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A bibliometric analysis and visualization of the scientific publications on multi-period portfolio optimization: From the current status to future directions

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A B S T R A C T

Portfolio optimization is a widely recognized strategy for investing that involves selecting a combination of assets that offers the optimal balance between potential gains and volatility. Traditional portfolio optimization typically focuses on a single period, considering only the current market conditions. However, multi-period portfolio optimization takes a more comprehensive approach by incorporating the dynamic nature of financial markets over multiple periods. Hence in this study, we focus on multi-period portfolio optimization. We conduct a bibliometric analysis of articles on multi-period portfolio optimization in the Web of Science (WoS) database. Through quantitative methods and the utilization of the Bibliometrix R package, we analyze publication trends, key research sites, and historical output in this field. Our findings provide valuable insights into the current state of research on multi-period portfolio optimization. This bibliometric analysis contributes to the existing literature on multi-period portfolio optimization and serves as a valuable resource for researchers, policymakers, and practitioners in the field of finance.

1. Introduction

In the field of economics, there is a widespread consensus that efficient financial markets play a vital role in stimulating economic growth. One significant component of the financial market is the stock exchange market, which has been extensively studied and recognized (Ghanbari et al., 2022; Kumar et al., 2022). In the modern world, the stock market is viewed as a measure of a country's economic progress and advancement, making it a crucial indicator of economic health to monitor (Fooeik et al., 2022). The stock market allows investors to forecast the state of an economy and determine if it is viable by serving as an indicator of economic growth, activities, and other economic functions (Khan et al., 2020). Investors have the option to put their savings and wealth into bank accounts or they can purchase shares of companies through stockbrokers on the stock market. Hence, it is crucial for investors to have a complete understanding of the stock market (Kumar et al., 2022). Asset Management Firms (AMFs) and investors often conduct technical analyses to forecast future market or price movements. They utilize historical market data and trading information along with technical indicators for this purpose (Hoseinzade & Haratizadeh, 2019; Khan & Mehlawat, 2022). Market trends refer to the pattern of financial markets moving in specific directions during certain time periods, which can impact the investment habits of individuals (Alhnaity & Abbod, 2020; Fontanills & Gentile, 2001; Ngoc, 2013). In a specific time frame, there are three types of market trends: bullish market predicts rising asset prices; bearish market predicts falling asset prices; stagnant market shows minimal or no growth in asset prices (Kumar et al., 2022; Tsinaslanidis, 2018). Investors have various methods to choose portfolios, such as forecasting prices using news, investor sentiment, and company financial reports. Other computational optimization models include the capital asset pricing model (CAPM), price/earnings ratio models, and multicriteria decision models. Investors are able to utilize a variety of approaches based on their own judgment. Moreover, investors have access to a variety of data sources containing risk factors such as news, sentiment, and financial reports. Hence, relying solely on a single approach, like analyzing the news, could result in missing crucial risk details from other

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channels (Surtee & Alagidede, 2023). Portfolio Optimization aims to increase profits while reducing market risks by diversifying investments in portfolio management during a given period (Almahdi & Yang, 2017; Leković, 2018). It keeps a varied selection of securities with low correlations to ensure effective diversification in a portfolio (Yeo et al., 2023). The risk in the original Markowitz model, as described in Markowitz's 1952 paper, is assessed using standard deviation or variance, resulting in quadratic optimization issues. Many additional risk measures have been examined subsequently, leading to the development of a complete range of mean-risk (Markowitz type) models. In specific, downside risk measures (Fishburn et al., 1977; Ghanbari, Shabani, et al., 2023) are often preferred over symmetric measurement like standard deviation (Ogryczak et al., 2017). In the case of discrete random variables, a risk measure can be computed using LP. This pertains to a broad category of risk measures known as Polyhedral, which were introduced by Eichhorn and Römisch (2006), and are characterized by convex polyhedral functions for discrete random variables. Portfolio optimization has seen the application of numerous polyhedral risk measures (Mansini et al., 2014). Common measures of risk are of the deviation type. Basic polyhedral risk measures are dispersion measures that resemble variance (Ogryczak et al., 2017). Markowitz in 1959 suggested using downside risk measures like downside standard deviation and semi-variance (SV) instead of variance as the risk measure. Konno and Yamazaki (1991) presented a portfolio selection model incorporating the mean absolute deviation (MAD). Young (1998) introduced the Minimax model, while Yitzhaki et al. (1982) previously proposed the mean risk model utilizing Gini's mean (absolute) difference (GMD) as the risk measure (Ogryczak et al., 2017). Many rational investors prioritize underperforming rather than overperforming in a portfolio. These constraints have prompted exploration into methods that utilize realistic risk measures to differentiate between unfavorable downside shifts and favorable upside shifts. value-at-risk (VaR) (Manganelli & Engle, 2001) and expected shortfall or conditional value-at-risk (CVaR) (Rockafellar & Uryasev, 2000, 2002) are recognized as popular risk measures among the many available. Rockafellar and Uryasev (2002) provided an in-depth analysis of VAR and CVaR using typical distributions. The decision on which risk measure to use is influenced by various factors including differences in mathematical properties, stability of statistical estimation, ease of optimization procedures, and the level of acceptance by financial industry and regulators. Even though VaR is widely used in finance, its computational complexity poses a challenge for portfolio optimization with real-world constraints due to its non-linear and non-tractable nature (Lwin et al., 2017). Certain polyhedral risk measures, such as mean below-target deviation, Minimax, VaR, and CVaR, embody a common emphasis on downside risk. Conversely, metrics such as MAD or GMD exhibit more symmetry. However, they can still be expanded to improve focus on downside risk (Krzemienowski & Ogryczak, 2005; Michalowski and Ogryczak, 2001) while maintaining their polyhedrality (Ogryczak et al., 2017). In essence, a portfolio consists of stocks, bonds, or other financial or real assets owned by an individual, a group, or a company to generate profits. A prudent investor will opt for a portfolio from the efficient frontier as it offers the best balance between risk and return, with risk being assessed through standard deviation and return being the average percentage change in stock prices (Kumar et al., 2022). Portfolio optimization is a crucial concern in financial markets with various uses in financial planning and decision making (Jezeie et al., 2022; A. M. Larni-Fooeik et al., 2024). Portfolio optimization is the efficient allocation of a finite amount of capital among various financial assets in order to strike a balanced deal between return and risk. Portfolio optimization involves building an investment portfolio that aims to maximize returns and reduce risk (Lwin et al., 2017). Markowitz established the theoretical basis for this topic and modern portfolio theory in the early 1950s (Markowitz, 1952). Using various quantitative tools and models, portfolio optimization helps investors achieve diversification, lower transaction costs, and make well-informed investment choices (Jezeie et al., 2022; Larni-Fooeik et al., 2024). The initial study on portfolio selection can be traced to Markowitz (1952) and focused on the mean-variance model for the problem of selecting a portfolio for a single period. It has been crucial in shaping the advancement of contemporary portfolio analysis. Following Markowitz's groundbreaking research, many academics expanded the traditional mean-variance model to encompass portfolio selection over multiple time periods (Liu et al., 2013).
The lack of attention given to the mean-variance approach in long-term investment planning is quite intriguing. Markowitz does not take into account genuine multi-period models (in which the portfolio may be adjusted multiple times throughout the planning horizon). These considerations employ a utility function that focuses on wealth consumption across time instead of the average and variability of final wealth, thereby placing the issue within the scope of dynamic programming (Steinbach, 1999). Multi-period portfolio optimization involves a dynamic strategy that extends the mean-variance optimization problem. The optimization problem is not always fixed, and in certain situations, the solution may vary depending on the finite horizon. The objective is to determine the dynamic asset allocation strategy while taking into account various factors such as rebalancing costs, trading impacts, changing constraints, price trends, and more.

