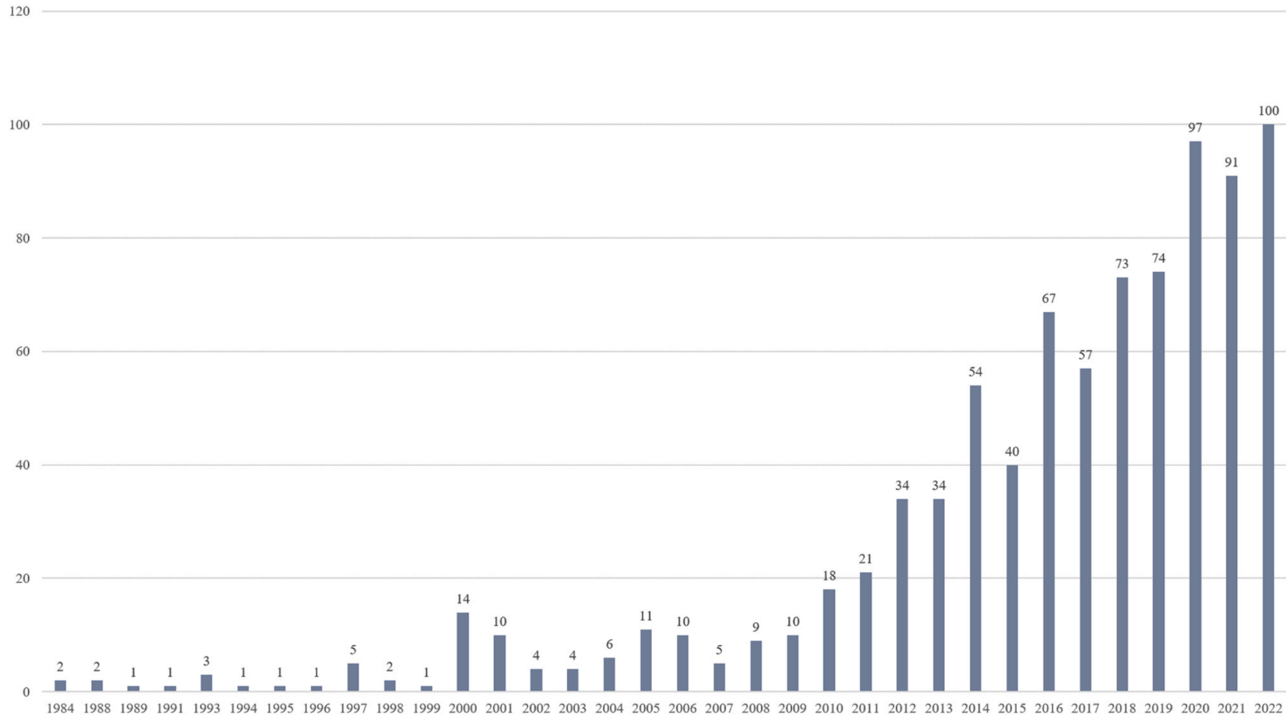

Fig. 2. Articles published per year.

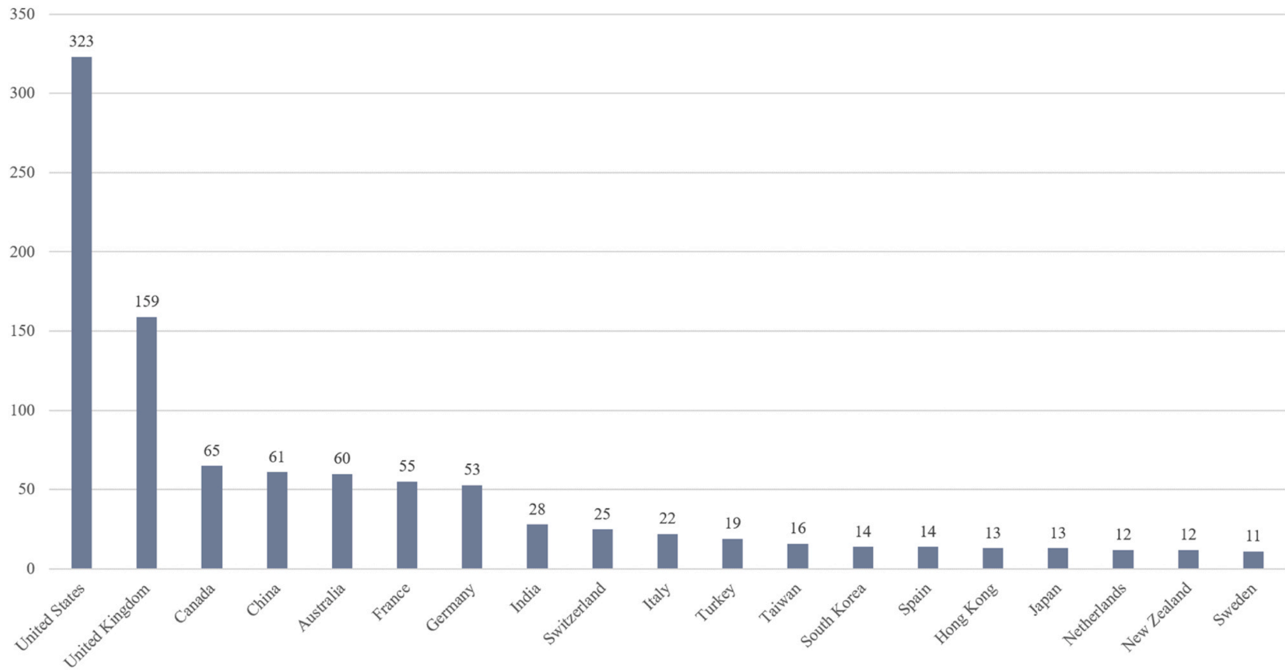

Fig. 3. Most contributing countries.

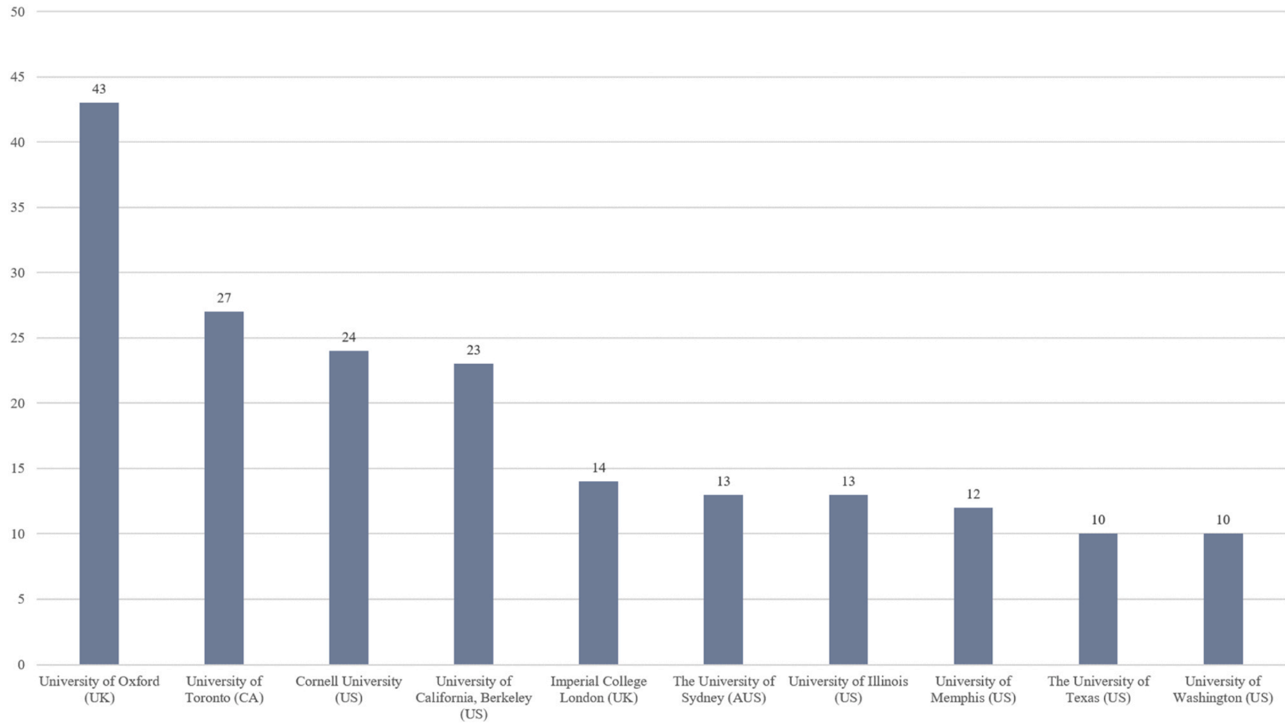

Fig. 4. Most influential institutions.

parameter, users can control the level of granularity in the displayed network, with larger values yielding more clusters. The clustering algorithm employed in VOSviewer is a variation of the modularity function initially introduced by Newman (2004) and Newman and Girvan (2004) for node clustering in networks. To optimize this function, a local moving algorithm is employed (Waltman and van Eck, 2013; Markscheffel and Schröter, 2021).

