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Exploring the evolution of scientific publication on portfolio optimization in the light of artificial intelligence: A bibliometric study

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C H R O N I C L E

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A B S T R A C T

The rapid evolution of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has profoundly influenced various domains, including portfolio optimization. In today's dynamic and interconnected global economy, understanding the development of scientific publications in this field is crucial for both academics and practitioners. This paper aims to conduct a comprehensive bibliometric study of the scientific literature on portfolio optimization, focusing on the impact of AI, ML, and DL advancements. By analyzing key trends, influential publications, and emerging research areas, this study provides valuable insights into the progression of portfolio optimization research in the context of these transformative technologies, helping to map future directions and identify knowledge gaps in the field. This paper endeavors to present an exhaustive synthesis of the most recent advancements and innovations within the domain of portfolio optimization, particularly as influenced by progressive developments in AI, ML and DL from 1996 to 2024. Employing a rigorous bibliometric analysis, this study scrutinizes the structural and global paradigms governing this field. The analytical framework integrates several dimensions, including: (1) comprehensive dataset interrogation, (2) critical evaluation of source repositories, (3) contributions of seminal authors, (4) geographical and institutional affiliations, (5) document-centric analysis, and (6) exploration of keyword dynamics. A corpus of 745 bibliographic entries, meticulously curated from the Web of Science database, forms the basis of this inquiry, which utilizes advanced Scientometric network methodologies to extrapolate substantive research insights. The discourse culminates in a robust critique of the inherent strengths and methodological limitations, while delineating strategic avenues for future research, with the objective of steering ongoing scholarly discourse in the realm of portfolio optimization. The empirical outcomes of this study enhance the understanding of prevailing intellectual trajectories, thus laying a fortified foundation for future investigative pursuits in this critically evolving discipline.

1. Introduction

Portfolio optimization has long been a cornerstone of financial decision-making, enabling investors to balance risk and return effectively. However, the advent of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) has revolutionized this process (Ma et al., 2021). Portfolio optimization in the light of AI, ML, and DL advancements allows for a shift away from traditional models toward more sophisticated techniques that can analyze vast datasets, uncover subtle patterns, and generate more accurate forecasts of market trends and behavior. The integration of AI, ML, and DL into portfolio optimization opens new possibilities for improving performance, managing risk, and adapting strategies in real-time (Castilho et al., 2019). AI algorithms can now analyze both historical and live market data, providing insights that were

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previously out of reach. Machine learning models, especially those utilizing supervised and unsupervised techniques, reveal deeper relationships between assets, while deep learning models excel at capturing complex, multi-dimensional patterns that traditional models may miss (Ma et al., 2020). These technologies have fundamentally changed the way portfolio management is approached, allowing for more accurate, responsive, and forward-thinking strategies. Despite the significant progress, the academic literature on this subject remains scattered and fragmented, making it challenging to get a clear picture of how research has evolved in this field (Ban et al., 2018). As AI, ML, and DL continue to disrupt and reshape financial markets, it is more important than ever to understand how scientific inquiry in portfolio optimization has developed and where it is headed. This bibliometric study aims to fill that gap. By thoroughly analyzing trends in research publications, citation networks, and emerging keywords, this study seeks to map the evolution of scientific work in this area, identify influential studies, and highlight key research themes (Hu & Lin, 2019). The insights gained will not only help scholars understand the trajectory of portfolio optimization research in the age of AI, ML, and DL, but will also offer practical guidance for future studies. In essence, this paper provides a comprehensive overview of how these advanced technologies are revolutionizing portfolio optimization. By tracing the evolution of scientific thought, we can better grasp the potential that AI, ML, and DL hold for reshaping financial decision-making and driving innovation in this space.

The subsequent sections of this paper are delineated as follows: Section 2 furnishes a meticulous exposition of the data sets and the sophisticated methodologies employed throughout the study. Section 3 delves into the outcomes of the bibliometric analysis, providing a nuanced dissection of contemporary research trajectories, while offering profound insights into influential authors, high-impact journals, institutional affiliations, and cornerstone publications. Section 4 engages in a rigorous critique, evaluating both the methodological rigor and the inherent constraints of the study. Lastly, Section 5 encapsulates the principal findings, articulating a comprehensive synthesis and charting prospective research trajectories that hold the potential to shape future academic endeavors.

2. Materials and methods

Bibliometric analyses furnish exhaustive insights, offering nuanced perspectives within the academic landscape. The advanced capabilities of the R package, meticulously tailored for quantitative assessments, serve as essential instruments in the domains of Scientometrics and Informetrics. Moreover, bibliometric methodologies enable the systematic classification and critical appraisal of extensive volumes of historical research data, thereby facilitating the extraction and synthesis of valuable information from scholarly repositories (Aria & Cuccurullo, 2017). In the current research at hand, bibliometric analysis was employed to rigorously investigate prevailing trends in the frequency of portfolio optimization in the light of AI, ML, and DL advancements. A thorough exploration of diverse manifestations of portfolio optimization in the light of AI, ML, and DL advancements was executed through the deployment of sophisticated network analysis methodologies, employing word co-occurrence matrices and conceptual taxonomies facilitated by Scientometric protocols. These analytical frameworks were leveraged to conduct an in-depth examination of: (1) the dataset, (2) publication venues, (3) authorial contributions, (4) geopolitical and institutional affiliations, (5) scholarly outputs, and (6) keywords. Visualization of the analytic outcomes was rendered via the VOSviewer software and the R Bibliometrix suite. The scholarly corpus for search and retrieval was derived from the Web of Science (WoS) database, with the final search query delineated in Table 1.

Table 1
Compilation of Search Keywords Applied in the WOS Database

Level	Search Term Status
1	("Portfolio Optimization" OR "Portfolio Selection" OR "Portfolio Management" OR "Portfolio Rebalancing" OR "Portfolio Allocation" OR "Portfolio Construction")
	AND
2	("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Network" OR "Natural Language Processing" OR "Supervised Learning" OR "Unsupervised Learning" OR "Semi-Supervised Learning" OR "Reinforcement Learning")
	AND
3	("Financial Markets" OR "Invest*" OR "Risk Management" OR "Asset Management" OR "Wealth

A cumulative total of 749 scholarly articles were extracted from the Web of Science (WoS) database, encompassing the timeframe from 1996 to April 2024. It is noteworthy that four publications were excluded from this dataset due to their non-English language of publication, specifically 2 in Chinese, 1 in Polish, and 1 in Portuguese. The structural framework adopted for executing the present review is delineated in Fig. 1.

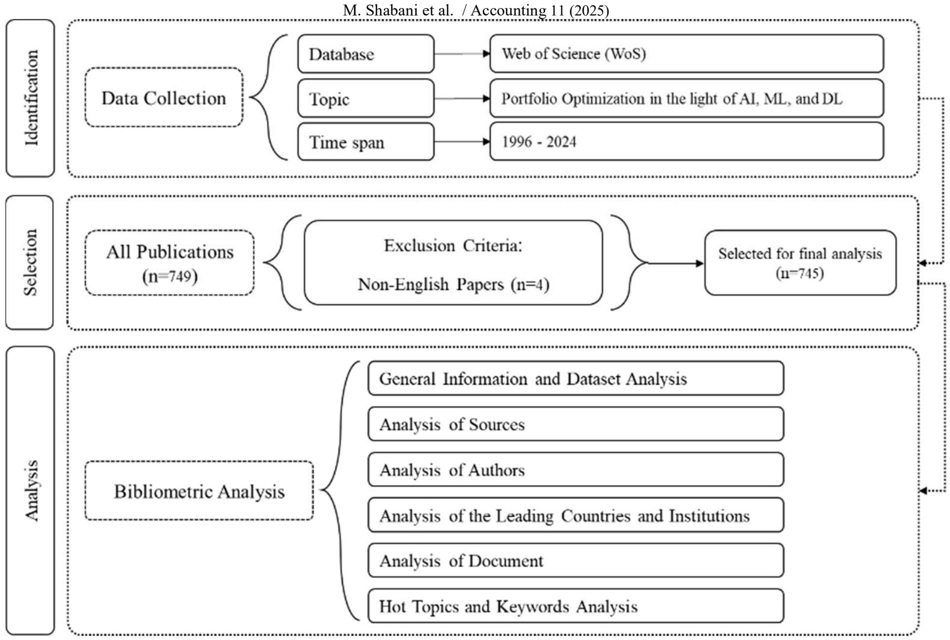


Fig. 1. Research Procedures and Methods for Portfolio Optimization in the Light of AI, ML, and DL Advancements (Javadi et al., 2025)

3. Scientometrics analysis

In Section 3 of our review paper, we focus on Scientometric analysis, rigorously examining various dimensions associated with portfolio optimization in the light of AI, ML, and DL advancements. This section is systematically divided into six distinct subsections, each addressing a critical aspect of the research landscape.