The objective of this research was to conduct a bibliometric analysis of articles on multi-period portfolio optimization found in the Web of Science (WoS) database. A quantitative method was utilized to perform a bibliometric analysis of published articles in order to reach this goal. This research utilizes Bibliometrix, which is an R package that includes a web-based interface and VOSviewer for conducting bibliometric analysis. Finding key research sites for multi-period portfolio optimization can assist in developing national and institutional research strategies. Moreover, the data visualization can help analyze the historical trends of research output in a specific field and pinpoint possible future research directions and partnerships.

The remaining sections of the paper are structured as follows. In Section 2, we outline the Materials and Methods that have been employed in the analysis, offering insights into the research approach and data utilized. Following that, in Section 3, we present an extensive Scientometric Analysis. Section 4 is dedicated to presenting and discussing the results derived from the analysis. Finally, in Section 5, we wrap up the paper by providing a concise yet comprehensive conclusion.

2. Materials and Methods

Bibliometric research enables the creation of a distinct viewpoint through a thorough examination. The R package's bibliometrics tool is designed for numerical analysis in the fields of Scientometrics and Informetrics (Ejaz et al., 2022; Javadi et al., 2025). Additionally, bibliometric technologies enable the classification and examination of extensive historical data collected from research completed during a specific timeframe for the purpose of extracting information from the database. Bibliometric analysis and meta-analysis use quantitative techniques to prevent or lessen bias, unlike systematic literature reviews that use qualitative techniques and may be influenced by interpretation bias from scholars with different academic backgrounds (Eskorouchi et al., 2023; Ghanbari, Safari, et al., 2023; Marín-Rodríguez et al., 2022). This research utilized bibliometric analysis to investigate current developments in multi-period portfolio optimization research. Bibliometric analysis involves a quantitative statistical assessment of publications that is unbiased, thorough, clear, and iterative. Content analysis and descriptive analysis are the two most important bibliometric methods. The process of descriptive analysis includes examining various publications and journal indices to assess the effectiveness of authors and sources in their publications. On the other hand, content analysis reveals the intellectual frameworks of specific fields by analyzing keywords and citations to determine popular subjects, themes, and research focuses. Several databases are available for bringing in bibliographic information, like Scopus, Web of Science (WoS), Dimensions, Cochrane Library, Lens, and PubMed, each with distinct features and capabilities. The most commonly utilized literature databases for nearly all fields are currently the Web of Science and Scopus. In this research, we performed a search for documents on the Web of Science database, which is known for its vast paper collection and comprehensive citation information. Web of Science is a unified database that enables educators to examine and assess publications, patents, and policy papers. We examined titles of publications, summaries, and keywords of authors. The search parameters included ("Multi period") And ("Portfolio Optimization" OR "Portfolio Selection" OR "Portfolio Management"). The search was narrowed down by specifying a publication date between January 1900 and October 2023. The information was obtained on 1 November 2023 and resulted in an initial compilation of 344 publications. The study incorporated English original articles, review and conference papers, and book chapters. We did not include studies containing comments, editorials, letters, articles, or reviews from preprint websites. Within this study, the search equation employed was as follows:

Table 1
The main keyword combination structure

Level	Search Terms
1	Portfolio
	AND
2	Optimization OR Selection OR Management
	AND
3	Multi Period
(("Multi period") And ("Portfolio Optimization" OR "Portfolio Selection" OR "Portfolio Management"); (All Fields)).	

In conclusion, we assessed all published information to pinpoint the resources that solely delved into multi-period portfolio optimization while disregarding those that discussed Portfolio Optimization in different contexts. By applying these specific criteria for inclusion and exclusion, we discovered a set of 330 research papers from January 1900 to October 2023. This dataset of 330 records served as the basis for the bibliometric analysis conducted in this research.