Finally, the map is translated, rotated, and reflected in the third step (van Eck and Waltman, 2010).

To ensure consistent results, VOSviewer applies three transformations to the solution:

(1) Translation: The solution is shifted so that it is centered at the origin, ensuring that the overall position of the items is adjusted without changing their relative positions.
(2) Rotation: The solution is rotated to maximize the variance along the horizontal dimension. This transformation, known as principal component analysis, helps in aligning the items in a way that emphasizes the most significant patterns in the data.
(3) Reflection: If the median of the x-coordinates of the items is greater than zero, the solution is reflected in the vertical axis. Similarly, if the median of the y-coordinates is greater than zero, the solution is reflected in the horizontal axis. These reflections help to achieve a consistent orientation of the map (van Eck and Waltman, 2010).

By applying these three transformations, VOSviewer ensures that the results are consistent and reliable, allowing for meaningful interpretations and comparisons across different analyses.

3. Performance analysis: Exploration of the evolution of research on a topic

The following subsections address the first three RQs (see Table 1), offering a detailed examination of the publication trends, the key contributors by country, author, journal, and institution, and highlighting the influential publications that have shaped the field.

3.1. Publication trends

Fig. 2 illustrates the annual number of publications throughout the duration of our selected timeframe. The x-axis spans from 1984 to 2022, while the y-axis represents the number of articles published each year. Evidently, the graph depicts a consistent upward trajectory in research activity within this domain. Notably, the number of published papers exhibited stability and relative scarcity between 1984 and 1999. However, a gradual and sustained surge in scholarly interest is observable from 2010 onward, culminating in a marked upswing between 2020 and 2022. Specifically, between 2018 and 2022, 435 papers were published, representing a notable 50 % of the total dataset.

The notable increase in publications from 2010 onward, particularly the significant increase between 2018 and 2022, can be attributed to several key factors. First, this period coincides with rapid advancements and widespread adoption of new technologies in the financial sector. The emergence and integration of artificial intelligence, machine learning, and advanced algorithms have revolutionized the landscape of automated trading, sparking increased academic interest and research.

Additionally, significant regulatory changes and market evolution were observed during this period, potentially driving scholarly exploration. The aftermath of the global financial crisis in 2008 also played a crucial role, as it prompted a reevaluation of trading practices and risk management strategies, leading to a surge in research focusing on automated and technology-driven trading.

Moreover, the growing accessibility and availability of massive datasets, along with improved computational power, have enabled more sophisticated and in-depth analyses in this field. This technological democratization has not only expanded research capabilities but also attracted a broader range of scholars to the domain of automated trading. Finally, the increased volatility and dynamic nature of global financial markets, partly driven by geopolitical uncertainties and economic shifts, have further heightened the relevance and urgency of research in automated trading technologies, as both practitioners and scholars seek to understand and leverage these developments for enhanced market efficiency and stability.

3.2. Influential countries and institutions

Studies in this field were published in a total of 64 countries. Fig. 3 shows the country-level numbers of papers in this field (n>10). Most research is conducted in the USA, with a total of 323 publications. The United Kingdom emerged as the country with the second highest number of publications (159), followed by Canada (65).

The institutional data were retrieved from the Scopus database and analyzed according to the number of articles published. The statistics of the institutions reveal the top contributing institutions in the field, which are presented in Fig. 4.

Fig. 4 clearly shows that the University of Oxford (UK), the University of Toronto (CA), and Cornell University (US) were the top three contributing institutes, publishing 43, 27, and 24 articles, respectively, in this field.

3.3. Most influential journals

The articles were published in 228 different journals. Fifty percent of journals published only one article, and 17 % of journals published more than 10 articles. This finding suggests that the literature on this topic is spread across a diverse range of journals. To better understand the distribution of publications, we compiled a list of the top journals based on the number of articles published (n>10), which is presented in Table 3. Together, these journals accounted for 44 % of the analyzed articles. Notably, Quantitative

Table 3
Top contributing journals according to number of articles (n>10).

Journal	<2015	2015	2016	2017	2018	2019	2020	2021	2022	TOTAL	H-Index	SJR	SJR Rank
Journal of Finance	8	1	0	1	0	1	1	0	0	12	317	16,463	4
Journal of Financial Economics	3	3	2	2	2	1	1	6	1	21	273	10,418	8
Research in International Business and Finance	1	0	2	5	0	0	5	0	1	14	216	1043	51
Finance Research Letters	0	1	1	1	2	2	3	3	4	17	62	2007	94
Journal of Financial Markets	14	0	3	2	3	4	1	2	5	34	63	1661	116
Journal of Banking and Finance	9	3	0	2	0	1	1	2	2	20	172	1466	135
Economy and Society	3	0	7	0	1	0	0	0	1	12	95	1384	150
Journal of Empirical Finance	3	0	2	0	2	2	2	0	2	13	80	1196	183
SIAM Journal on Financial Mathematics	4	3	1	1	0	1	2	3	2	17	32	1141	194
Journal of Futures Markets	20	3	2	1	2	0	4	1	2	35	58	0989	223
Quantitative Finance	19	4	4	7	3	5	4	3	3	52	73	0865	258
Pacific Basin Finance Journal	4	1	1	5	2	0	1	1	0	15	62	0824	273
Financial Review	12	0	1	0	0	2	1	0	1	17	50	0692	324
European Journal of Finance	6	0	1	1	0	0	0	2	1	11	39	0578	379
Applied Economics	1	1	0	1	2	1	2	1	2	11	91	0563	392
Applied Mathematical Finance	3	0	0	2	2	2	4	2	2	17	395	0561	395
Computational Economics	0	0	1	1	1	2	2	3	3	13	43	0454	497
International Journal of Theoretical and Applied Finance	3	0	2	0	0	1	2	2	1	11	35	0357	607
Investment Management and Financial Innovations	6	0	0	0	2	0	3	0	0	11	20	0199	886
Algorithmic Finance	7	2	3	1	0	1	0	0	1	15	9	0103	1163
Journal of International Financial Markets Institutions and Money	5	1	0	1	2	1	0	3	0	13	n.a	n.a	n.a

Source: Authors' elaboration

Finance emerged as the leading journal, with 52 articles published, followed by the Journal of Futures Markets and the Journal of Financial Markets, which published 35 and 34 articles, respectively. These three journals alone accounted for 14 % of the total sample, indicating their significant contribution to the literature on this topic.

3.4. Most cited articles

The number of citations an article receives measures its quality and impact and reflects its contribution to advancing existing theories. Highly cited articles are generally regarded as more influential than those with fewer or no citations (Culnan, 1986). Analyzing citation counts helps to identify the most influential articles, journals, and countries (Liu, 1993). Citation data were collected from the Scopus database and analyzed for citation statistics. The main objective of citation statistics is to identify and analyze the most influential and highly cited articles. The top 20 articles with the most citations are listed in Table 4.