First, we scrutinize the dataset employed in our study, assessing its attributes, including volume, scope, and temporal coverage, to achieve a granular understanding of the research domain pertaining to portfolio optimization in the light of AI, ML, and DL advancements. This foundational analysis provides a comprehensive overview of the research breadth within this evolving field. Second, we investigate the sources from which the literature has been curated, identifying pivotal journals, conferences, and academic platforms. This enables us to discern dissemination trends and pinpoint the most influential publication venues that drive scholarly discourse in this domain. The third segment of our analysis concentrates on the contributing authors, where we dissect authorship structures, collaboration matrices, and individual research productivity. This examination allows us to identify leading scholars, collaborative networks, and the magnitude of their academic influence within the global research community. Subsequently, we analyze the countries and institutions engaging in research on portfolio optimization in the light of AI, ML, and DL advancements. This geopolitical and institutional mapping sheds light on the international distribution of scholarly activities, highlighting leading nations and institutions, as well as tracing the patterns of cross-border collaborations. In the fifth section, we turn our focus to the documents themselves, performing a deep dive into publication trends, citation patterns, and the types of scholarly outputs such as journal articles, conference proceedings, and review papers that have contributed to the consolidation of knowledge in this field. Finally, we employ advanced Scientometric techniques to examine the keywords associated with portfolio optimization in the light of AI, ML, and DL advancements. Through network analysis, co-word diagrams, and conceptual mapping, we elucidate key thematic clusters, emerging concepts, and the intricate relationships that define the research discourse.

Overall, this exhaustive Scientometric analysis furnishes a holistic perspective on the research landscape surrounding portfolio optimization in the light of AI, ML, and DL advancements. By integrating advanced network analysis techniques with sophisticated visualization tools, this study unveils pivotal insights and discernible trends, significantly enriching our comprehension of this critical and rapidly evolving domain.

3.1. General information and data set analysis

3.1.1. Main information

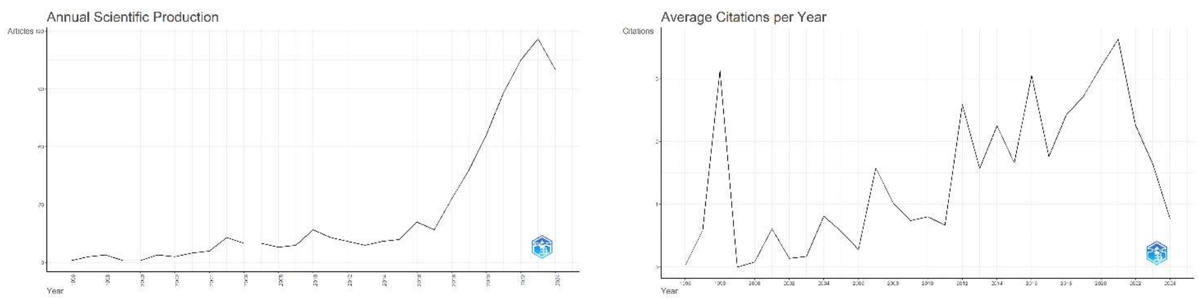
Out of the 745 documents selected for this investigation, a total of 1,886 distinct authors were identified. The average citation count per document stands at 11.15, a figure regarded as highly reputable within academic circles. The study also observed a substantial annual growth rate of 17.88%, underscoring the expanding scholarly interest in this domain. Articles represent the predominant document type, constituting 432 publications. Furthermore, a total of 724 Keywords Plus and 1,909 author-specific keywords were extracted, reflecting the breadth of thematic coverage. Table 2 presents a concise summary of the general metrics and characteristics of the papers analyzed in this study.

Table 2
The summary of the descriptive information

Description	Results	Description	Results
Main Information About Data		**Document Types**	
Timespan	1996:2024	Article	434
Sources (Journals, Books, etc.)	432	Article; Book Chapter	4
Documents	745	Article; Early Access	30
Annual Growth Rate %	17.88	Article; Proceedings Paper	14
Document Average Age	5.29	Book Review	3
Average citations per doc	11.15	Editorial Material	2
References	21143	Editorial Material; Book Chapter	1
Document Contents		Proceedings Paper	235
Keywords Plus (ID)	724	Review	20
Author's Keywords (DE)	1909	Review; Early Access	1
Authors Collaboration		Review; Retracted Publication	1
Single-authored docs	75	**Authors**	
Co-Authors per Doc	3.32	Authors	1886
International co-authorships %	22.01	Authors of single-authored docs	65

3.1.2. Publication output

Fig. 2a illustrates a pronounced upward trajectory in the volume of studies published in recent years. The annual growth rate has undergone a significant shift, escalating from a single publication in 1996 to 113 documents by 2023. Notably, as of September 2024, 78 studies have already been published on this subject, suggesting that this upward trend is likely to persist through 2024 and beyond. The publication trends can be segmented into two distinct phases. The first phase, extending up until 2017, saw relatively sparse research activity. In contrast, the second phase, from 2017 to April 2024, experienced a dramatic proliferation in research output, largely attributable to methodological advancements in addressing the subject matter. Fig. 2b further highlights the average number of citations per year, with 2021 and 1998 emerging as the most highly cited years, accounting for approximately 9% and 8% of the total citations, respectively.



(a) (b)

Fig. 2. Publication output. (a) Document output and (b) Average number of citations per year

Fig. 3 provides a comparative analysis of the growth trajectories for both the number of published articles and corresponding citations from 1996 to 2024. The figure distinctly demonstrates a steady upward trend throughout the specified period. Notably, the year 2022 saw the highest volume of published articles, while 2023 recorded the peak in citations. It is important to underscore that the statistics displayed in this chart are cumulative, representing the aggregated total of articles and citations accrued over time, further emphasizing the sustained expansion of scholarly activity in this field.

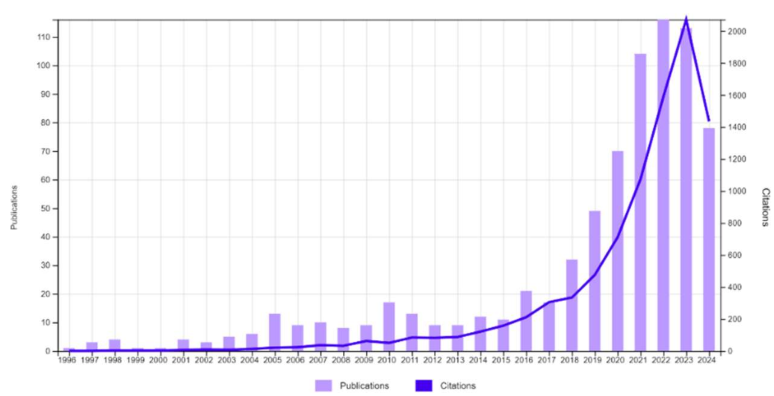


Fig. 3. Publication and citation over the time

3.2. Analysis of sources

3.2.1. Discipline-wise analysis

Table 3 outlines the distribution of the most highly cited sources within the field. The data clearly indicates substantial academic interest in this topic, with *Expert Systems with Applications* emerging as the most influential journal, accumulating 1,609 citations. The second most frequently cited source is *Computers & Operations Research*, with 318 citations. Following closely are *Mathematical Finance*, which garnered 227 citations, and *Applied Soft Computing*, with 223 citations. These results underscore the pivotal role these journals play in advancing research on this topic, serving as key platforms for the dissemination of influential scholarly work.

Table 3
Most cited sources

Sources	Number of Citation
Expert Systems with Applications	1609
Computers & Operations Research	318
Mathematical Finance	227
Applied Soft Computing	223
Quantitative Finance	218
Journal of Behavioral and Experimental Finance	218
Machine Learning	163
Management Science	160
Acm Computing Surveys	155
Journal of Forecasting	154

3.2.2. Most relevant sources

This section examines the most prominent and impactful sources within the research domain of portfolio optimization in the light of AI, ML, and DL advancements. In this area of inquiry, several key sources have emerged as highly influential in shaping the foundational knowledge and discourse. One of the primary methods for identifying these influential sources is Bradford's Law, which offers critical insights into the distribution patterns of scholarly publications (Brookes, 1969). Bradford's Law, as depicted in Fig. 4, categorizes journals into distinct zones based on their frequency of publication within a specific field. Zone 1, often referred to as the core zone, consists of journals that are the most prolific and frequently cited in the literature related to portfolio optimization in the light of AI, ML, and DL advancements. These core publications are of significant importance due to their broad scope, extensive scholarly contributions, and central role in advancing the field.

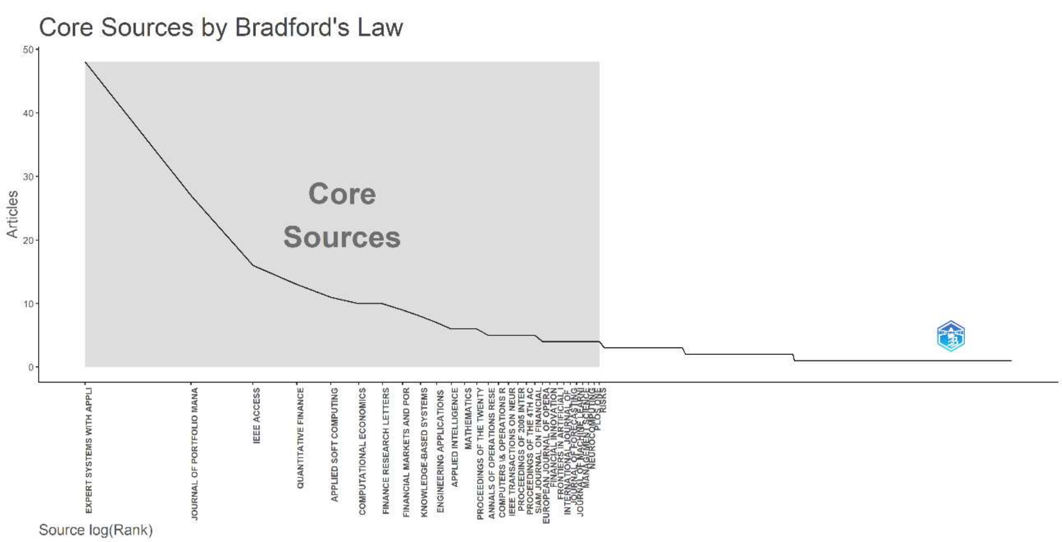


Fig. 4. Bradford's Law (Core sources)