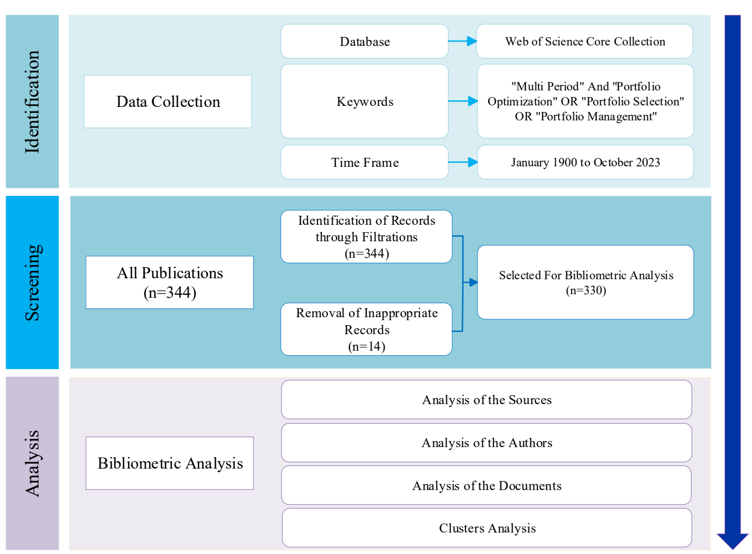


Fig. 1. Flow chart of the search approach

All bibliographic information was downloaded in .csv format from the Web of Science database. At first, the Bibliometrix R package was installed and activated in R Studio. Biblioshiny was inputted into the R console to launch the Biblioshiny application. Biblioshiny is an online tool that allows non-programmers to utilize the Bibliometrix package in R. Bibliometrix offers researchers a variety of tools for carrying out thorough analysis of bibliometrics. Biblioshiny, a statistical software tool, was employed in bibliometrics for data mining to identify how often keywords appeared together in two scientific articles, with the goal of streamlining the complex network of keyword connections. An Excel file in .csv format was added to the Biblioshiny platform.

CSV and PNG files were downloaded and utilized for data analysis in alignment with the study's goals. To present in-depth information in the research on multi-period portfolio optimization, we utilized VOSviewer for extracting additional patterns. The VOSviewer software, developed for creating and displaying bibliometrics maps, was utilized for analyzing the global publication landscape. When citing an article or issue, readers have the opportunity to create and see a network or connection with the help of a text-mining feature. It is able to display longer articles and publications with a variety of options and features, such as zooming, scrolling, and searching. The VOSviewer allows for displaying detailed data in the Bibliometrics graphic map. Academics often analyze relationships by visualizing a large bibliometric map, and many past research studies have employed this tool for bibliometric analysis.

3. Scientometric Analysis

3.1. Analysis of the Sources

3.1.1. General Information

Out of the 330 documents included in the study, 625 authors were recognized. The mean number of references per paper is 14.76, a figure held in high esteem by the academic community. The yearly growth rate has risen by 12.18% annually. It should be noted that the search timeframe was from 1900 to 2023, however the initial desired outcome was achieved in 1995. Fig. 2. provides an overview of the key details of the chosen papers in this research.

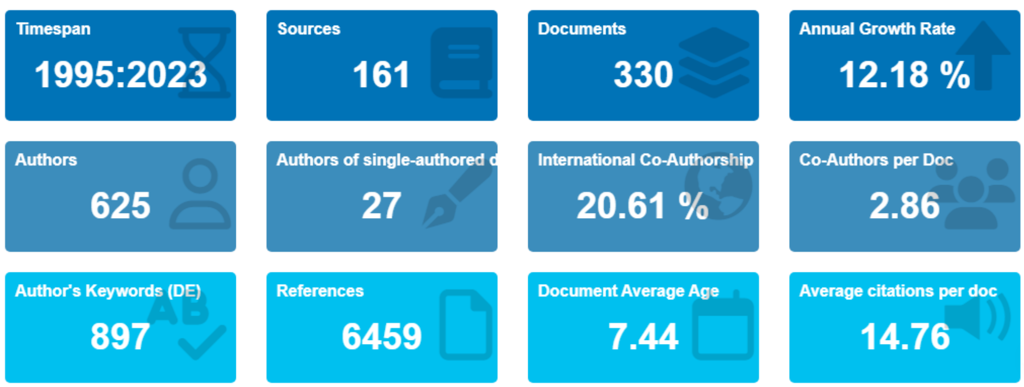
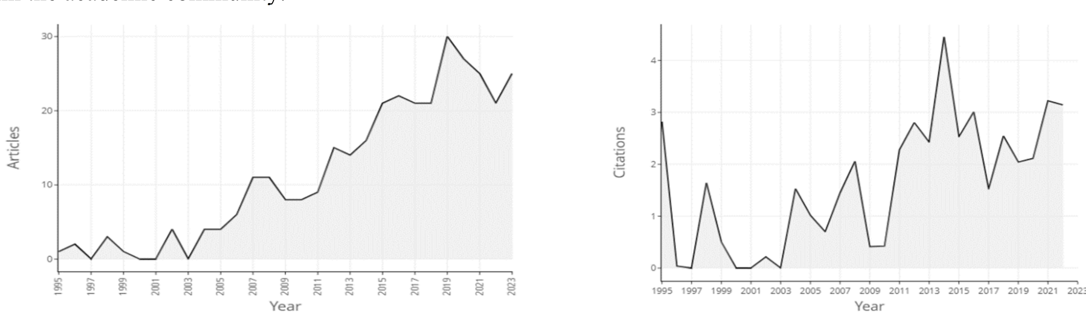


Fig. 2. General Information

3.1.2. Publication Output

Fig. 3a illustrates a notable rise in the number of research papers published in recent years, demonstrating a growing interest within the academic community.



3 (a) Annual Scientific Production

3 (b) Average Citation Per Year

Fig. 3. Publication output

The number of documents produced annually increased from 4 in 2005 to 30 in 2019. As of November 2023, 25 studies have been published on this subject, indicating that this trend is likely to persist into 2024 and beyond. Until 2005, the lack of research contributions was clear. However, starting in 2005, there was a notable rise in research contributions because of advancements in methodologies aimed at tackling the problem. Fig. 3b. shows the mean number of citations per year, revealing that 2014 had the highest average of citations.

3.1.3. Discipline-Wise Analysis

Fig. 4 displays the articles by source in order of significance for studying multi-period portfolio optimization. It has been determined that this subject has been thoroughly researched, primarily in the European Journal of Operational Research (EJOUR). Journal of Industrial and Management Optimization came in second place in terms of occurrences, while Expert Systems with Applications and Quantitative Finance took the third and fourth spots, respectively. This indicates that these sources are crucial for the related study.