Table 4 clearly shows that Hendershott et al. (2011) received the most citations, with 674, followed by Brogaard et al. (2014b), with 453, and Hasbrouck and Saar (2013), with 331. Hendershott et al. (2011) and Brogaard et al. (2014b) also received the highest field-weighted citation impacts (FWCIs) of 26.78 and 24.14, respectively. The FWCI is utilized to assess the influence of a specific topic or discipline within the realm of scientific research and considers the average citation rates of publications in a broader reference set and the citation rates of works published within a particular field. By accounting for factors such as the field's size and overall citation patterns, the FWCI helps estimate the relative importance and impact of the field. The FWCI provides a normalized measure of influence, facilitating meaningful comparisons across different domains or specialties. A higher FWCI indicates a greater impact within the field (Purkayastha et al., 2019; Zanotto and Carvalho, 2021; Bahmanabadi et al., 2023).

3.5. Most influential authors

Author data were obtained from the Scopus database. Table 5 displays the top contributing authors (n≥5), revealing that Jaimungal, Cartea, and Frino were the leading contributors. These authors have collaborated with numerous other researchers, and their collective publications in the field amount to twenty-three, twenty-two, and eleven articles, respectively.

4. Science mapping: Exploration of the structural and dynamic characteristics of the research domain

Science mapping is a powerful tool for revealing a research domain's structural and dynamic characteristics (Cobo et al., 2011) and is based on the two-dimensional visualization map created using VOSviewer, a text-mining approach that allows for analyzing bibliometric data (van Eck and Waltman, 2010; Cobo et al., 2011). The nodes in the map represent items (e.g., articles, scholars, countries,

Table 4
Articles with the most citations.

#	Document Title	Authors & Publication Year	Journal Title	<2019	2019	2020	2021	2022	2023	Total	FWCI
				2137	561	618	651	615	234	4816	
1	Does algorithmic trading improve liquidity?	Hendershott et al. (2011)	Journal of Finance	379	59	76	75	65	20	674	26,78
2	High-frequency trading and price discovery		Review of Financial Studies	180	60	63	73	55	22	453	24,14
3	Low-latency trading	Hasbrouck and Saar (2013)	Journal of Financial Markets	151	38	41	44	39	18	331	17,25
4	Location matters: An examination of trading profits	Hau (2001)	Journal of Finance	215	18	18	20	22	5	298	2,85
5	High frequency trading and the new market makers	Menkveld (2013)	Journal of Financial Markets	140	34	36	28	26	14	278	16,05
6	The Flash Crash: High-Frequency Trading in an Electronic Market	Kirilenko (2017)	Journal of Finance	37	54	42	55	52	22	262	20,34
7	The high-frequency trading arms race: Frequent batch auctions as a market design response	Budish et al. (2015)	Quarterly Journal of Economics	78	34	38	48	41	19	258	15,2
8	High frequency market microstructure	O'Hara (2015)	Journal of Financial Economics	56	40	35	45	41	13	230	9,46
9	Recent trends in trading activity and market quality	Chordia et al. (2011)	Journal of Financial Economics	130	26	22	20	23	6	227	8,22
10	Individual investors and financial disclosure	Lawrence (2013)	Journal of Accounting and Economics	61	26	37	35	46	19	224	4,84
11	Rise of the machines: Algorithmic trading in the foreign exchange market	Chaboud et al. (2014)	Journal of Finance	86	28	41	34	25	9	223	11,88
12	Algorithmic trading and the market for liquidity	Hendershott and Riordan (2013)	Journal of Financial and Quantitative Analysis	82	15	25	25	23	8	178	10,07
13	High-frequency trading in a limit order book	Avellaneda and Stoikov (2008)	Quantitative Finance	88	11	19	26	23	5	172	1,95
14	Statistical arbitrage in the US equities market	Avellaneda and Lee (2010)	Quantitative Finance	74	18	20	16	23	10	161	2,67
15	Very fast money: High-frequency trading on the NASDAQ	Carrion (2013)	Journal of Financial Markets	81	14	20	16	16	10	157	7,62
16	The diversity of high-frequency traders	Hagströmer & Norden (2013)	Journal of Financial Markets	67	25	22	12	18	9	153	7,82
17	Equilibrium fast trading	Biais et al. (2015)	Journal of Financial Economics	43	25	21	19	25	9	142	7,26
18	Market technologies and the pragmatics of prices	Muniesa (2007)	Economy and Society	95	7	9	12	11	2	136	5,53
19	Stock price prediction using support vector regression on daily and up to the minute prices	Henrique et al. (2018)	Journal of Finance and Data Science	1	23	21	42	36	11	134	11
20	Should securities markets be transparent?	Madhavan et al. (2005)	Journal of Financial Markets	93	6	12	6	5	3	125	3,34

Source: Authors' elaboration

Table 5
Top contributing authors.

Author	Frequency	References	Affiliation	Country	H – index
Jaimungal, S.	23	Casgrain et al. (2022), Fouque et al. (2022), Cartea et al. (2021), Ning et al. (2021), Casgrain and Jaimungal (2020), Cartea et al. (2020), Cartea et al. (2020), Casgrain and Jaimungal (2019), Cartea et al. (2019), Huang et al. (2019), Cartea et al. (2019a), Cartea et al. (2019b), Cartea et al. (2018), Jaimungal et al. (2017), Cartea et al. (2017), Cartea and Jaimungal (2016a), Cartea and Jaimungal (2016b), Cartea and Jaimungal (2016c), Cartea et al. (2016), Cartea and Jaimungal (2015a), Cartea and Jaimungal (2015b), Cartea et al. (2014), Cartea and Jaimungal (2013)	University of Toronto	CA	16
Cartea, Á.	22	Cartea et al. (2022), Cartea, Sánchez-Betancourt (2021), Cartea et al. (2021), Cartea et al., (2020a), Cartea and Wang (2020), Cartea et al., (2020b), Cartea and Wang (2019), Cartea et al. (2019a), Cartea et al. (2019b), Cartea et al., (2019c), Cartea et al., (2019d), Cartea et al. (2018), Cartea et al. (2017), Cartea and Jaimungal (2016a), Cartea and Jaimungal (2016b), Cartea and Jaimungal (2016c), Cartea et al. (2016), Cartea and Jaimungal (2015a), Cartea and Jaimungal (2015b), Cartea et al. (2014), Cartea and Jaimungal (2013), Cartea and Penalva (2012).	University of Oxford	UK	18
Frino, A.	11	Frino et al. (2021), Zhou et al. (2020), Frino et al. (2020), Frino et al. (2017a), Frino et al. (2017b), Frino et al. (2017c), Frino et al. (2014), Bortoli et al. (2004), Aitken et al. (2004), Frino et al. (2020), Frino et al. (2000), Brailsford et al. (1999)	Rozetta Institute	AUS	23
Garcia, P.	9	Huang et al. (2022), He et al. (2021), Wang et al. (2020), Frino et al. (2020), Couleau et al. (2020), Hu et al. (2020), Couleau et al. (2019), Lehecka et al. (2014), Wang (2014), Frank and Garcia (2011)	University of Illinois	US	24
Tse, Y.	9	Indriawan et al. (2021), Martinez et al. (2011), Gutierrez and Tse (2009), Ning and Tse (2009), Tse et al. (2006a), Tse et al. (2006b), Fung et al. (2005), Cheng et al. (2005), Tse and Zabotina (2001)	University of Missouri-St. Louis	US	27
Manahov, V.	9	Manahov (2021), Manahov et al. (2019), Manahov and Zhang (2019), Manahov (2016a), Manahov (2016b), Manahov (2016c), Manahov et al. (2015), Manahov and Hudson (2014), Manahov et al. (2014)	University of York	UK	9
Hendershott, T.	8	Brogaard et al. (2017), Hendershott and Madhavan (2015), Brogaard et al. (2014a), Ding et al. (2014), Brogaard et al. (2014b), Hendershott and Riordan (2013), Hendershott et al. (2011), Barclay et al. (2006)	University of California, Berkeley	US	24
Brogaard, J.	6	Brogaard and Garriott (2019), Baron et al. (2019), Brogaard et al. (2018), Brogaard et al. (2017), Brogaard et al. (2014a), Brogaard et al. (2014b)	The University of Utah	US	13
Donnelly, R.	6	Donnelly (2022), Cartea et al. (2020), Donnelly and Lorig (2020), Donnelly and Gan (2018), Cartea et al. (2018), Cartea et al. (2017)	King's College London	UK	3
Sensoy, A.	6	Akyildirim et al. (2021), Nguyen et al. (2021), Sensoy et al. (2021), Aslan and Sensoy (2020), Corbet et al. (2019), Mensi et al. (2019)	Bilkent Üniversitesi	TR	31
Hudson, R.	6	Manahov et al. (2019), Hudson et al. (2017), Manahov et al. (2015), Cai et al. (2015), Manahov and Hudson (2014), Manahov et al. (2014)	Hull University Business School	UK	19
Van Vliet, B.	6	Cooper et al. (2023), Li et al. (2018), Van Vliet (2017), Cooper et al. (2016), Cooper et al. (2015), Kumiega and Van Vliet (2012)	Illinois Institute of Technology	US	7
Dunis, C.L.	5	Dunis et al. (2013), Dunis et al. (2012), Dunis et al. (2011), Dunis et al. (2010), Dunis et al. (2009)	Liverpool John Moores University	UK	16
Irwin, S.H.	5	Irwin et al. (2022), Huang et al. (2022), Wang et al. (2020), Yan et al. (2018), Wang (2014)	University of Illinois	US	26
Laws, J.	5	Dunis et al. (2013), Dunis et al. (2012), Dunis et al. (2011), Dunis et al. (2010), Dunis et al. (2009)	University of Liverpool Management School	UK	12
Levendovszky, J.	5	Ceffer et al. (2019), Levendovszky et al. (2019), Ceffer et al. (2018), Sipos et al. (2017), Sipos and Levendovszky (2013)	Budapest University of Technology and Economics	HU	10
McInish, T.H.	5	Kemme et al. (2022), Jain et al. (2021a), McInish et al. (2020), Jain et al. (2016), Ferris et al. (1997)	University of Memphis	US	25
O'Hara, M.	5	O'Hara and Zhou (2021a), O'Hara and Zhou (2021b), O'Hara et al. (2019), O'Hara (2015), O'Hara et al. (2014)	Cornell University	US	43