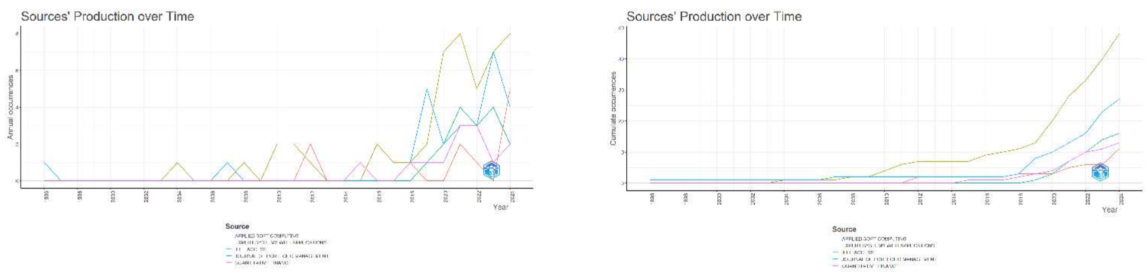
Table 4 showcases the publication frequency of the ten most influential sources in the domain of portfolio optimization in the light of AI, ML, and DL advancements. This table offers crucial insights into the publication trends of these sources, enabling us to assess their relative impact and prominence within the field. A detailed examination of the data in Table 4 reveals that *Expert Systems with Applications* clearly emerges as the leading source in this area of research. With the highest number of published documents among the top ten sources, this journal has cemented its position as the premier outlet for scholars and researchers engaged in portfolio optimization in the light of AI, ML, and DL advancements. The journal's considerable contribution is underscored by its high publication frequency, which demonstrates a sustained and prolific production of pioneering research within the field. This consistent output of innovative studies highlights its central role in advancing the discourse on portfolio optimization in the light of AI, ML, and DL advancements.

Table 4
Effect of the sources

Sources	Rank	Freq	Zone
Expert Systems with Applications	1	48	Zone1
Journal of Portfolio Management	2	27	Zone1
IEEE Access	3	16	Zone1
Quantitative Finance	4	13	Zone1
Applied Soft Computing	5	11	Zone1
Computational Economics	6	10	Zone1
Finance Research Letters	7	10	Zone1
Financial Markets and Portfolio Management	8	9	Zone1
Knowledge-Based Systems	9	8	Zone1
Engineering Applications of Artificial Intelligence	10	7	Zone1

3.2.3. Sources dynamics

Fig. 5 depicts the growth trajectory of article publications across the top 10 journals identified in the previous section. The figure clearly highlights a marked and accelerated increase in the number of publications, both annually and cumulatively, over recent years. This upward trend underscores the strong momentum driving research output in these journals, reflecting their pivotal role in disseminating scholarly work on portfolio optimization in the light of AI, ML, and DL advancements. Given the current pace, it is projected that this publication momentum will persist in the coming years, further solidifying the influence of these journals in the field.



(a) (b)

Fig. 5. Top sources dynamics (a) Annual occurrences (b) Cumulative occurrences

3.2.4. Most relevant publishers

Fig. 6 illustrates the distribution of articles on portfolio optimization in the light of AI, ML, and DL advancements across various publishers. As shown, *Elsevier* dominates as the leading publisher in this domain, contributing 155 articles, which represent 21% of the total publications. Springer Nature Publishing follows closely with 143 articles (19%), while *IEEE*, *MDPI*, and *Taylor & Francis* have published 142 articles (19%), 36 articles (5%), and 32 articles (4%) respectively. These publishers are identified as the most prolific sources, significantly contributing to the growing body of literature on portfolio optimization in the light of AI, ML, and DL advancements.

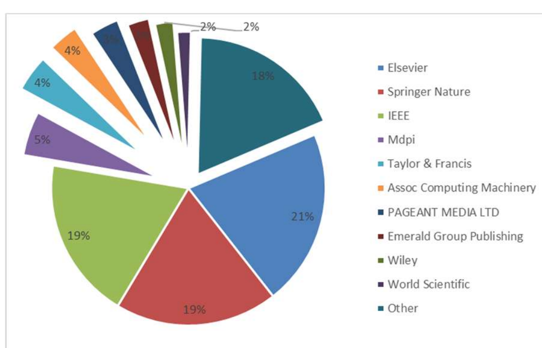


Fig. 6. Most relevant publishers

3.3. Analysis of authors

3.3.1. Authors productivity

Lotka's Law is a principle that quantifies and describes the distribution of researchers based on their frequency of publication within a specific knowledge domain (Pao, 1985). Fig. 7 illustrates the results for papers on portfolio optimization in the light of AI, ML, and DL advancements, juxtaposed with the predicted distribution as per Lotka's Law. The findings from this study reveal a Lotka's index where 87.6% of authors have contributed a single article, 9% have authored two articles, 1.9% have published three articles, and only 0.7% have produced four articles. These results suggest that the current authorship distribution in the field deviates from the expected distribution under Lotka's Law. The dashed line in Figure 7 represents the theoretical curve that would align with Lotka's Law, highlighting the divergence observed in this study.

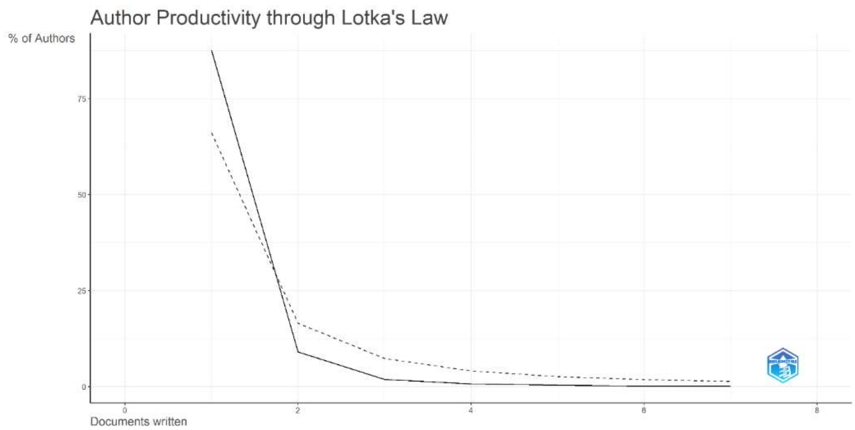


Fig. 7. Lotka's Law (The frequency of scientific productions)

Table 5
The frequency of scientific productions

Documents written	Number of Authors	Proportion of Authors
1	1831	87.6%
2	189	9.0%
3	40	1.9%
4	15	0.7%
5	9	0.4%
6	3	0.1%
7	3	0.1%

3.3.2. Authors productivity over time

Fig. 8 presents a detailed visualization of the leading authors' scholarly output concerning portfolio optimization in the light of AI, ML, and DL advancements over an extended temporal span. The chromatic intensity of the graph corresponds to the citation year, while the magnitude of the bubbles signifies the author's annual publication frequency. For example, in 2011, *Li Bin* contributed his seminal work in this area, which has accrued a total of 65 citations to date. This graphical representation elucidates the temporal distribution of authorship and citation metrics, offering an intricate depiction of the authors' academic productivity and influence over the years.

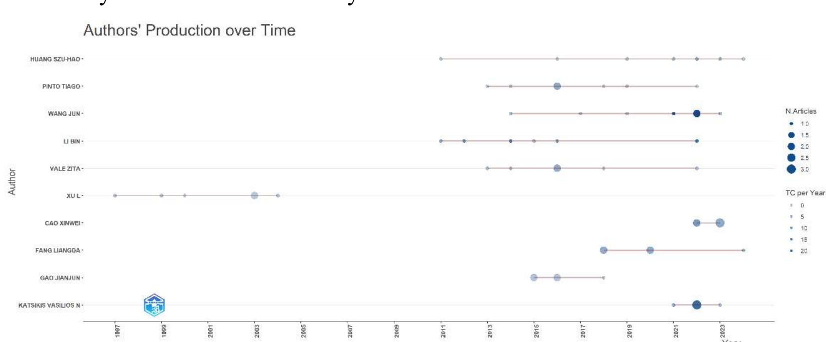


Fig. 8. Top author's production over time in researching the Portfolio optimization in the light of AI, ML, and DL advancements

3.3.3. Most relevant authors and authors impacts

In this section, we conduct an in-depth analysis of the most prominent and influential authors who have made substantial contributions to the domain of portfolio optimization in the light of AI, ML, and DL advancements. Fig. 9 offers a comprehensive overview of the top 10 authors based on the number of articles they have published, while Table 6 presents the top 10 authors ranked by local citation count, reflecting their scholarly impact on this specialized area of study. The most notable contributor is *Pinto Thiago*, whose prolific output has significantly advanced the field. Another key contributor is *Wang Jun*, whose research has played a critical role in enhancing our understanding of the complexities and methodologies surrounding portfolio optimization in the light of AI, ML, and DL advancements. These scholars have demonstrated a profound influence on shaping the discourse and addressing the challenges within this evolving research area.