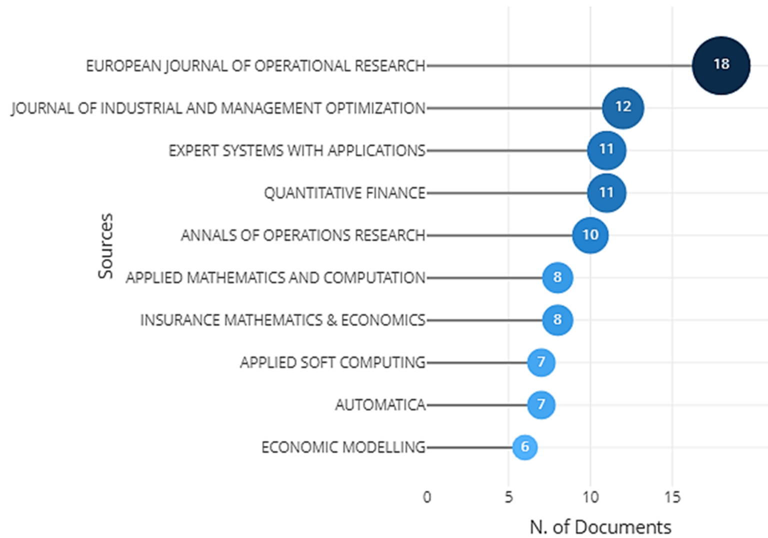
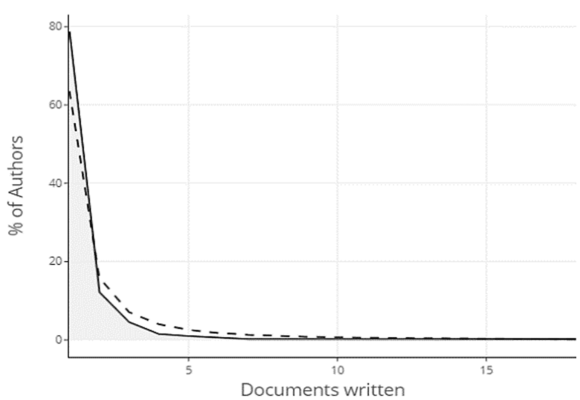


Fig. 4. Distribution of documents across sources

3.2. Analysis of the Authors

3.2.1. Authors' Productivity

Lotka's Law characterizes and explains researchers who have a greater frequency of output in a specific field of knowledge. The outcomes for studies on multi-period portfolio optimization are shown in Fig. 5, along with the projected distribution based on Lotka's law. In this research, the findings show a Lotka's index where 78.72% of the authors would write one article, 12.16% would write two, 4.48% would write three, and 4.64% would write four or more. This suggests that authors of multi-period portfolio optimization do not currently conform to Lotka's Law. The graph in the figure should follow Lotka's Law, as shown by the dashed line.

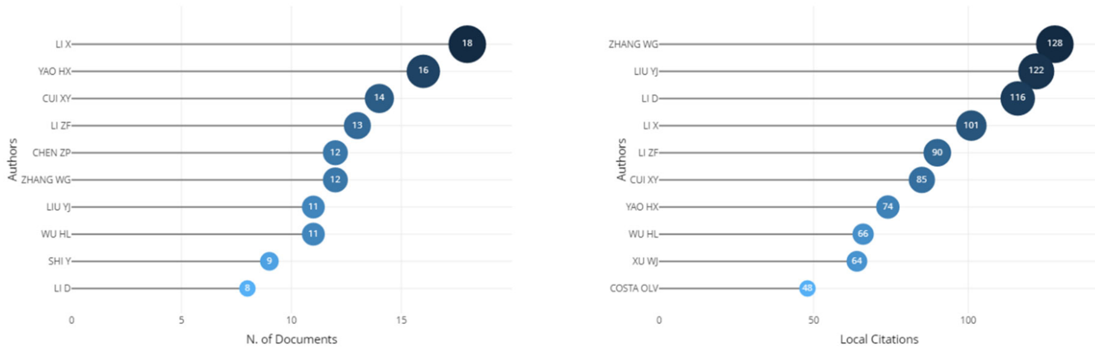


Documents Written	No. of Authors	Proportion of Authors
1	492	0.7872
2	76	0.1216
3	28	0.0448
4 (or more)	29	0.0464

Fig. 5. Authors' productivity according to Lotka's Law production of research

3.2.2. Most Relevant Authors and Authors' Impacts

Fig. 6 shows the top five authors who are most important according to the number of articles they've published: (i) LI X, (ii) YAO HX, (iii) CUI XY, (iv) LI ZF, and (v) CHEN ZP. The top five authors who have the most local citations regarding their impact on multi-period portfolio optimization publication outputs are (i) ZHANG WG, (ii) LIU YJ, (iii) LI D, (iv) LI X, and (v) LI ZF.



6 (a). Most Relevant Authors

6 (b). Most Local Cited Authors

Fig. 6. Most Relevant Authors and Authors' Impacts

3.2.3. Authors' Production over Time

Fig. 7 shows the most prominent authors' works on multi-period portfolio optimization in recent years. The graph's color intensity is linked to the year of citation, while the bubble size indicates the annual publications of different authors. For instance, YAO HX released his initial paper on this subject in 2011. In 2014, three papers were published, followed by four papers in 2016.