*Affiliation information is based on the most recent publication
Source: Authors' elaboration

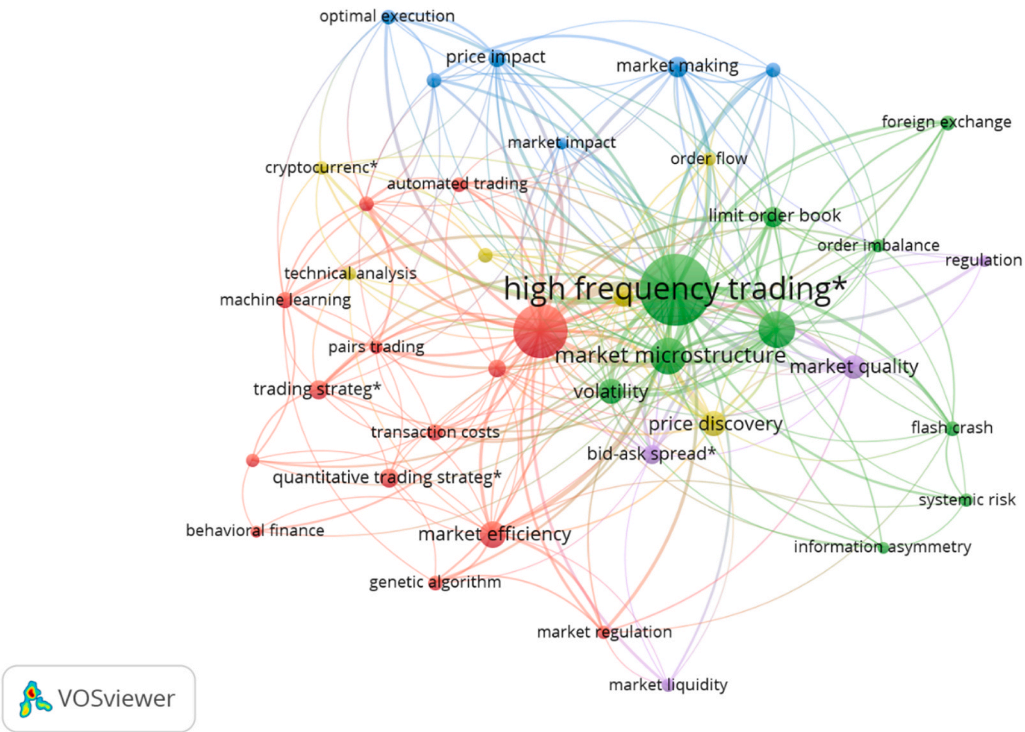

Fig. 5. Network visualization of cooccurring keywords.

journals, institutions or keywords), and their size and label reflect their occurrence frequency. Links between nodes reflect associations between them, such as cooccurrence, and the link's thickness indicates the association's strength. The map can also be used to group nodes into different clusters based on their characteristic similarities. This approach provides valuable insights into the connections and trends within a particular research domain (Small, 1999; Rizzi et al., 2014; Kabongo, 2020).

The present study considers cooccurrence analysis of keywords under science mapping. Cooccurrence analysis is a technique used to identify the frequency with which a keyword appears with other keywords and can reveal research gaps and potential areas for further exploration (Farrukh et al., 2020). Specifically, coword analysis examines the joint appearances of two terms in a given text to identify a scientific domain's conceptual and thematic structure (Bautista-Bernal et al., 2021). In this study, we conducted a clustering analysis based on the cooccurrence of keywords using VOSviewer to create a network of items. The software generates clusters represented by different colors, each representing a set of closely related nodes and lines representing the links between the keywords. The size of the circles of each item is proportional to the relevance of the words shown (Waltman et al., 2010; Van Eck and Waltman, 2014). The map shown in Fig. 5, which involves all keywords and uses a full counting method, reveals the research trends and areas of interest.

The technique applied by VOSviewer uses the "smart local moving algorithm" introduced by Waltman and Van Eck (2013) to solve an optimization problem. We selected keywords with a minimum of 8 occurrences to obtain a representative sample of different clusters. We obtained 5 different clusters—with a minimum cluster size of 3—that define the main research areas, which are summarized in Table 6 and discussed in the following sections.

4.1. Research stream overview

In this section, we present the findings from our cluster analysis using science mapping techniques. This analysis explores the intellectual structure (RQ4) and identifies the research fronts (RQ5) within this field.

4.1.1. Cluster 1–Algorithmic strategies, market efficiency, and machine learning

Cluster 1 articles focus on algorithmic trading (154) (e.g., Chang and Chou, 2022; Li et al., 2022; Muravyev and Picard, 2022), automated trading (13) (e.g., Creamer and Freund, 2010; Vezeris et al., 2020), and machine learning (15) (e.g., Arifovic et al., 2022; Frattini et al., 2022; Guo et al., 2022). Additionally, concepts such as behavioral finance (e.g., Kumiega and Van Vliet, 2012; Fang et al., 2022), market efficiency, and market regulation are explored, indicating an interest in understanding the behavioral factors influencing financial markets and the effectiveness of regulatory mechanisms. The articles in this cluster also focus on specific trading strategies such as pairs trading (e.g., Endres and Stübinger, 2019; Cerda et al., 2022; Luo et al., 2022; Xiang et al., 2022), which involves exploiting price differentials between related assets, and statistical arbitrage, which utilizes statistical models to identify trading opportunities. High-frequency data analysis, a key aspect of modern trading, is another theme present in this cluster (e.g.,

Table 6
Cluster composition.