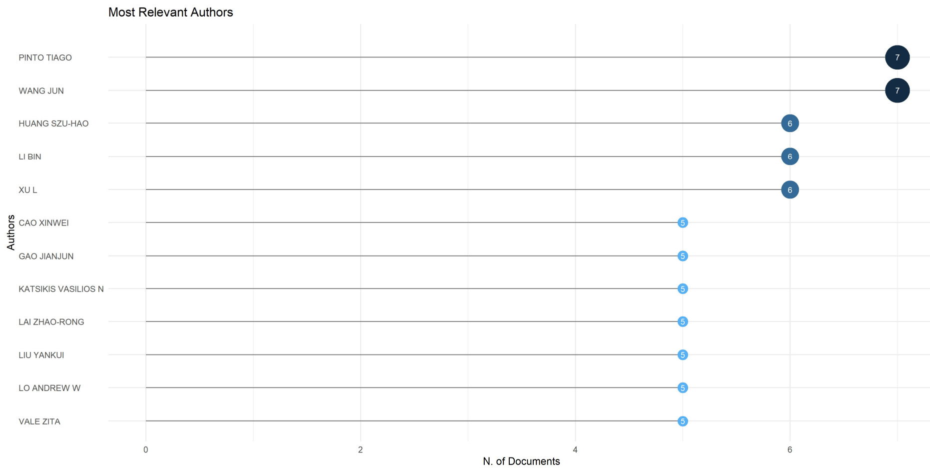


Fig. 9. Effect of the Authors (Number of publications by authors)

These authors have not only enriched the corpus of knowledge concerning portfolio optimization in the light of AI, ML, and DL advancements but have also exerted a profound influence on the field, as demonstrated by the substantial number of local citations attributed to their works. Local citations serve as a robust indicator of their scholarly impact and the recognition they have garnered within the research community, underscoring their pivotal role in propelling forward the discourse in this domain. Collectively, their contributions have indelibly shaped the trajectory of research in portfolio optimization in the light of AI, ML, and DL advancements, and continue to provide a foundational basis for ongoing investigation and innovation in this dynamic field.

Table 6
Effect of the authors (Most local cited authors)

Authors	Articles	Articles Fractionalized
Pinto Tiago	7	1.70
Wang Jun	7	2.92
Huang Szu-Hao	6	1.83
Li Bin	6	1.54
Xu l	6	2.83
Cao Xinwei	5	1.19
Gao Jianjun	5	2.08
Katsikis Vasilios N	5	1.29
Lai Zhao-Rong	5	1.20
Liu Yankui	5	2.00

Table 7 elucidates the hierarchical rankings of the top 10 preeminent scholars in the realm of portfolio optimization in the light of AI, ML, and DL advancements from 1996 to 2024. The rankings are derived from a suite of sophisticated bibliometric indicators, including the H-index, G-index, and M-index, along with other pertinent citation-based metrics. These indices are ubiquitously acknowledged within the academic milieu as robust evaluative tools for quantifying an author's scholarly impact and intellectual productivity.

- The **H-index** serves as a dual-purpose metric, encapsulating both the research productivity and the citation resonance of a scholar by determining the number of publications (h) that have accrued at least h citations each. Scholars possessing a higher H-index are perceived as exerting a more formidable influence within their respective fields of inquiry (Bornmann & Daniel, 2007).
- The **G-index**, another advanced citation metric, emphasizes an author's cumulative output of highly cited works, thus accounting for the asymmetric distribution of citations across their oeuvre. It amplifies the weight of highly

influential publications, with a higher G-index signifying a pronounced scholarly impact across a more substantial body of influential research (Egghe, 2006).

- The **M-index**, in contrast, offers a granular focus on an author's h-core the collection of their most cited works—and calculates the average number of citations per publication within this critical corpus. This index provides a more nuanced appraisal of citation impact, supplementing the H-index by delivering insights into the profundity of an author's most seminal contributions (Hirsch, 2005).

Table 7 delivers an exhaustive depiction of these bibliometric metrics for the foremost authors in the domain of portfolio optimization in the light of AI, ML, and DL advancements. By scrutinizing these indices, researchers and domain practitioners can glean valuable insights into the scholarly prominence, intellectual productivity, and citation dynamics of the field's most influential contributors.

Table 7
Top 10 most relevant authors on Portfolio optimization in the light of AI, ML, and DL advancements

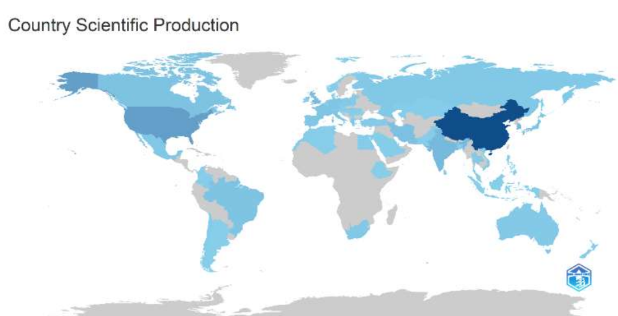
Element	H index	G index	M index	TC	NP	PY Start
Li Bin	6	6	0.429	456	6	2011
Wang Jun	6	7	0.545	220	7	2014
Fang Liangda	5	5	0.714	69	5	2018
Lai Zhao-Rong	5	5	0.714	69	5	2018
Wu Xiaotian	5	5	0.714	69	5	2018
Hoi Steven C H	4	4	0.286	400	4	2011
Huang Szu-Hao	4	6	0.286	36	7	2011
Katsikis Vasilios N	4	5	1	73	5	2021
Wong Hoi Ying	4	4	0.4	58	4	2015
Babaei Golnoosh	3	3	0.6	57	3	2020

Notes. TC: Total Citation, NP: Number of Publications, PY start: Publication Year Start

3.4. The leading countries and institutions

3.4.1. Most relevant countries

In this section, we undertake an exhaustive examination of the preeminent nations and institutions within the field, elucidating their contributions and academic influence. Our analytical inquiry reveals compelling insights into the document production across various countries during the specified temporal span. Predictably, *China* ascends as the foremost leader, securing the apex position in scholarly output, with an extraordinary total of 804 publications. This prodigious output underscores China's formidable presence and its influential role in propelling the frontiers of research in this domain. Such a remarkable achievement exemplifies the nation's unwavering dedication to research and development, reflecting its sustained commitment to augmenting and advancing the corpus of knowledge. The *United States*, an emerging superpower in academic discourse, claims the second position, cementing its escalating influence and significant contributions to the field. With an impressive catalog of 279 publications, the *U.S.* has made remarkable strides, establishing itself as an indispensable force in the international research ecosystem concerning portfolio optimization in the light of AI, ML, and DL advancements. *India* secures the third rank with a documented total of 119 publications. While its output is quantitatively less prolific in comparison to *China* and the *U.S.*, *India's* contributions are marked by their consistency and substantive impact. The nation's sustained pursuit of academic rigor has facilitated key innovations and intellectual breakthroughs, solidifying its stature within the global scholarly landscape. Fig. 10 offers an extensive overview of other leading nations contributing significantly to this domain. Although these countries do not dominate the uppermost echelon of rankings, their collective scholarly efforts have substantially enriched the knowledge base and catalyzed transnational academic collaboration. These nations have played an instrumental role in shaping the trajectory and intellectual evolution of the field, reinforcing the global scientific community's collective progress.



Region	Freq	Region	Freq
China	804	Iran	80
USA	279	Canada	64
India	119	Brazil	62
South Korea	118	Italy	56
UK	104	France	55

Fig. 10. Scientific production by countries

Table 8 provides an intricate examination of the nations that have accrued the highest citation counts within the domain of portfolio optimization in the light of AI, ML, and DL advancements. These citation figures serve as a robust indicator of the scholarly impact and academic gravitas of research contributions originating from various countries. The table ranks the top 10 nations by their cumulative citation counts, offering a precise portrayal of their intellectual dominance and influence within the field. *China* unequivocally leads the citation hierarchy, amassing an impressive total of 2,169 citations, thus cementing its preeminent role in shaping the discourse and advancing the frontiers of knowledge in this domain. The *United States* follows in second place, accruing 1,171 citations, a testament to its substantial contributions and sustained scholarly activity. *Brazil* claims the third rank with 589 citations, reflecting its emergent significance and growing intellectual footprint in this specialized area of research. The table further delineates the rankings and citation metrics for the remaining countries within the top 10, providing a detailed panorama of their scholarly visibility and research impact. This citation data enables both researchers and practitioners to discern the nations whose academic endeavors have been most extensively cited and whose contributions have left a profound imprint on the theoretical and practical advancements in portfolio optimization in the light of AI, ML, and DL advancements.

3.4.2. Most relevant affiliations

The *Chinese University of Hong Kong* and *Islamic Azad University in Iran* jointly occupy the premier position among the top 10 academic institutions, each having contributed 34 publications on the topic of portfolio optimization in the light of AI, ML, and DL advancements. Closely following, *City University of Hong Kong* has produced 24 articles in this domain. The table further enumerates other prestigious institutions that have made significant scholarly contributions, providing a detailed overview of the academic entities that are at the forefront of research in this field.

Table 8
Most cited countries

Country	TC	Average Article Citations
China	2169	9.30
USA	1171	15.00
Brazil	589	28.00
India	500	12.80
Singapore	432	36.00
Korea	428	11.60
Greece	382	22.50
United Kingdom	336	12.00
Spain	328	21.90
Italy	225	12.50

Table 9
Most relevant affiliations.

Affiliations	Articles
Chinese University of Hong Kong	34
Islamic Azad University	34
City University of Hong Kong	24
Columbia University	23
Nanyang Technological University	21
Shanghai University of Finance and Economics	20
Xi'an Jiaotong-Liverpool University	19
Jinan University	18
Hebei University	16
National and Kapodistrian University of Athens	16

In conjunction with the data presented in Table 9, additional insights are offered through Fig. 11. This figure graphically illustrates the temporal trajectory of research productivity across various affiliations in the field of portfolio optimization in the light of AI, ML, and DL advancements. The visualization captures the research output of numerous entities, including universities, research institutes, organizations, and other academic or industrial contributors engaged in advancing knowledge within this specialized area. By mapping the productivity of these affiliations over time, Fig. 11 provides a dynamic representation of the evolving landscape of scholarly contributions, highlighting key institutions that have played a pivotal role in shaping the field's progress.