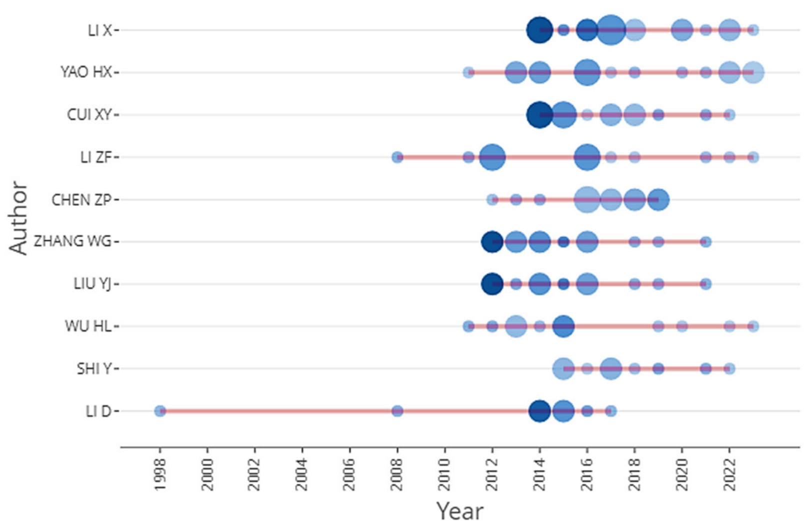


Fig. 7. Authors' Production over Time

3.2.4. The Leading Countries and Institutions

This study examined the most prominent countries and institutions globally. Table 2 displays the top 10 Most Relevant Countries. China dominates in producing the most publications on this topic, with 153 documents in total. The United States is ranked second with 29 points, while Iran is ranked third with 27 points. Figure 8 displays both the quantity and ratio of collaborative efforts among different countries. SCP and MCP categorize articles as either Single Country Publications, where all authors are from one country showing intra-country collaboration, or Multiple Country Publications, where authors are from different countries showing inter-country collaboration (i.e. international collaboration). Shanghai University of Finance and Economics in China ranks first among the top 10 institutions, having published 26 articles. The Sun Yat Sen University (China) is represented in this position with a total of 25 articles. Table 3 displays additional prestigious institutions.

Table 2
The top 10 corresponding author countries

Rank	*Country*	*No. of Articles*	*SCP*	*MCP*
1	CHINA	153	129	24
2	USA	29	18	11
3	IRAN	27	24	3
4	CANADA	14	9	5
5	ITALY	13	11	2
6	AUSTRALIA	11	7	4
7	SWITZERLAND	8	6	2
8	INDIA	6	6	0
9	UNITED KINGDOM	6	4	2
10	BRAZIL	6	6	0

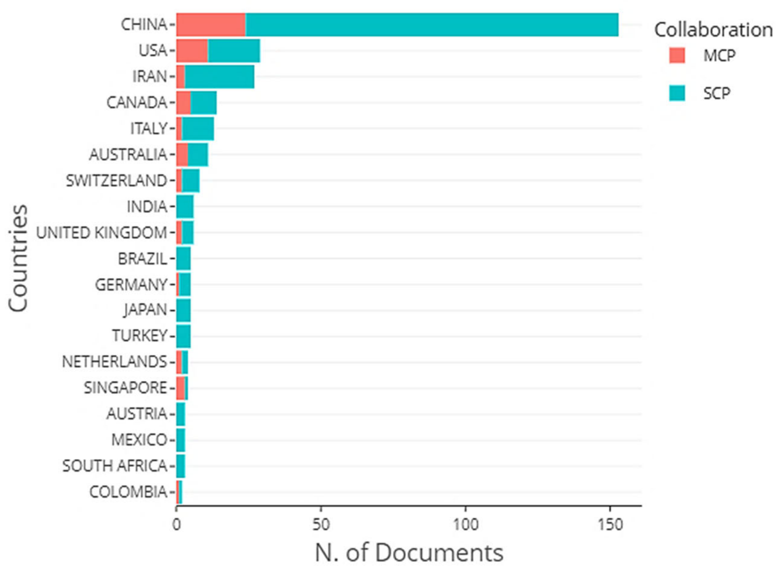


Fig. 8. Corresponding Author's Country

Table 3
The top 10 institutions publishing articles

Rank	*Affiliation*	*Articles*
1	SHANGHAI UNIV FINANCE AND ECON	26
2	SUN YAT SEN UNIV	25
3	GUANGDONG UNIV FOREIGN STUDIES	18
4	HONG KONG POLYTECH UNIV	17
5	CENT UNIV FINANCE AND ECON	14
6	XI AN JIAO TONG UNIV	14
7	CHINESE UNIV HONG KONG	11
8	GUANGDONG UNIV TECHNOL	10
9	UNIV WATERLOO	10
10	ISLAMIC AZAD UNIV	9

3.2.5. Co-Author Analysis

The presence of multiple researchers collaborating on a single document is a key factor to consider in co-author analysis. The colored lines on the map visualization represent the connections between the items. The weight characteristics indicate the significance of the recognized network, as demonstrated by the size of the item. In conclusion, the quantity of lines written by the co-authors indicates their importance in the analysis of bibliographic data. Fig. 9 shows how researchers are connected based on the documents they are working on together. Therefore, this diagram enables us to analyze the presence and attributes of collaboration networks and potential author groups focusing on researching multi-period portfolio optimization.

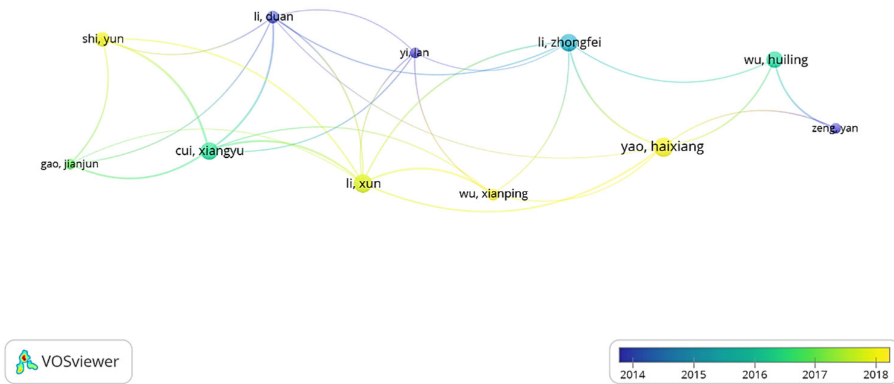


Fig. 9. Co-authorship network

3.3. Analysis of the Documents

3.3.1. The Most Impactful Documents

Table 5 displays the top 10 most cited documents worldwide in multi-period portfolio optimization research, with citations ranging from 79 to 278. The publications titled "60 Years of portfolio optimization: Practical challenges and current trends", "A Stochastic-Based Decision-Making Framework for an Electricity Retailer: Time-of-Use Pricing and Electricity Portfolio Optimization", and "A possibilistic mean-semivariance-entropy model for multi-period portfolio selection with transaction costs" are the top three most cited worldwide, with 278, 140, and 119 citations, respectively.