Cluster	Keywords and frequencies	Focus
#Cluster 1: Red	algorithm trad* (154), automated trading (13), behavioral finance (8), genetic algorithm (11), high-frequency data (18), machine learning (15), market efficiency (36), market regulation (10), pairs trading (9), quantitative trading strateg* (19), statistical arbitrage (13), stock market (10), trading strateg* (21), transaction costs (14)	*Algorithmic Strategies, Market Efficiency, and Machine Learning*
# Cluster 2: Green	flash crash (11), foreign exchange (11), high-frequency trading* (269), information asymmetry (8), limit order book (23), liquidity (69), market microstructure (73), order imbalance (9), systemic risk (9), volatility (32)	*Dynamics of High-Frequency Trading: Market Microstructure, Liquidity, and Systemic Risk*
# Cluster 3: Blue	adverse selection (13), market impact (8), market making (23), optimal execution (12), price impact (17), stochastic control (12)	*Strategies and Impacts in Financial Trading: Market Making, Optimal Execution, and Adverse Selection*
# Cluster 4: Yellow	Cryptocurrenc* (10), electronic trading (23), futures (12), order flow (9), price discovery (35), technical analysis (9)	*Emerging Trends in Digital Markets: Cryptocurrencies, Electronic Trading, and Price Discovery*
# Cluster 5: Purple	Bid–ask spread* (19), market liquidity (10), market quality (30), regulation (8)	*Market Dynamics and Regulation: Bid–Ask Spread, Liquidity, and Market Quality*

Source: Authors' elaboration

Stübinger, 2019; Yang and Xue, 2021). Furthermore, in this cluster, the significance of transaction costs in trading is acknowledged, and the development and implementation of quantitative trading strategies that consider these costs is emphasized (e.g., Tse and Zabotina, 2001; Stoikov and Waeber, 2016; Yang et al., 2018). The cluster also comprises articles that refer to the impact of fast trading technologies and machine learning on financial markets (see, e.g., Harikrishnan et al., 2021; Arifovic et al., 2022). Machine learning methods have significantly advanced in terms of predicting financial time series (Ghosh and Ransinchung, 2022). For example, Tran et al. (2018), Sezer and Ozbayoglu (2018), and Singh et al. (2020) utilized neural networks for time series prediction, Xue and Li (2018) employed convolutional neural networks, and Mallqui and Fernandes (2019) utilized artificial neural networks, support vector machines, and ensemble algorithms to predict the direction, maximum, minimum, and closing prices of Bitcoin. In general, numerous machine learning techniques have demonstrated the ability to capture nonlinear relationships among relevant factors in time series data (Atsalakis and Valavanis, 2009; Cavalcante et al., 2016). Among these techniques, artificial neural networks (ANNs) have gained widespread popularity for time series forecasting due to their data-driven and self-adaptive nature, enabling them to capture nonlinear behaviors without imposing statistical assumptions on the data (Tay and Cao, 2001; Lu et al., 2009; Kumbure et al., 2022). Similarly, support vector machines (SVMs) (Huang et al., 2005) and their variations (Enke and Thawornwong, 2005; Pan et al., 2017) are widely used due to their promising predictive capabilities. Various models based on fuzzy theory, including fuzzy time series approaches (Yolcu and Alpaslan, 2018), adaptive network-based fuzzy inference systems (Wei et al., 2011), Takagi–Sugeno–Kang (TSK)-type fuzzy systems (Chang and Liu, 2008), and other related variants (Pal and Kar, 2019), have been proposed. As stated by Cavalcante et al. (2016), in recent years, there has been growing interest among machine learning and pattern recognition communities in exploring various techniques to extract valuable features from extensive datasets in a hierarchical manner (Bengio et al., 2013).

4.1.2. Cluster 2–Dynamics of high-frequency trading: Market microstructure, liquidity, and systemic risk

Cluster 2 articles focus on the topics of market microstructure (73), high-frequency trading (269), and risk factors affecting financial markets. This cluster includes articles on elucidating various aspects related to flash crashes, foreign exchange markets, and information asymmetry.

One of the main aspects analyzed is the relationship between systemic risk and HFT, which has garnered significant interest and debate among researchers and financial experts. Pagano et al. (2019) defined systemic risk as the risk of a disruption in a financial system that results in widespread instability in asset prices, significant losses for investors and financial intermediaries, and the potential collapse of crucial financial intermediaries. Within the realm of HFT, Kumiega et al. (2016) discussed how systemic risk can arise due to several factors, including the synchronized actions of prominent algorithmic traders, the occurrence of unintended order messages and transactions due to unregulated algorithms, or vulnerability to cybersecurity breaches. Sánchez Serrano (2021) identified four primary systemic vulnerabilities associated with HFT: (i) adverse selection in orders, which can lead to the displacement of non-HFT market makers during periods of market stress; (ii) correlation of positions and herd behavior; (iii) market power, which may create barriers to entry through technological costs; and (iv) a potentially negative impact on price discovery under certain circumstances. One aspect of HFT that is often discussed in relation to systemic risk is its role in market flash crashes. Flash crashes have attracted significant attention in the academic literature (see, for example, Lange et al., 2016; Seyfert, 2016; Thompson, 2017; Virgilio, 2019; Yagi et al., 2023). There have been numerous studies on the impact of HFT on the market during flash crashes, such as the flash crash of May 6, 2010 (Sornette and Von der Becke, 2011; Golub et al., 2012; Kirilenko et al., 2017). For instance, Sornette and Von der Becke (2011) expressed a strong belief that HFT would inevitably result in a greater occurrence of crashes. They argued that if there was substantial aggressive high-frequency selling that frequently wiped out all 10 levels of market depth before the offer price could adjust downward, it would contribute to flash crashes such as the one on May 6, 2010. Similarly, Golub et al. (2012) concluded that HFT activity is likely responsible for mini-flash crashes, considering the speed and magnitude of these market disruptions. Several

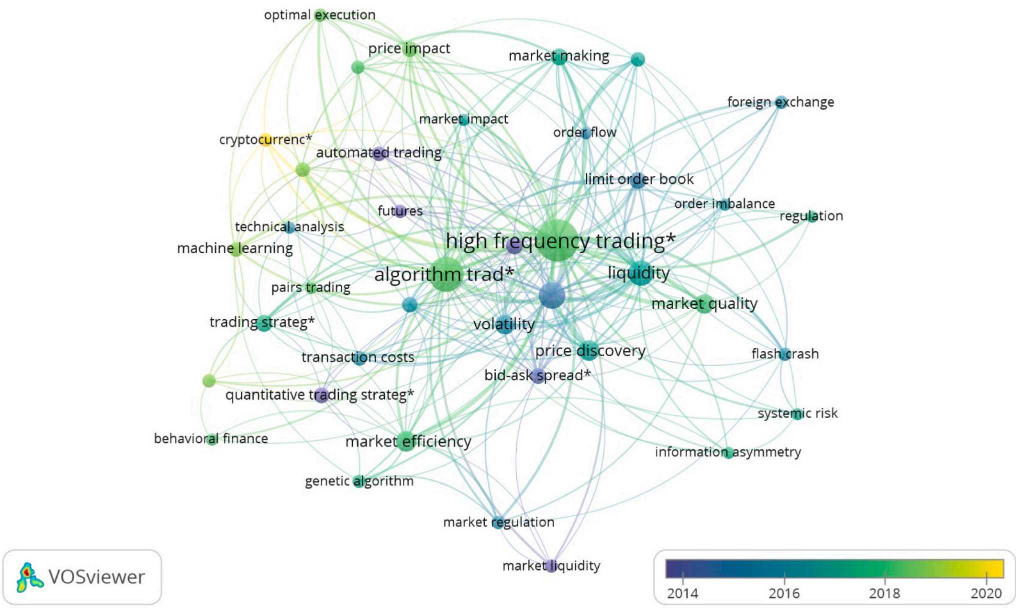

Fig. 6. Overlay visualization chart.

studies have examined the impact of order imbalance, referring to the discrepancy between sell and buy orders in the market. One area of research focuses on the order book imbalance (OBI), which represents the difference between the numbers of buy and sell orders in the order book surrounding the best quote. Empirical analysis suggests that HFT may rely on the correlation between OBI and future returns (Cao et al., 2009; Goldstein et al., 2023). For example, Cartea and Jaimungal (2015a) and Cartea and Jaimungal (2015b) explored the relationship between OBI and high-frequency price changes and proposed a linear model to describe their correlation. Goldstein et al. (2023) asserted that as the number of buy orders relative to sell orders in the limit order book increases, the future relative level of stock prices also increases. Stoikov (2017) introduced a concept known as the microprice, which adjusts the mid-price by incorporating OBIs and bid–ask spreads by discovering that the microprice outperforms traditional mid-prices and volume-weighted mid-prices as a predictor of short-term movements in mid-prices. The articles in this cluster also examined information asymmetry in the context of its impact on market efficiency and trading strategies (e.g., Wee and Yang, 2016; Jain et al., 2021b). Additionally, the articles in this cluster highlight the importance of market volatility (see Assaf, 2005; Ma et al., 2018; Bazzana and Collini, 2020; Yang and Xue, 2021) and its implications for trading and risk management.