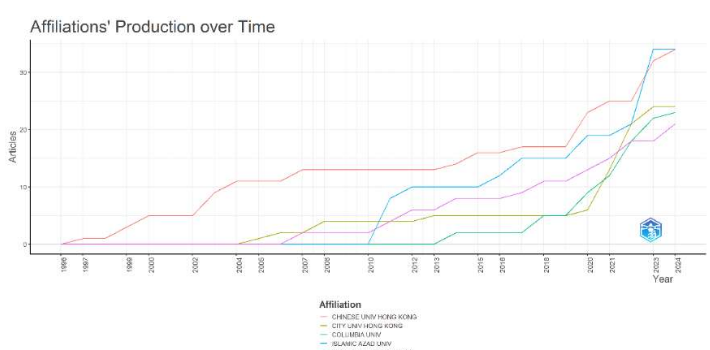


Fig. 11. Affiliation production over time

3.4.3. Countries and authors collaborations

A thorough exploration of the intricacies of international collaboration in the field of portfolio optimization in the light of AI, ML, and DL advancements offers critical insights into the foremost active collaborators and the dominant global research enterprises in this specialized domain. Such insights are paramount for cultivating meaningful academic alliances and facilitating the cross-border dissemination of knowledge, methodologies, and expertise on an international scale. Fig. 12 graphically delineates the global collaboration network, where nodes represent clusters of collaborating countries, and the thickness of the interconnecting lines signifies the magnitude and intensity of these collaborative engagements. As illustrated in the figure, the *United States* stands out as possessing the most extensive and multifaceted collaboration network, linking with numerous countries across the globe. This robust connectivity emphasizes the United States' preeminent role in spearheading international research initiatives, positioning it as a central nexus for fostering transnational academic partnerships and catalyzing interdisciplinary research efforts with scholars from a broad array of geographical regions.

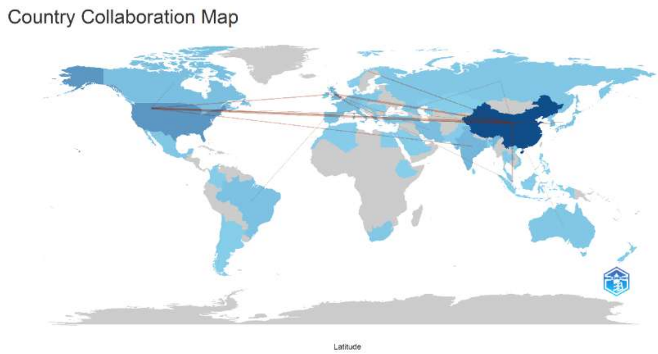


Fig. 12. Network map of cooperation countries/regions

Fig. 13 provides a comprehensive depiction of both intra-national and international research collaboration by utilizing the SCP (Single-Country Collaboration) and MCP (Multiple-Country Collaboration) indices. The MCP index signifies cross-border or inter-country collaboration, whereas the SCP index reflects collaboration occurring within a single country (Li et al., 2023). As depicted, China holds the top position in both MCP and SCP, highlighting its leadership in fostering extensive collaborations both domestically and internationally across the realm of portfolio optimization in the light of AI, ML, and DL advancements. In contrast, nations such as France, Australia, and Portugal demonstrate a higher proportion of MCP, signaling their strong involvement in multinational research endeavors. Conversely, countries like the United States, China, India, Iran, and Japan exhibit a pronounced emphasis on SCP, indicating that a significant portion of their collaborative efforts occurs domestically, with researchers predominantly engaging with colleagues within their own national boundaries. The analysis of SCP and MCP indices thus furnishes critical insights into the scope, orientation, and extent of both intra-country and cross-border collaborations in this specialized field, delineating patterns of academic cooperation and influence at both the national and international levels.

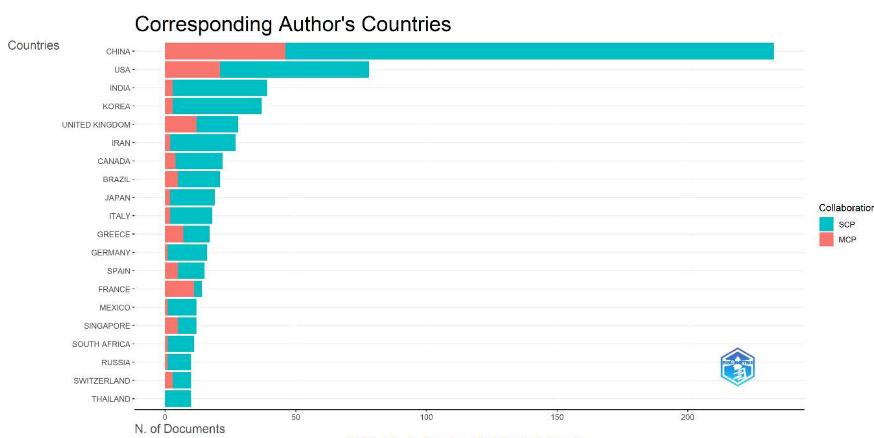


Fig. 13. Top corresponding author countries

Table 10
The top 10 corresponding author countries

Country	Article	SCP	MCP	Freq	MCP_Ratio
China	233	31.3	187	46	19.7
USA	78	10.5	57	21	26.9
India	39	5.2	36	3	7.7
Korea	37	5	34	3	8.1
United Kingdom	28	3.8	16	12	42.9
Iran	27	3.6	25	2	7.4
Canada	22	3	18	4	18.2
Brazil	21	2.8	16	5	23.8
Japan	19	2.6	17	2	10.5
Italy	18	2.4	16	2	11.1

3.5 Analysis of documents

3.5.1. The most impactful documents

Table 11 shows the 10 most globally cited documents in the research of portfolio optimization in the light of AI, ML, and DL advancements, with worldwide citation counts ranging from 132 to 331. *Cavalcante rc* (2016), *Goodell jw* (2021), *Fernandez a* (2007), *Helmbold dp* (1998), and *Li b* (2014) have the most citations worldwide, receiving 331, 213, 200, 181 and 155, respectively, and their papers are ranked among the top five most frequently referenced publications.

Table 11
Top 10 cited documents in the research of Portfolio optimization in the light of AI, ML, and DL advancements

Authors	Top cited documents	TC per year	Normalized TC
Cavalcante, 2016	331	36.78	12.07
Goodell, 2021	213	53.25	14.67
Fernandez, 2007	200	11.11	7.04
Helmbold, 1998	181	6.70	2.14
Li, 2014	155	14.09	6.27
Moody, 1998	153	5.67	1.81
Huang, 2012	143	11.00	4.25
Buehler, 2019	134	22.33	8.21
Fang, 2022	134	44.67	19.73
Bustos, 2020	132	26.40	8.27

Cavalcante et al. (2016) conducted a thorough review of computational intelligence techniques applied to financial markets, with a particular focus on improving the accuracy and efficiency of market predictions. The paper highlights the critical role of information in the fast-paced environment of financial trading, noting that the sheer volume of available data can often overwhelm traders. The authors divide their review into three primary objectives: firstly, to compile a comprehensive survey of computational techniques like deep learning, online learning, and text mining as they apply to financial markets; secondly, to propose a systematic methodology for constructing intelligent trading systems; and thirdly, to address the major challenges and unresolved issues in the field. They observed that traditional statistical models, though once dominant, are increasingly being replaced by machine learning methods, which better capture the nonlinear, chaotic nature of financial time series data. The review stresses the importance of preprocessing methods, such as feature selection and de-noising, in enhancing model performance. Finally, the authors call for future research to focus on refining these intelligent systems and integrating more sophisticated risk management strategies to mitigate the financial impact of market volatility.

Goodell et al. (2021) conducted an extensive bibliometric analysis to review the landscape of AI and ML research within the finance domain. Their study aimed to provide a comprehensive retrospective of the growing body of literature on the application of AI and ML in finance by identifying key themes and research clusters. Through co-citation and bibliometric coupling analyses, the authors discovered nine thematic clusters in finance that utilize AI and ML techniques. These clusters primarily revolve around three overarching areas: portfolio construction and investor behavior, financial fraud and distress, and sentiment analysis along with forecasting and planning. The review highlights the transformative effect AI and ML have had on the finance industry, specifically in areas such as asset pricing, fraud detection, and predictive analytics. By mapping publication trends and analyzing top journals, authors, and countries contributing to the field, the authors underscore the growing significance of AI and ML in shaping the future of finance. The paper also points to future research directions, advocating for more sophisticated risk management strategies and deeper integration of AI and ML technologies in financial systems.