Table 4
Top 10 cited documents

Rank	*Author*	*Source*	*Total Citations*	*TC per Year*
1	Kolm, Tuetuencue, Fabozzi	European Journal of Operational Research	278	27.8
2	Hatami, Seifi, Sheikh-El-Eslami	IEEE Transactions on Power Systems	140	10.77
3	Zhang, Liu, Xu	European Journal of Operational Research	119	9.92
4	Leippold, Trojani, Vanini	Journal of Economic Dynamics & Control	116	5.8
5	Rosenberg, Haghnegahdar, Goddard, Carr, Wu, de Prado	IEEE Journal of Selected Topics in Signal Processing	102	12.75
6	Calafiore	AUTOMATICA	101	6.31
7	Low, Alcock, Faff, Brailsford	Journal of Banking & Finance	100	9.09
8	Costa, Araujo	AUTOMATICA	83	5.19
9	Farinelli, Ferreira, Rossello, Thoeny, Tibiletti	Journal of Banking & Finance	79	4.94
10	Golub, Holmer, Mckendall, Pohlman, Zenios	European Journal of Operational Research	79	2.72

3.3.2. Most Frequent Keywords

Fig. 10 displays the author keywords that appear most often from 1900 to November 2023. Analysis of author keywords provides insights on research trends from the perspective of the researchers. The most frequent terms in the keyword analysis are "portfolio optimization" and "multi period portfolio optimization". Furthermore, "portfolio optimization" and "portfolio selection" are essentially synonymous and can be used interchangeably. The author's keywords provide indications about the primary methods utilized to assess the interconnectedness among the variables examined.

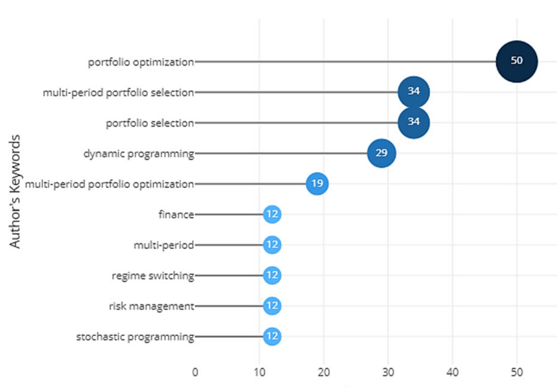


Fig. 10. Most frequent words (author keywords)

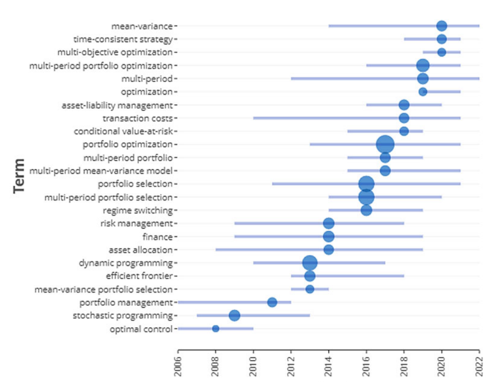


Fig. 11. Trend topics over the years

3.3.3. Trend Topics over the Years

Analyzing trending topics is a crucial mapping tool that illustrates the development of literature. Figure 11 illustrates the subjects found in author keywords with at least five occurrences per article every three years.

Over the past few years (2019, 2023), there has been a focus on several key areas such as mean variance, time consistent strategy, multi objective optimization, multi-period portfolio optimization, and multi-period, showcasing the evolving research trends in the search for multi-period portfolio optimization in response to recent global economic and financial market shifts. From 2016 to 2018, popular subjects included asset liability management, transaction costs, C-VaR, portfolio optimization, multi-period portfolio, multi-period mean variance model, portfolio selection, multi-period portfolio selection, and regime switching.

3.3.4. Thematic Map

This evaluation showcases a thematic map that is split into four topic quadrants according to the density and centrality of the issues (Figure 12). It is important to analyze and research the themes in the top-right quadrant more extensively because of their high concentration and importance.

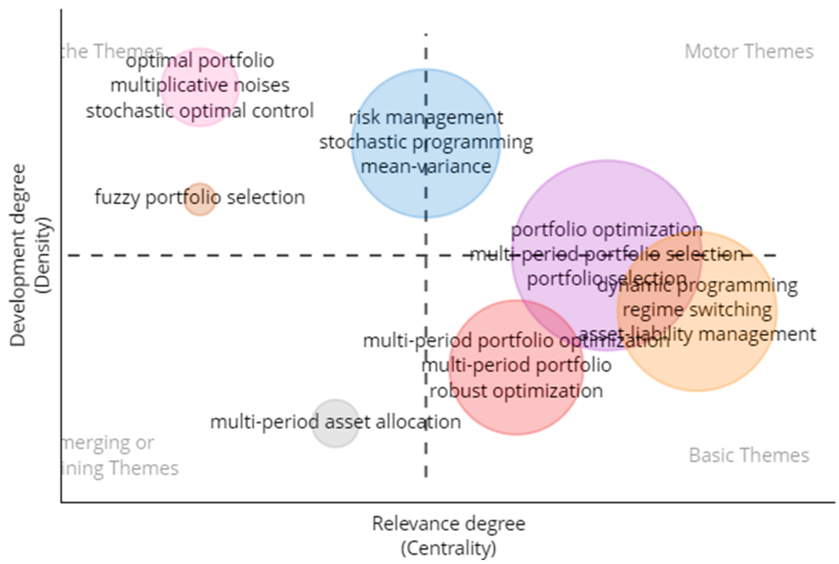


Fig. 12. Thematic map

Fig. 12 illustrates the primary areas for future study in analyzing multi-period portfolio optimization, including portfolio optimization, multi-period portfolio selection, and portfolio selection. Fig. 12 also demonstrates the second highest importance for the keywords dynamic programming, regime switching, and asset liability management, indicating the need to incorporate such analysis in future research.