4.1.3. Cluster 3–Strategies and impacts on financial trading: market making, optimal execution, and adverse selection

Cluster 3 articles focus on the concepts of market impact (8), optimal execution (12), and risk management in the context of trading activities and various aspects related to adverse selection (13), market making (23), price impact (17), and stochastic control (12).

Enhanced connectivity in high-speed markets enhances investors' capacity to find appealing quotes across fragmented markets, resulting in increased gains from trade. Additionally, enhanced connectivity enables rapid traders to access information ahead of slower traders, leading to adverse selection and the subsequent occurrence of negative externalities (Biais et al., 2015). Adverse selection is a central focus within this cluster, with articles exploring its impact on trading decisions and the strategies employed to mitigate its effects. Similarly, articles in this cluster focus on the concept of order flow toxicity, which refers to adverse selection risk but is applied to the world of HFT. In their study, Easley et al. (2012) introduced the term "order flow toxicity" to describe the risk of adverse selection in the context of HFT. According to the authors, "order flow is considered toxic when it adversely selects market makers who may unknowingly provide liquidity at a loss" (p. 1458). Thus, adverse selection extends beyond the issue of asymmetric information and encompasses additional risks associated with liquidity provision. Kang et al. (2020) investigated the correlation between HFT, order flow toxicity, and short-term price volatility in the KOSPI 200 futures market, considering both regular and turbulent market conditions.

The articles in the cluster also explore the use of volume-synchronized probability of informed trading (VPIN) as a metric to determine the extent of informed trading activity in financial markets, examining the relationship between trading volume and price changes (e.g., Andersen and Bondarenko, 2014b; Easley et al., 2014; Pöppe et al., 2016; Yildiz et al., 2020). VPIN, initially proposed by Easley et al. (2012) as a measure of order flow toxicity, has gained significant recognition as an effective proxy for assessing order flow toxicity, as evidenced in studies by Low et al. (2018) and Kang et al. (2020). However, there is criticism concerning its application, as highlighted by Andersen and Bondarenko (2014), (2015).

Market impact, another crucial aspect, refers to the effect of a trade or series of trades on market prices and liquidity. The articles in this cluster examine market impact in terms of price movement and the ability to execute trades effectively while minimizing adverse effects on market conditions.

A central theme in Cluster 3 is optimal execution, highlighting the significance of executing trades in a way that maximizes efficiency and minimizes costs. Optimal execution involves considerations such as timing, order size, and liquidity. Within the context of optimal execution, Bechler and Ludkovski (2015) and Cartea et al. (2018) utilized order flow information to develop models for optimal execution, considering market impact and informational costs.

The articles in this cluster also explore market making, which involves providing liquidity by quoting bid and ask prices and examining the impact of market making on market dynamics and trading strategies, as well as the role of market makers in maintaining orderly markets and their interactions with other participants. Roncella and Ferrero (2022) investigated the evolution of market making, primarily driven by the widespread adoption of HFT, which now constitutes more than 50 % of the total US equity trading volume.

Furthermore, price impact, which refers to the relationship between incoming orders (buy or sell orders) and resulting price changes, is analyzed within this cluster. Articles within the cluster explore the factors influencing price impact and develop models and techniques to effectively estimate and manage it (e.g., Jia et al., 2020; Philip, 2020; Chi et al., 2021).

4.1.4. Cluster 4–Emerging trends in digital markets: Cryptocurrencies, electronic trading, and price discovery

Cluster 4 articles explore various aspects related to cryptocurrencies, futures, order flow, price discovery, and technical analysis. A central theme in this cluster is cryptocurrency trading, emphasizing the trading and investment activities involving the three mainstream cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), and Litecoin (LTC). Cryptocurrency trading explores the unique characteristics and challenges associated with cryptocurrency markets, including their volatility, liquidity, and regulatory considerations. Ahn and Kim (2021) investigated the impact of emotion on Bitcoin price fluctuations and found that future Bitcoin returns are not associated with emotional factors. However, they discovered that Bitcoin trading volume and return volatility are significantly predicted by a range of emotions. Emotions have an effect on the overall variation in investor returns, which in turn may influence the financial market by causing extraordinary price movements. Several researchers have dedicated their attention to analyzing technical indicators and patterns for trading in cryptocurrency markets. For instance, Ha and Moon (2018) explored the use of genetic programming (GP) to identify favorable technical patterns in the cryptocurrency market. Similarly, Hudson and Urquhart (2019) discovered that technical trading rules offer investors substantial predictive power and the potential for profitability. Another study by Corbet et al. (2019) examined different technical trading rules, such as moving average oscillators and trading range break-out strategies, to generate enhanced returns in cryptocurrency markets.

The articles in this cluster also focus on futures trading, which involves the trading of standardized contracts for the future delivery of assets at predetermined prices. Specifically, futures trading explores the role of index futures markets in facilitating HFT. Due to their high liquidity, index futures markets allow high-frequency traders to frequently enter and exit positions, ultimately aiming to achieve a flat end-of-day position. As a result, high-frequency traders likely show a preference for index futures, as noted by Lee (2015).

Price discovery, a process by which market participants determine the fair value of an asset through the interaction of supply and demand, is another key theme within this cluster. Given the importance of price discovery in financial markets, there has been significant interest in academic research. For example, Chaboud et al. (2014) demonstrated that the involvement of algorithmic traders' tradeable orders had a positive impact on enhancing price efficiency. This was achieved by mitigating opportunities for triangular arbitrage within the foreign exchange market. After analyzing the NASDAQ market, Carrion (2013) revealed that higher levels of marketable orders submitted by high-frequency traders led to increased market efficiency. Similarly, Brogaard et al. (2014b) noted that high-frequency traders play a role in facilitating price discovery through their execution of tradeable orders, particularly by aligning their trades with persistent price changes. Nevertheless, an investigation by Brogaard et al. (2019) focusing on a Canadian equity market yielded unexpected findings. In contrast to earlier research that underscored the significance of market orders, their study revealed a different trend. Specifically, they found that limit orders made a more substantial contribution to price discovery. Surprisingly, high-frequency traders' limit orders contributed more than twice the amount of their market orders in terms of enhancing price discovery.

4.1.5. Cluster 5–Market dynamics and regulation: Bid–ask spread, liquidity, and market quality

Articles in Cluster 5 focuses on the bid–ask spread, market liquidity, market quality, and regulation. Market quality is a central focus within Cluster 5 and includes various dimensions such as the liquidity, transparency, fairness, and efficiency of financial markets. Numerous empirical studies have been conducted to assess the impact of AT on various dimensions of market quality, including liquidity, price spreads, adverse selection, trade-related price discovery, and asset price volatility (Kelejian and Mukerji, 2016). However, the findings remain inconclusive, as some studies indicate a positive impact of AT, while others report a negative impact (Dubey et al., 2021). Others have documented errors in colocation dates that appear to have a pronounced effect on conclusions drawn in some papers using an international context (Aitken et al., 2015, 2017, 2023). Several researchers have suggested that HFT firms generally contribute to an enhancement of market quality. For instance, Chang and Chou (2022) examined the effects of different algorithmic traders on market quality and the price discovery process, ultimately concluding that algorithmic trades do not have a detrimental effect on market quality. Hasbrouck and Saar (2013) demonstrated that low-latency activity improves liquidity and reduces short-term volatility, while Brogaard et al. (2014b) argued that high-frequency traders enhance price efficiency through their utilization of marketable orders. On the other hand, alternative research perspectives suggest that HFT activity may have more harmful consequences. For instance, Gao and Mizrach (2011) found that during periods of market stress, HFT firms tend to reduce their provision of liquidity. Importantly, the literature presents diverse viewpoints regarding the impact of HFT on market quality, with varying conclusions drawn about both positive and negative effects.