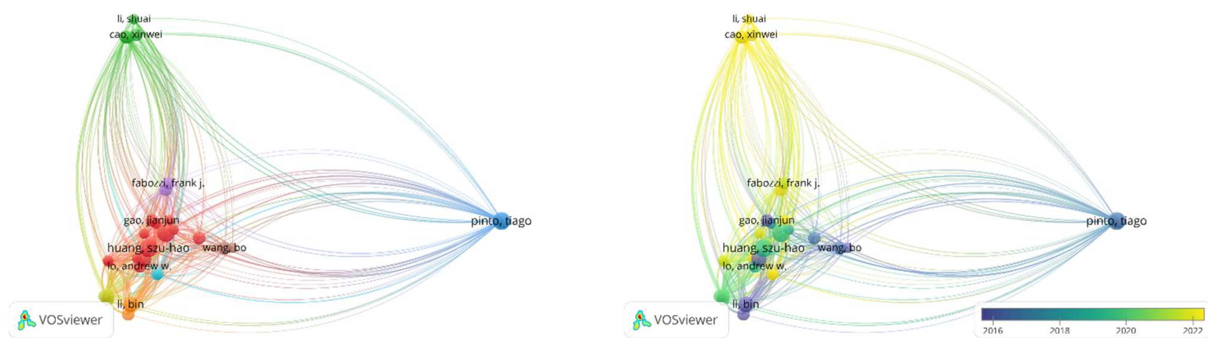
Fernández & Gómez (2007) explored the use of Neural Networks for solving the portfolio selection problem by applying the Hopfield network to trace the efficient frontier. This study generalizes the classic Markowitz mean-variance model to include cardinality and bounding constraints, allowing for more practical and diversified investment strategies. The authors demonstrated how the Hopfield network can provide a heuristic solution to the mixed quadratic and integer programming problem posed by these constraints, contrasting its performance against other heuristic methods such as genetic algorithms, tabu search, and simulated annealing. The results showed that while the Hopfield network excels in situations with high-risk aversion where risk minimization is prioritized it performs less effectively when mean return is the primary objective. Nevertheless, the NN approach provided superior solutions in scenarios that required significant diversification across assets. The study underscores the utility of neural networks in financial optimization, particularly in handling complex investment policies where diversification is key to managing risk. Furthermore, the authors highlight that, despite its slower computational speed, the NN-based method yields more precise outcomes for specific types of portfolios compared to other heuristics, particularly when dealing with risk-averse scenarios.

Helmbold et al. (1998) developed an online portfolio selection algorithm that utilizes multiplicative updates to achieve wealth growth comparable to the best constant-rebalanced portfolio, determined in hindsight. The authors introduced a simple yet effective algorithm based on the multiplicative update rule, derived from the framework of Kivinen and Warmuth, which is efficient in terms of both time and storage, growing linearly with the number of stocks. They tested the algorithm on historical data from the New York Stock Exchange over a 22-year period, where it outperformed the best single stock and even surpassed Cover's well-known universal portfolio algorithm. The multiplicative update method works by adjusting portfolio weights iteratively based on past market performance, ensuring that the investment strategy closely follows the optimal portfolio strategy without requiring knowledge of future market outcomes. This approach also proved efficient in handling real-world scenarios where investors might have access to side information, allowing the algorithm to further enhance returns by exploiting additional market signals. The experimental results demonstrated that the multiplicative update rule not only performs better in volatile markets but also maintains its advantage across various portfolio sizes, making it a robust tool for financial portfolio management.

Li & Hoi (2014) conducted an extensive survey on the state-of-the-art techniques for online portfolio selection. The paper provides a structured understanding of algorithms categorized into major groups, including Follow-the-Winner, Follow-the-Loser, Pattern-Matching-based approaches, and Meta-Learning Algorithms (MLAs). The authors aimed to bridge the gap between theory and application by connecting these algorithms to capital growth theory, emphasizing their ability to maximize cumulative wealth over time. This survey is particularly relevant for researchers in machine learning and quantitative portfolio management, providing insights into the performance and mechanisms of each algorithm type. Li and Hoi conclude that Follow-the-Winner and Follow-the-Loser strategies excel in specific market conditions, with some algorithms leveraging mean reversion to enhance performance. However, they highlight open challenges in handling real-world complexities like transaction costs, which are often oversimplified in theoretical models. Additionally, the survey advocates for further exploration of machine learning advancements to improve the robustness and adaptability of portfolio selection algorithms in volatile markets.

3.5.2. Cluster analysis

In co-author analysis, the investigation of the frequency with which two or more researchers engage in collaborative authorship constitutes a pivotal facet for discerning the intricate dynamics of scholarly networks within a given field. A map visualization can be utilized to graphically depict these collaboration networks, wherein colored lines symbolize the interconnections between nodes, which represent the individual researchers. The size of the nodes, determined by weight attributes, reflects the prominence and influence of each researcher within the collaborative network. Moreover, the density and multiplicity of lines connecting co-authors indicate the strength of their collaborative ties, with a greater number of connections signifying more frequent and substantial co-authorship. By deploying such visualizations to scrutinize the connections, weighted significance, and the density of lines among co-authors, one can derive valuable insights into the architecture and cohesion of the collaborative research networks. Figure 14 elucidates these relationships by mapping the co-authorship connections based on jointly authored documents. This figure serves as a lens through which the existence and characteristics of collaborative networks, as well as potential author clusters devoted to Portfolio optimization in the light of AI, ML, and DL advancements, can be examined. These analytical insights are crucial for unveiling the collective intellectual efforts and the scholarly synergies that underpin research advancement within this specialized domain.



(a) (b)

Fig. 14. Bibliographic coupling (a) Cluster analysis based on subjects (b) Cluster analysis based on periods

3.6 Hot topics and keywords analysis

3.6.1. Most frequent words

Table 12 presents the most frequently occurring keywords, encompassing both author keywords and Keywords Plus, for the period spanning 1996 to 2024. The analysis of author keywords provides insight into research trends from the perspective of the researchers themselves (Garfield, 1970). In contrast, Keywords Plus are terms algorithmically extracted from the titles or abstracts of publications, offering additional layers of thematic analysis. In the author keyword analysis, "Portfolio Optimization" and "Machine Learning" emerge as the most prevalent terms, with 104 and 100 occurrences, respectively. Conversely, in the Keywords Plus analysis, "Model" and "Selection" rank as the most frequent, with 94 and 91 occurrences, respectively. Notably, the term "Optimization" appears in both categories, underscoring its central importance in the discourse. This intersection suggests a recurring thematic focus across various studies within the research domain.

Table 12

Most frequent words (author keyword and keywords plus) found in the research of Portfolio optimization in the light of AI, ML, and DL advancements

Author's Keywords	Occurrences	Keywords Plus	Occurrences
Portfolio Optimization	104	Model	94
Machine Learning	100	Selection	91
Portfolio Management	68	Optimization	77
Deep Learning	65	Risk	77
Portfolio	64	Algorithm	38
Portfolio Selection	63	Neural-Networks	35
Optimization	61	Prediction	34
Reinforcement Learning	56	Returns	34
Artificial Intelligence	34	Market	33
Learning	34	Neural-Network	33

Fig. 15, referred to as the "Three-Field Plot," offers a sophisticated visual synthesis of three critical dimensions: "Author," "Disciplinary Evolution (Author's Keywords) " and "Author Country". These parameters are methodically correlated according to their relative prominence and academic significance within the corpus of literature. The proportional size of the tiles or boxes within the diagram represents the magnitude and relevance of the interconnections between these parameters, allowing for the discernment of their hierarchical impact. The larger the tiles, the more influential or predominant the parameter is within the analyzed literature, with greater dimensions signifying parameters that wield substantial intellectual influence or exhibit pronounced visibility. The three-field plot thus provides a nuanced visualization of the intricate relationships between authorship, thematic evolution (as indicated by author keywords), and geographical research origins. This visualization enables an in-depth understanding of the symbiotic dynamics underpinning scholarly contributions and the spatial distribution of intellectual activity within the domain of Portfolio optimization in the light of AI, ML, and DL advancements.

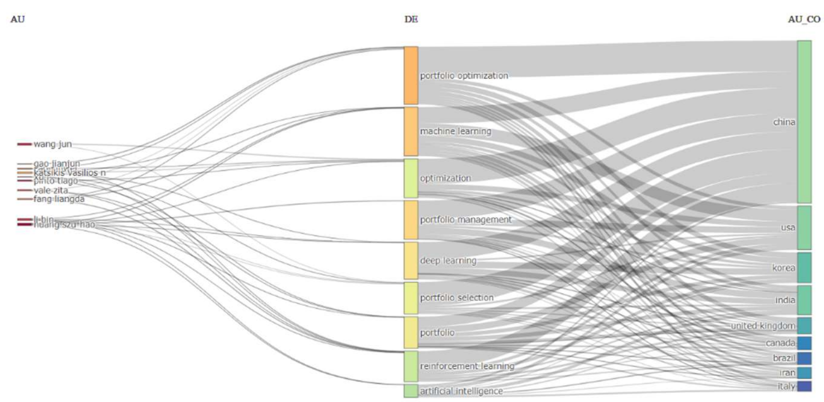


Fig. 15. Three-field plot

3.6.2. Trend topics over time

A trending topic analysis functions as a crucial bibliometric tool that facilitates the visualization of the temporal evolution of scholarly literature. Fig. 16 captures this progression by presenting the emergent themes identified through an in-depth analysis of author keywords. The analysis ensures a minimum occurrence threshold of five keywords per article over successive triannual intervals. This methodology highlights the shifting focus of research interests and trends over time, offering a comprehensive overview of the thematic development within the domain. The identified subjects in Fig. 16 reflect both the continuity and transformation of the intellectual landscape, mapping the dynamic progression of literature in the context of Portfolio optimization in the light of AI, ML, and DL advancements.