3.3.5. Thematic Evolution

Thematic evolution is a method in the field of bibliometrics that provides a historical context to research and helps guide future research themes with a science-based approach. It highlights the key research themes in evolution over time, providing insights into the field's future direction. Fig. 13 displays how the most used terms have evolved in the study of multi-period portfolio optimization using co-occurrence network data from 1995 to 2023. Two time periods, 2013 and 2019, were selected as cut-off points based on various sample events. These points encompass the worldwide economic downturn in 2008, the global COVID-19 crisis, and the recent period from 2020 to November 2023. The sizes of the boxes in Fig. 13 indicate the frequency of keyword usage and topics. Between 1995 and 2013, the top terms included managing portfolios, optimizing portfolios, selecting dynamic portfolios, efficient frontier, dynamic programming, and optimizing portfolios over multiple periods. During that time frame, the focus of explorations was on the fundamental concepts and principles of portfolio optimization. The next time slice (2014-2019) saw the consolidation of topics such as multi-period portfolio selection, portfolio optimization, regime switching, asset allocation, and mean variance optimization. The concept of " multi-period portfolio selection" is split into four categories in the upcoming time frame (2020-2023).

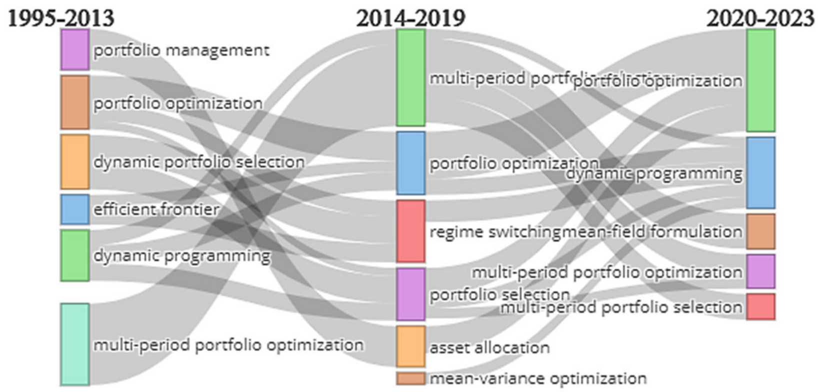


Fig. 13. Thematic Evolution

3.3.6. Most Cited Countries

Fig. 14 shows the most cited countries in analyzing multi-period portfolio optimization, in which the first country is China with 1994 citations, in second place is the USA with 575 citations, and in third place is Iran with 467 citations.

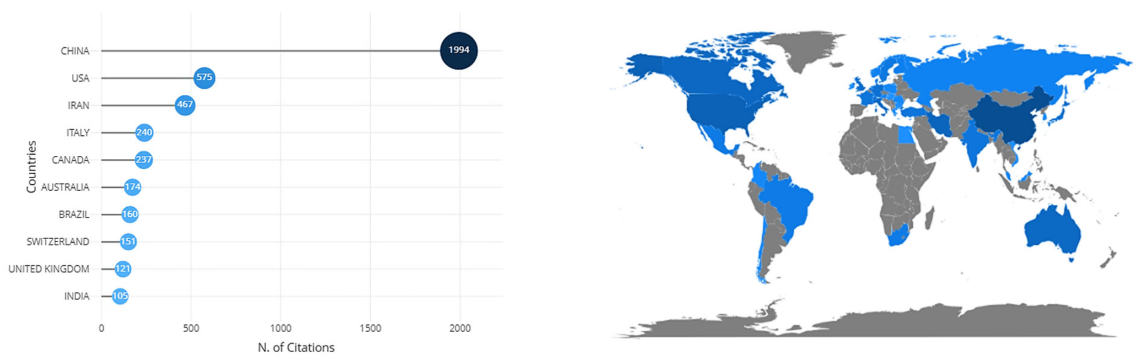


Fig. 14. Most Cited Countries

3.3.7. Three-Field Plot

A three-field plot based on Sankey diagram that depicts the connections from authors to authors' keywords and authors' countries is displayed in Fig. 15. The height of the rectangle nodes is proportional to the frequency of occurrence of a certain author, keyword or country within the collaboration network. The width of lines between the nodes is proportional to the number of connections.

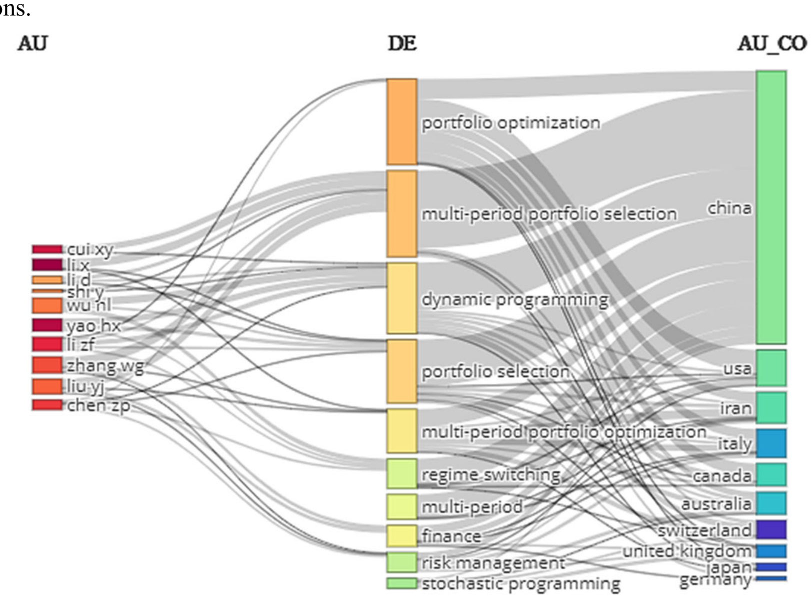


Fig. 15. Three-Field Plot

3.4. Clusters Analysis

3.4.1. Co-Word Analysis

Co-word or co-occurring keywords analysis helps identify the main keywords found in the bibliographic records under examination. Assisting in identifying the most pertinent analysis categories in study, a larger size indicates a higher frequency (Refer to Fig. 16). This evaluation is beneficial as it allows researchers to concentrate on the most important words found in the research findings. The terms multi-period mean variance model, regime switching, stochastic programming, dynamic portfolio selection, genetic algorithm, fuzzy set, scenario tree, and conditional value-at-risk have significantly contributed to research in the analysis of different methodologies for multi-period portfolio optimization.