Table 7
Future research directions.

Macro Area	Potential Future Research Questions	Suggested Readings
Microstructure Issues and Corporate Finance	1. How do AT and HFT impact corporate finance through market manipulation, long-term equity value trends, and stock price informativeness? 2. What are the effects of microstructure developments on the ability of firms to raise future equity or the probability and pricing of mergers? 3. How does microstructure affect the quality and rate of corporate innovation?	Aitken et al. (2023), Jung et al. (2023)
Cryptocurrencies and Entrepreneurial Activities	4. How does trading of cryptocurrencies impact the frequency and quality of entrepreneurial activities? 5. In what ways can entrepreneurial activities legitimize cryptocurrencies and their trading?	Kumari et al. (2024), Rawhouser et al. (2024), Rakshit et al. (2022)
Digital Currencies and Market Efficiency	6. How could central banks' potential switch to digital currencies impact the efficiency of exchange, trading costs, and investment?	Keister and Sanches (2023), Schilling et al. (2024)
Machine learning and cryptocurrencies	7. What are the most effective machine learning models for predicting short-term and long-term price movements in various cryptocurrencies? 8. What is the impact of global crises, such as the COVID-19 pandemic, on cryptocurrency markets, and how can predictive models incorporate these macroeconomic shocks along with public sentiment to enhance forecasting accuracy? 9. How can machine learning algorithms be designed to detect and prevent the use of cryptocurrencies in illicit activities, such as money laundering, considering the varying regulatory frameworks across different countries?	Ren et al. (2022), Awotunde et al. (2021)
Enhancing HFT Identification with Machine Learning Algorithms	10. How can machine learning algorithms be optimized to identify high-frequency trading patterns in real-time financial data?	Bazzana and Collini (2020), Alaminos et al. (2023), Goudarzi and Bazzana (2023)

Source: Authors' elaboration

4.2. *Evolution of the research domain*

We obtained a detailed representation of the evolution of the research domain over time using the overlay visualization tool provided by VOSviewer. This visualization effectively showcases the dynamic evolution of research subjects, their interconnections, and trends within the field. Specifically, the overlay visualization map (Fig. 6) maintains uniformity in display, node size, and clusters compared to that of the network visualization map (Fig. 5). However, the distinguishing feature lies in the color scheme alteration, which stems from incorporating a chronological parameter. In this instance, the VOSviewer calculates an average publication year, which is then depicted using a continuous color scale ranging from blue to yellow, with green denoting the median (McAllister et al., 2022).

According to our analysis, the latest emergent themes are cryptocurrencies and machine learning. These two terms are the most recent focal points within the field. The discovery of these tendencies not only clarifies the direction in which research is currently ongoing but also opens new study directions. The dynamic interaction between cryptocurrencies and machine learning offers scholars a chance to explore unexplored territory and make new discoveries that could fundamentally alter our understanding of the subject. As the digital landscape continues to evolve, these emergent themes offer an open invitation for further investigation and scholarly contributions. In essence, the pronounced trend toward topics such as cryptocurrencies and machine learning can be largely attributed to the dual forces of technological evolution and financial market development. The proliferation of digital currencies and the increasing complexity of financial transactions demand innovative approaches to market analysis and prediction, thus propelling machine learning to the forefront of research. Cryptocurrencies, a relatively new asset class, have disrupted traditional financial paradigms, creating fertile ground for academic inquiry into their implications for market dynamics, regulation, and security. Concurrently, advancements in computational power and data analytics have rendered previously impossible research feasible, facilitating complex modeling and real-time processing, which are essential for high-frequency and algorithmic trading studies. Furthermore, the evolution of the financial market, characterized by increased automation, the integration of global markets, and the emergence of new financial instruments, necessitate a deeper understanding of these sophisticated elements, another factor driving research attention.

On the other hand, certain terms appear to have reached a point of saturation, as they were among the first to be extensively explored. Concepts such as "bid–ask spread" and "market liquidity," while fundamental in their own right, have undergone thorough investigation over time. These terms, while well established, indicate the maturity of research in these areas. As we acknowledge the comprehensive body of knowledge they have generated, it is also interesting to witness the emergence of new frontiers such as cryptocurrencies and machine learning, which signal the evolving nature of the field. The shift in research focus, as visualized in Fig. 6, not only reflects the natural progression of academic curiosity but also mirrors the rapid technological advancements and transformative changes sweeping through financial markets. This ongoing interplay between technology and financial practices continues to expand the horizons of research and opens up new questions for scholars to investigate, indicating a lively and dynamic field that keeps pace with the very markets it studies.

5. Discussion

The analysis revealed a consistent upward trajectory in research activity within the studied domain. A gradual and sustained surge in scholarly interest became evident from 2010 onward, culminating in a significant increase in publications during 2020 and 2022. By examining the influential countries and institutions, the USA was the primary contributor, followed by the United Kingdom and Canada. The University of Oxford, the University of Toronto, and Cornell University emerged as the top three contributing institutions, further highlighting their prominence in this field.

The analysis of influential journals revealed a diverse distribution of publications across numerous journals. However, Quantitative Finance, the Journal of Futures Markets, and the Journal of Financial Markets stood out as the leading journals in terms of the number of articles published, collectively contributing significantly to the literature in this area.

Furthermore, the examination of the most cited articles demonstrated the impact and influence of specific research contributions. The articles by Hendershott et al. (2011), Hasbrouck and Saar (2013), and Brogaard et al. (2014b) emerged as the most cited, showcasing their substantial influence in the field. Finally, the analysis revealed five distinctive clusters that encapsulate the evolving landscape of research in financial markets. The articles in Cluster 1 focused on a comprehensive exploration of algorithmic trading, automated trading, and machine learning techniques. Researchers within this cluster delved into behavioral finance, market efficiency, and trading strategies such as pairs trading and statistical arbitrage. They also recognized the significance of transaction costs in trading and explored the impact of fast trading technologies and machine learning on financial markets. This cluster highlights the continuous evolution of trading strategies and technologies, keeping pace with the dynamic financial landscape. Cluster 2 articles focused on the relationship between systemic risk and HFT, scrutinizing flash crashes, order flow toxicity, and market volatility. Here, researchers assessed the impact of HFT on market conditions and trading strategies, emphasizing the critical role of market makers and price impacts. This cluster underscores the ongoing debate surrounding the risks and rewards associated with HFT in modern financial markets.

The articles in Cluster 3 explored adverse selection, order flow toxicity, and the use of VPIN as a metric for assessing order flow toxicity. The cluster emphasizes the importance of optimal execution, market making, and price impact in trading strategies. Researchers also delved into the dynamics of market impact and execution efficiency in financial markets.

Cluster 4 articles present studies on technical indicators and pattern analyses for cryptocurrency trading, futures trading exploration, and price discovery examination. Here, researchers assessed the impact of emotions on cryptocurrency price fluctuations and delved into the role of technical trading rules in achieving profitability. This cluster highlights the growing interest in cryptocurrency trading and the development of trading strategies in this emerging field. In Cluster 5 articles, the impact of algorithmic trading (AT) on various dimensions of market quality, including liquidity, price spreads, and adverse selection, was assessed. Researchers within this cluster offered diverse viewpoints on the effects of AT on market quality, with some emphasizing its positive contributions and others highlighting potential risks. This cluster underscores the ongoing debate surrounding the impact of AT on market liquidity and regulatory frameworks.

The evolution of this research domain, as depicted in the overlay visualization, showcases emerging trends in cryptocurrencies and machine learning. These areas represent the latest frontiers in financial market research, offering opportunities for further exploration and insights. As the financial landscape continues to evolve, researchers can delve into new territories and contribute to the ever-evolving understanding of this dynamic field.