In recent years, the literature on Portfolio optimization in the light of AI, ML, and DL advancements has shown a clear evolution, with several key topics gaining prominence over time. Notably, Particle Swarm Optimization emerged as one of the most frequently discussed methodologies, with significant attention in the early 2010s, peaking in 2013 and maintaining relevance until 2020. Similarly, Genetic Algorithms, a critical approach in AI-driven optimization, first gained traction in 2012 and continued to be a focal point of research up until 2020. Other noteworthy topics include Portfolio Selection Problem, which had a notable presence as early as 2010 and saw significant development by 2012, and Electricity Markets, which became prominent in 2014 and maintained relevance through to 2018. The domain of Financial Forecasting has also seen increasing attention, starting in 2016 and remaining highly relevant in 2023, as AI techniques continue to evolve in predicting financial market trends. Moreover, techniques such as Feature Selection and Fuzzy Logic have seen periodic growth, with the former rising in importance around 2012 and peaking in 2020, while Fuzzy Logic gained traction starting in 2014 and remained a significant area of focus through 2022. Additionally, Technical Analysis and Decision Making, which integrate AI methods to optimize portfolio strategies, have continued to develop, with discussions on these topics spanning from the early 2010s and still being highly relevant today. This evolving focus on various optimization techniques reflects the dynamic nature of Portfolio optimization in the light of AI, ML, and DL advancements, as researchers increasingly seek to leverage AI methodologies to address complex problems in financial markets and asset management.

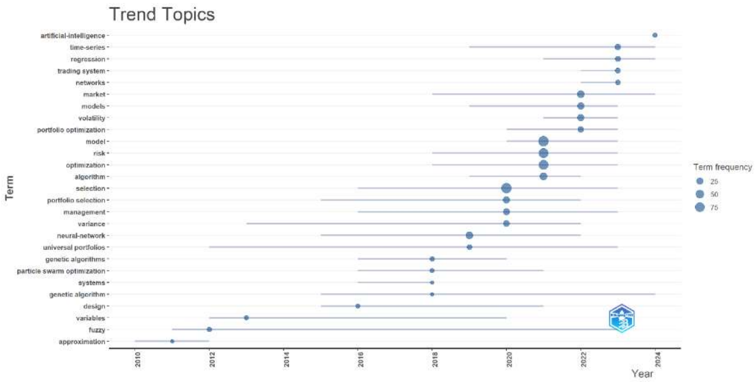


Fig. 16. Trends topics over the years

Table 13
Trending topics by year

Item	Freq	Year Q1	Year Med	Year Q3
Portfolio Selection Problem	6	2010	2010	2012
Particle Swarm Optimization	11	2011	2013	2020
Function	5	2011	2013	2020
Electricity Markets	7	2014	2016	2018
Genetic Algorithms	6	2012	2016	2020
Financial Forecasting	5	2016	2016	2023
Technical Analysis	5	2011	2016	2023
Decision Making	7	2010	2017	2022
Feature Selection	5	2012	2017	2020
Fuzzy Logic	5	2014	2017	2022

3.6.3. Thematic map

One of the principal analyses performed in this study involves the development of a thematic map focusing on Portfolio optimization in the light of AI, ML, and DL advancements .The aim of this analysis is to gain a nuanced understanding of the current landscape and to explore the field's sustainability and future growth potential (Moral-Munoz et al., 2018). By constructing this thematic map, researchers and stakeholders can extract valuable insights into promising research avenues, guiding them toward areas of inquiry that hold potential for further development and innovation. This type of analysis is instrumental in providing strategic knowledge to those invested in advancing the field. The thematic map is created by examining clusters of author keywords and their interconnections, identifying and defining significant themes. Each theme is characterized by two key attributes: density and centrality. In this context, density is plotted on the vertical axis and centrality on the horizontal axis. Centrality reflects the extent of interconnectedness among different themes in the network. It measures the thematic network's integration, with higher centrality indicating a greater number of connections to other topics, signifying its importance within the research ecosystem. Density, on the other hand, represents the internal cohesiveness of a thematic cluster, showing how well-developed and structured the topic is. Higher density implies that a theme has a strong internal structure, suggesting its ability to sustain future research efforts. Figure 17 displays the thematic map of Portfolio optimization in the light of AI, ML, and DL advancements, divided into four quadrants (Q1 to Q4). The map offers a visual depiction of the identified themes, their density, and their centrality within the field. This graphical representation facilitates a comprehensive understanding of the thematic structure and development of the research landscape, aiding researchers in identifying both mature and emerging areas of inquiry that can inform and shape future research directions.

In the thematic map presented, the upper right quadrant (Q1) represents driving themes within the context of financial markets and investment strategies. These themes hold strong relevance and development, significantly shaping the research landscape. The lower right quadrant (Q4) consists of foundational themes that serve as essential building blocks, contributing fundamental concepts and methodologies to the field. Themes in the upper left quadrant (Q2) are considered specialized or niche; while they are highly developed within their scope, their overall contribution to the broader development of the field remains limited. Lastly, the lower left quadrant (Q3) includes emerging or potentially declining themes, indicating areas that are either gaining momentum or fading in relevance within the research domain. From the figure, it is evident that themes like "bitcoin," "gold," and "oil" occupy prominent positions in Q1, showcasing their importance and well-developed nature in driving current research in financial markets. These themes are influential and continue to lead the discourse in areas like asset management and hedging strategies. Meanwhile, themes such as "model selection," "optimization," and "neural networks" in Q4 represent foundational concepts that are crucial for advancing research in algorithmic trading and portfolio optimization. They provide essential frameworks that underpin developments in the field. In Q2, themes like "naive diversification" and "Markowitz" are internally well-connected but have a more focused or niche application, contributing marginally to the overall advancement of the broader field. These themes may require further integration to have a larger impact on the financial research landscape. Finally, the lower left quadrant (Q3) houses emerging or less developed themes, such as "artificial intelligence" and "trust." These themes are at a crossroads, either gaining attention or potentially becoming less relevant in future research. Overall, this thematic map offers valuable insights into the various themes shaping financial markets, their interconnections, and their role in the development and evolution of the field.

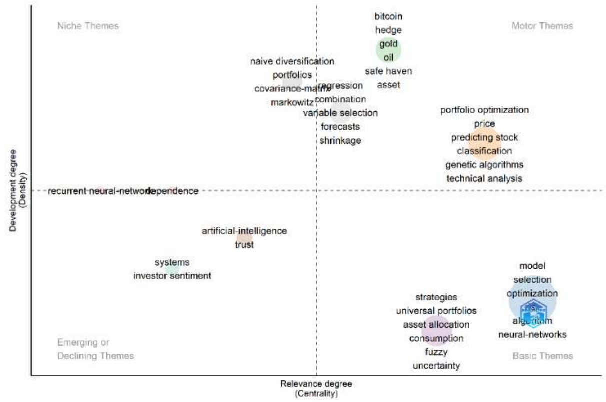


Fig. 17. Thematic map

3.6.4. Thematic evaluation

Thematic evolution is a bibliometric technique that provides a historical perspective on research trends, helping to establish a science-based framework for guiding future research directions (Moral-Munoz et al., 2018). It highlights the most significant research themes and tracks their development over time, offering valuable insights into how a field progresses. The figure above illustrates the evolution of the most frequently used terms in the study of portfolio management and optimization from 1996 to 2024, divided into three distinct time periods. The first phase, from 1996-2010, showcases foundational themes such as "portfolio management," "risk," "portfolio selection," and "optimization." These topics were central during this time, laying the groundwork for advancements in financial research, especially in terms of managing portfolios and evaluating risk. In the second phase, from 2011-2020, the landscape begins to diversify. While core themes like "portfolio optimization" and "portfolio management" remain relevant, new themes emerge, including "artificial intelligence," "deep learning," "neural networks," and "conditional value-at-risk." These reflect a shift towards integrating machine learning and AI-driven techniques in portfolio analysis and decision-making processes, marking an important expansion of the field. Finally, the third phase, from 2021-2024, shows a strong continuation of AI-related research. Themes such as "machine learning," "deep learning," and "neural networks" dominate the field, alongside emerging topics like "multi-objective optimization," "genetic algorithms," and "online learning." This period represents a significant leap towards more complex and automated approaches to portfolio management, with a clear focus on innovation and the application of advanced computational methods. Overall, this thematic evolution highlights how portfolio management research has transitioned from traditional methods in the late 1990s to more sophisticated, AI-driven approaches in recent years, providing a roadmap for future research trends in this rapidly evolving field.