Fig. 16. Word cloud of Author Keywords

In Fig. 17, the keyword co-occurrence map is divided into five clusters. Every group is formed around the most commonly used keywords. One key idea links all five categories in the multi-period portfolio optimization research and forms the theoretical basis for this study. Keyword analysis not only helps identify research topics but also enables the examination of their development over time. In this way, Fig. 18 demonstrates the keyword network's overlay visualization. The color represents the mean year of publication (mean pub. year). A violet hue is found in older documents, while newer documents have a color similar to yellow.

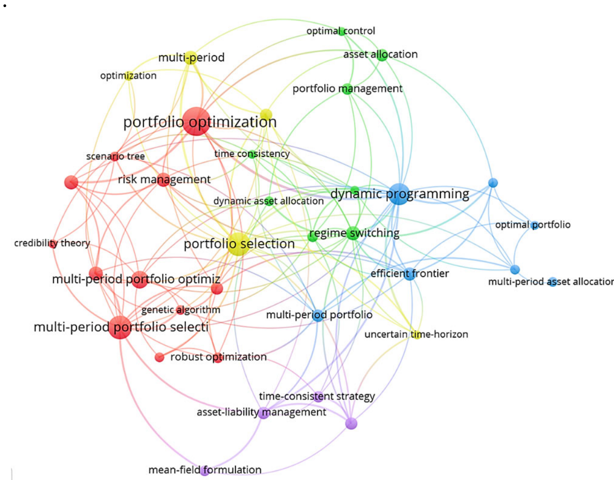


Fig. 17. Network of co-occurring keywords

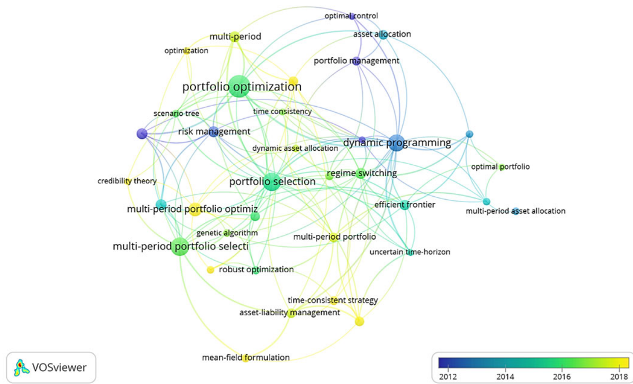


Fig. 18. Network of co-occurring keywords over time

4. Discussion

We conducted a bibliometric analysis of multi-period portfolio optimization papers in this study. This section attempts to explain and evaluate our results, compare them with previous research, examine their limitations and consequences, take into account alternate theories, and make recommendations for further study. First, our analysis provided important insights into the state of multi-period portfolio optimization research. Over the years, we have seen a consistent rise in publications in this area, which suggests that interest in and understanding of its significance has grown. This pertains to the growing intricacy of financial markets and the requirement for advanced investing approaches that take into account the effects of time delays. After comparing our findings with the body of current literature, we discovered that, with regard to the primary research locations and influential figures in the field of multi-period portfolio optimization, our findings are in line with earlier investigations. This demonstrates the robustness and reliability of our analysis. To illustrate the range and scope of study in this field, we also found notable disparities in the individual research topics and methodology used. The implications of our findings are twofold. Our paper offers a thorough review of the research landscape, which theoretically advances our understanding of multi-period portfolio optimization. Our results have practical implications that might guide the creation of institutional and national research strategies, assisting scholars and policymakers in identifying areas of unmet research need and possible joint ventures. Despite the valuable insights obtained from our analysis, it is important to acknowledge the limitations of our study. Initially, our examination relied on articles indexed in the Web of Science database, which might not encompass all relevant studies in the field. Additionally, our analysis focused on quantitative bibliometric techniques, which have limitations in capturing qualitative aspects of research. Considering alternative explanations for our findings, factors such as regional differences, disciplinary boundaries, and publication biases may have influenced the observed patterns. Future research could explore these factors in more depth to provide a nuanced understanding of the research landscape of multi-period portfolio optimization. Based on our findings, we propose several future research directions. First, in order to create sophisticated models and algorithms for multi-period portfolio optimization, more multidisciplinary research is required. This research should integrate insights from the fields of finance, economics, mathematics, and computer science. Second, future studies could investigate the practical implementation of multi-period portfolio optimization strategies in real-world investment settings and evaluate their performance compared to traditional approaches. Finally, research could focus on addressing the computational challenges associated with non-linear and non-tractable risk measures, such as Value-at-Risk, to make portfolio optimization more feasible and efficient.
In conclusion, our study provided a comprehensive analysis of the research landscape of multi-period portfolio optimization. The discussion part evaluated and analyzed the results, contrasted them with prior research, examined their limitations and consequences, took into account alternate theories, and made recommendations for further study. In addition to offering insightful information to scholars and practitioners interested in multi-period portfolio optimization, this study advances the field's understanding.

5. Conclusions

In summary, the analysis of the multi-period portfolio optimization research landscape was the main goal of this study. Our investigation demonstrated the wide range of study topics and approaches used, emphasized the growing interest in this sector, and identified important research locations and contributors. Our bibliometric analysis provided us with important new information on the state of research today and its implications. This research holds importance since it adds to our knowledge of portfolio optimization throughout multiple periods. Our findings can assist in identifying research gaps, direct future research goals, and promote collaboration between researchers and policymakers by offering a thorough picture of the state of the field. In addition, the study highlights the value of doing multidisciplinary research and applying cutting-edge models and algorithms in actual investment situations.

This study concludes by highlighting the importance of multi-period portfolio optimization within the financial markets' framework. The comprehensive analysis of the research landscape, along with the identification of future research directions, contributes to the advancement of knowledge in this field. Researchers and practitioners can improve investment methods and decision-making processes by tackling the intricacies and difficulties related to portfolio optimization. This study serves as a valuable resource for those interested in understanding and contributing to the field of multi-period portfolio optimization.

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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