6. Future research directions

Much of the focus on AT and HFT has been on microstructure issues. How do AT and HFT affect liquidity, manipulation, spreads, and related questions? However, one area that has received scant attention includes the broader corporate finance implications of AT and HFT. That is, microstructure developments have consequences for corporate finance. The channels through which microstructure affects corporate finance include deviations from fundamental equity valuations, such as in the case of market manipulation, impacts on long-term equity value trends, the ability of firms to increase future equity, the ability of insiders to profit from proprietary information, the long-term orientation of firms' management, stock price informativeness, and liquidity; in turn, this can impact the probability and price of mergers and the quality and rate of corporate innovation, among other things (Cumming et al., 2020). The use of new technologies such as cryptocurrencies and machine learning exacerbates the impact of microstructure events on corporate finance outcomes. Many cryptocurrencies are used alongside other entrepreneurial initiatives. Exactly how cryptocurrency trading impacts the frequency and quality of these entrepreneurial activities is another topic open for investigation. Entrepreneurial activities can be influenced by cryptocurrency trading and legitimize cryptocurrency and its trading (Phillips et al., 2023). Cryptocurrencies can potentially revolutionize entrepreneurship and innovation but also present significant challenges. Chen (2018) emphasized their potential to democratize entrepreneurship and innovation, with the latter noting their role in fundraising for startups. Lin and Nestarcova (2022) discussed the relationship between cryptocurrencies and traditional funding methods, such as venture capital, and the risks and opportunities this presents. On another note, central banks increasingly explore digital currencies (Keister and Sanches, 2023). As the market develops, research will focus on how this potential switch impacts the efficiency of exchanges, trading costs, and investment strategies. Finally, there is scope for more work in an international context. There has been some work to date, but that work has been affected by errors in dates used to identify AT through proxies such as colocation (Aitken et al., 2015, 2017, 2023). However, further research is warranted. Table 7 provides a comprehensive overview of the future research directions identified through content analysis.

7. Conclusions and limitations

Changes in the financial sector have given rise to an amazing stream of new microstructure research. We analyzed 863 papers in this study, covering the years from 1984 to 2022. These papers provided much insight into the impacts of AT and HFT on market quality, fairness, and efficiency. We reviewed the literature and suggested future research directions that bring in closer links with corporate finance, entrepreneurship, and central banks. Additionally, we identified the scope of this research in an international and comparative context.

Several potential limitations have been recognized within the literature, particularly concerning data sources, data quality, data types, sampling biases, and methodological constraints. A thorough examination revealed that bibliometric data, the cornerstone of our analysis, inherently possess well-known limitations, such as errors and inconsistencies that stem from subject indexing, a concern extensively discussed by Heberger et al. (2010). Additionally, our sample was limited to articles indexed exclusively in Scopus. Expanding future studies to include multiple data sources and enabling cross-database comparisons could significantly enhance the robustness and generalizability of our findings.

Our stringent inclusion criteria, excluding non-English journal articles, books, book chapters, and gray literature, might have excluded some significant insights within this research field. Future studies should aim to integrate these diverse knowledge sources to capture a more comprehensive spectrum of perspectives and deepen the analytical scope.

Moreover, the limitations of our study's keyword analysis warrant careful consideration. Although keyword cooccurrence analysis provides valuable initial insights, it may not fully capture the nuanced interrelations and thematic depth present within the data. A significant issue with keyword analysis is that authors often do not use keywords correctly, which can skew the results. We attempted to mitigate this problem through standardization, where we eliminated acronyms and corrected for singular and plural forms, among other discrepancies. Despite these efforts, the proper use of keywords by authors remains a significant challenge. A more detailed examination, including abstracts, titles, and full texts, is advisable to achieve a more comprehensive analysis, a recommendation supported by the studies of Feng et al. (2017) and Su et al. (2020).

Exploring additional bibliometric methodologies is clearly merited in anticipation of future research. Techniques such as cocitation analysis, bibliographic coupling, and direct citation offer alternative approaches that could enhance our understanding of the field's intellectual structure and evolving trends, providing a broader, more detailed landscape of research dynamics.

Declaration of Competing Interest

We have no conflicts of interest to declare

Data Availability

No data was used for the research described in the article.

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Appendix 1. Inclusion/exclusion criteria

Inclusion/ Exclusion	Criteria	Motivation
Inclusion	Only Scopus-indexed research articles	To narrow the focus of the research to articles curated by the Scopus indexing system, a well-regarded and extensively utilized academic database. Including only articles indexed in Scopus ensures the quality and reliability of the sources utilized in the analysis, aiding in maintaining consistency throughout the research process.
	Publication Type: Only peer-reviewed journal articles	To give precedence to articles that have undergone this review process, this method assists in preserving the integrity and dependability of the sources utilized in the research or literature review. Articles that are peer-reviewed are usually regarded as more trustworthy and authoritative within the scholarly community. By omitting sources that have not been peer-reviewed, such as conference abstracts, preprints, or magazine articles, researchers can concentrate on articles that have been rigorously assessed and are more likely to offer reliable and accurate information for their study.
	Language: Only articles published in English	To confine the scope of the study to publications in English. English functions as the common language in international collaborations and serves as the lingua franca within the academic community. By focusing on English-language articles, the research can ensure broader relevance and accessibility to an international audience.

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Inclusion/ Exclusion	Criteria	Motivation
	Subject Relevance: Include articles that are directly related to the research topic or field of interest	To concentrate on articles that directly address the research question or are aligned with the study's scope.
Exclusion	Duplicate Publications: Exclude multiple publications with the same content	To exclude redundant or repetitive articles that deliver identical findings or content.
	Loosely-related (LR) articles	To omit articles that are related to the research topic or field of interest but do not directly correspond with the study's specific focus. Including tangentially related articles can result in information overload, weaken the study's focus, and potentially introduce bias if these articles disproportionately affect the outcomes.
	Not related (NR) articles	To omit articles that have no relevance to the research topic or field of interest.

Source: Authors' elaboration

Appendix 2. Manual term processing and standardization activities

#	Standardization activity	Main references
1	Articles in which authors' keywords are missing but were added from the title and abstract	Ding et al. (2001); Murgado-Armenteros et al. (2015); Topalli and Ivanaj (2016)
2	Abbreviations were defined. For instance, "HFT" and "HFTs" became "High-Frequency Trading*"	Choi et al., (2011); Castriotta et al., (2021)
3	Synonyms were merged or converted into more general terms	Ding et al. (2001); Choi et al. (2011); Dehdarirad et al. (2014); Topalli and Ivanaj (2016); Castriotta et al. (2021)
4	Punctuation with no meaning, stop words (POS filtration) (e.g., "the", "a", "an", "in"), and abbreviations were removed	Ye and Ge (2019); Palshikar (2007); Strozzi et al. (2017); Choi et al. (2011)
5	Plural form to singular form transformation was applied, and uppercase and lowercase were removed (the first letter of the first word was capitalized)	Ye and Ge (2019); Choi et al. (2011); Dehdarirad et al. (2014); Murgado-Armenteros et al. (2015); Castriotta et al. (2021); Ding et al. (2001);
6	The Levenshtein and Damerau–Levenshtein distances and stemming techniques were applied to distinguish similar words. For example, words such as "investing" and "investment" were reduced to "invest*" after stemming	Ye and Ge (2019); Zhao and Sahni (2019);
7	Infrequent words (i.e., words that occur less than a specified number of times in the document), keywords unrelated to the field (e.g., country names such as India and Thailandia) and generalized words (e.g., "econometric analysis") were removed	Dehdarirad et al. (2014); Ding et al. (2001); Murgado-Armenteros et al. (2015); Castriotta et al. (2021)
8	After conducting some tests, and applying Bradford's law, the keywords with a frequency of 10 were included in the cluster analysis and those up to 10 were included in the final overlay visualization	Castriotta et al. (2021); Khasseh et al. (2017)

Source: Authors' elaboration

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