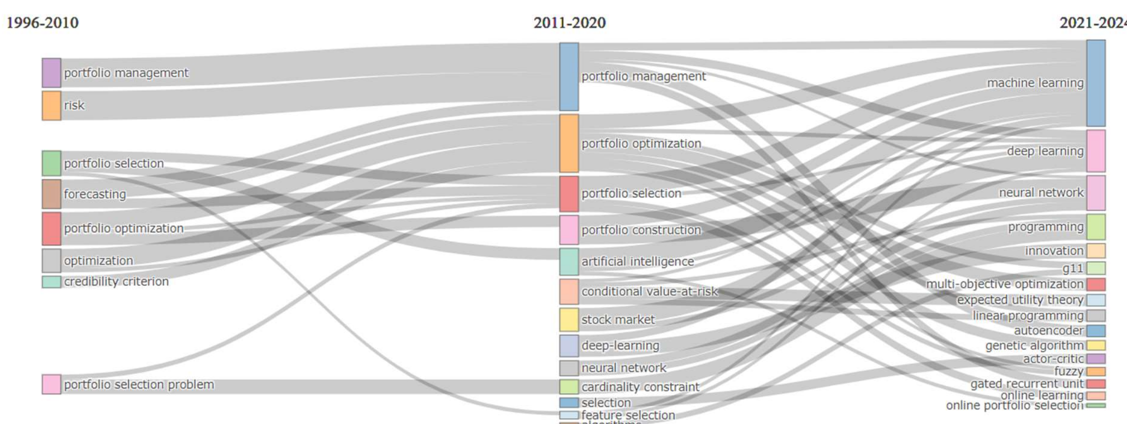
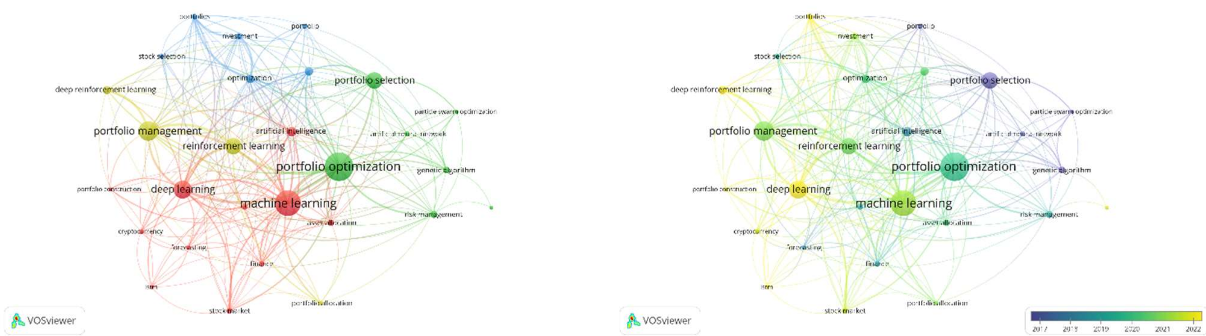


Fig. 18. Thematic evaluation

3.6. Co-Word and Word-Cloud analysis

The Co-Word or Co-Occurrence keyword analysis constitutes a sophisticated bibliometric methodology utilized to discern key terminologies that frequently co-occur within bibliographic datasets, thereby elucidating the most pertinent thematic classifications within a given research domain. In this analysis, the size of the keywords corresponds directly to their frequency of appearance, with larger keywords denoting a higher incidence of occurrence (refer to Figure 19). This method is particularly invaluable as it enables researchers to concentrate on the most prominent and influential terms emerging from the extant body of literature. In the documents under scrutiny, "Portfolio Optimization" and "Machine Learning" prominently emerge as the most frequently deployed author keywords (as depicted in Figure 19 (a)). Moreover, keywords such as "Risk Management" and "Optimization" have made substantial contributions to the scholarly discourse, reflecting their centrality within the research domain. This keyword analysis serves the dual function of not only identifying core research foci but also tracing the diachronic evolution of these thematic areas. Figure 19 (b) provides a visual overlay network, where the color scheme represents the average publication year associated with each keyword. Older terms are denoted in violet, whereas more recent contributions are shaded towards yellow. Some of the most contemporary keywords, such as "Deep Learning," "Machine Learning," and "Reinforcement Learning," exemplify the prevailing trends and current focal points in the study of portfolio optimization through the lens of AI, ML, and DL advancements. By analyzing this chromatically-coded representation, researchers gain critical insights into the temporal development of research themes and the emergence of novel topics, thereby facilitating a more nuanced comprehension of the intellectual trajectory within the field.



(a) (b)

Fig. 19. Co-occurring keywords analysis (min: 10 times occurring), (a) Cluster Analysis based on subjects (b) Cluster Analysis based on periods

A word cloud serves as a graphical representation of textual data, where the size of each word visually correlates with its frequency or significance within a given text corpus. It offers an intuitive and rapid means of discerning dominant themes or key terms within a body of research. This section introduces two types of word cloud visualizations, each providing critical insights into the keywords employed in the discourse surrounding Portfolio optimization in the light of AI, ML, and DL advancements. The first visualization focuses on authors' keywords (depicted in Fig. 19 (a)), where "Portfolio Optimization" and "Machine Learning" emerge as the most prominent terms, reflecting their central role within the scholarly discourse. In contrast, the second type of word cloud examines Keywords Plus (illustrated in Figure 19 (b)), with "Model" and "Selection" being identified as pivotal keywords in the analysis. Additionally, terms such as "Prediction," "Framework," "Risk Management," "Strategies," and "Uncertainty" also surface as integral methodologies and thematic elements within the research field. By identifying these frequently recurring keywords and examining their relationships, researchers can glean critical insights into the prevailing topics, conceptual frameworks, and methodological approaches that characterize the field. This, in turn, facilitates a deeper understanding of the key areas of focus and emerging trends in the study of Portfolio optimization in the light of AI, ML, and DL advancements.

(a) (b)

Fig. 20. Word cloud (a) Author's keywords (b) Keywords plus

Overall, the analysis of the Co-occurring and Word Cloud plots reveals that the paper centers on the complexities of portfolio optimization and risk management. The authors highlight the importance of employing advanced techniques like machine learning and deep learning to enhance portfolio selection, while also addressing the risks and uncertainties associated with market fluctuations and investment strategies.

4. Discussion

In recent years, the volume of academic research on portfolio optimization in the light of AI, ML, and DL advancements has witnessed a marked surge. The bibliometric analysis presented in this study illuminates this upward trajectory, reflecting a burgeoning corpus of work focused on integrating innovative computational techniques into portfolio optimization frameworks. This growing interest is largely driven by the escalating complexity of financial markets and the pressing need for more sophisticated methodologies capable of processing vast volumes of data, which traditional optimization models increasingly struggle to handle (Manogna & Anand, 2023).

The incorporation of AI, ML, and DL techniques into portfolio optimization in the light of AI, ML, and DL advancements has become a critical factor in refining decision-making processes, bolstering predictive accuracy, and facilitating real-time adaptive responses within fluid market environments. AI-powered algorithms have notably enhanced portfolio performance by exploiting historical data, detecting intricate market patterns, and adjusting dynamically to market fluctuations. Our bibliometric findings substantiate this trend, revealing a growing focus on real-time data analytics and automated decision-making mechanisms within the financial sector, consistent with broader advances in AI and ML technologies (Goodell et al., 2021).

Furthermore, the analysis underscores the rising prominence of Deep Learning methods in addressing the multifaceted challenges posed by portfolio optimization in the light of AI, ML, and DL advancements. While traditional ML models provide substantial solutions, DL has demonstrated superior efficacy in capturing nonlinear relationships and uncovering latent patterns in financial datasets, thereby enhancing forecasting precision and risk management strategies. This indicates that future research in portfolio optimization is likely to increasingly gravitate toward the exploration and refinement of DL techniques, with an eye toward improving model accuracy, resilience, and predictive robustness.

Despite the expanding body of literature in this field, several research avenues remain underexplored. First, while significant strides have been made in the application of AI and ML to portfolio optimization in the light of AI, ML, and DL advancements, further empirical investigation is warranted into the specific contributions of DL in augmenting financial decision-making processes. Second, as financial institutions adopt AI and ML models at a growing rate, there is a pressing need for more research focused on the ethical concerns and regulatory challenges that accompany the deployment of these technologies. Lastly, future studies should investigate the cross-disciplinary applications of AI, ML, and DL in portfolio optimization, particularly their intersection with emergent areas such as behavioral finance and sentiment analysis, which may offer new insights into market dynamics and investor behavior.

5. Conclusions and future research directions

This bibliometric study has provided an in-depth examination of the evolution of scientific publications in the realm of Portfolio optimization in the light of AI, ML, and DL advancements. The findings highlight the increasing significance of leveraging AI, ML, and DL techniques to improve decision-making processes and optimize portfolio management strategies, particularly in complex and volatile financial markets. Our analysis has revealed a growing interest in interdisciplinary approaches and a notable increase in collaboration between academia and industry, which has further enriched the development of portfolio optimization methodologies.

The study also identified critical trends, including the rising use of AI and ML to enhance portfolio diversification, improve risk assessment, and optimize performance. However, certain challenges persist, and future research must address these to fully unlock the potential of these advancements in portfolio optimization. Moreover, as with any bibliometric analysis, this study's limitations stem from the reliance on data retrieved from specific databases like the Web of Science, which may constrain the comprehensiveness of the review. Additionally, the quantitative focus of this study may overlook the deeper qualitative insights needed to better understand ongoing developments in this rapidly evolving field.

Looking forward, several promising research directions could further strengthen the field of Portfolio optimization in the light of AI, ML, and DL advancements:

- **Enhanced Predictive Analytics:** Future studies should explore the development of more advanced predictive models that utilize AI and ML algorithms to improve portfolio risk assessments and performance forecasting, particularly in the context of high market volatility.
- **Integration of Hybrid Models:** Investigating the potential of hybrid models that blend AI, ML, and traditional financial theories to create more robust and adaptive portfolio optimization frameworks.
- **Ethical and Interpretability Considerations:** Addressing the ethical challenges posed by AI-driven decision-making in portfolio management, with a focus on enhancing the interpretability and transparency of complex ML and DL models.

- **Real-time Portfolio Management:** Exploring the use of DL and AI for real-time data processing and decision-making in portfolio management, aimed at improving responsiveness to sudden market changes and external disruptions.

Exploring these research avenues can significantly advance the understanding of how portfolio optimization in the light of AI, ML, and DL advancements can enhance resilience, transparency, and efficiency in portfolio management. Future investigations in this area will provide both scholars and practitioners with valuable, actionable insights to better navigate the complexities of modern financial markets. By addressing these emerging challenges, researchers can contribute to the development of more robust and adaptable strategies that meet the demands of an increasingly dynamic financial landscape.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used OpenAI's tool Chat GPT in order to edit and write some parts of the paper. After using this service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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