

Optimizing Portfolios with Machine Learning: A Bibliometric Analysis Using VOS Viewer

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Abstract

This research aims to underscore the application of machine learning in achieving an optimal portfolio that incorporates both cryptocurrencies and traditional assets by mapping and analyzing the academic literature through bibliometric analysis. This study encompasses the Preferred Reporting and Items for Systematic Reviews and Meta-Analysis (PRISMA) Framework to exclude duplicate, missing information, and irrelevant studies. After a rigorous analysis based on inclusion/exclusion criteria, the bibliometric analysis, facilitated by VOSviewer, encompasses Performance Analysis and Science Mapping. The former involves the publication and citation-related metrics, while the latter incorporates co-authorship and co-occurrence analyses. The study offers the probability to improve the efficiency of a portfolio with the help of machine learning with a focus on cryptocurrencies. The value of this study lies in emphasizing publication growth, collaborative efforts, and influential keywords in the connection between machine learning, portfolio optimization, cryptocurrencies, and traditional assets. An emerging concern in this field is evident, yet very few studies of bibliometric analysis could be found. This study provides an evaluation of recent findings and emerging trends. Being an efficient method used to summarize literature; it also has some limitations as well. Thus, the study highlights the areas for scholars and professionals in further research based on the identified research gaps.

Keywords: Machine learning; portfolio optimization; cryptocurrencies; traditional assets; bibliometric analysis

1 Introduction

Modern computational tools have shifted the paradigms of contemporary finance with new approaches in the management of portfolios, specifically with the use of machine learning (ML)

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to improve the integration of traditional and emerging assets, including cryptocurrencies (Simar, [2023](#)). The integration of these technologies represents the shift in the financial analysis landscape that requires analyzing the current academic literature to determine the scope of this field. Bibliometric analysis in this study is used to categorically identify and evaluate literature specifically regarding the application of ML in portfolio management while focusing on integrating cryptocurrencies into the conventional assets' portfolio (Goodell et al., [2021](#)).

Bibliometric analysis, a quantitative research approach that evaluates the literature within a given field, offers a more appropriate framework for identifying the intellectual spine and the growth of the research themes (Goyal et al., [2021](#)). The emergence of digital finance Marchesi ([2021](#)), accompanied by cryptocurrencies, has altered the conventional Asset Management model and forced scholars to look for renewed ways of incorporating the new digital assets into their portfolios. The new dimensions and complicated machine learning methods have presented new approaches to identifying the right portfolio, utilizing huge quantities of data, and enhancing the algorithms (Mosavi et al., [2020](#)). In the current analysis, bibliometric analysis will be employed to establish the description and mapping of future innovations, famous works/scholars (Shemahonge et al., [2022](#)) in this growing discipline, and topics of interest in the future. Portfolio optimization has been the core of financial management since the mid-twentieth century, primarily because of the works carried out by Harry Markowitz (Markowitz, [2009](#)). The significance of diversification was first introduced by Markowitz in the Modern Portfolio Theory (Hali & Yuliati, [2020](#)), asserting that it is possible to minimize risks while still yielding higher returns (Puaschunder, [2023](#)). For many years now, the major focus has been on the well-established classes of assets, including company shares, government securities, and commodities. However, introducing digital currencies and the steady growth of machine-learning technologies have greatly diversified the portfolio's options (Huynh et al., [2020](#)).

Cryptocurrencies, after the emergence of the first such instrument, Bitcoin, in 2009 (Hairudin et al., [2022](#)), have attracted significant interest not only among the public and investors but also researchers because of the high profitability and diversification opportunities. These virtual currencies are managed and decentralized and most commonly rely on blockchain technology (Alam et al., [2024](#)). Even though these innovative financial instruments (Kapsis, [2020](#)) are rather a high-risk category with many unknown factors in legislation, cryptocurrencies are gradually recognized as possible additions to contemporary investment portfolios. Combining crypto assets with traditional securities like equities and bonds also requires the formulation of sophisticated methods to address the propensity of each asset type to vary in terms of risk and return (Seabe et al., [2024](#)). More specifically, with regard to the challenges presented by Mirete-Ferrer et al. ([2022](#)), portfolio optimization and machine learning, which have the potential to sort through and analyze numerous inputs efficiently, can be a possible solution for attaining the most effective asset management.

Classification algorithms, including supervised, unsupervised, and reinforcement learning, have been used in finance modeling and portfolio management (Snow, [2020](#)). Decision tree, logistic regression, K-nearest neighbors, Naïve Bayes, neurons, and support vector machines—all these supervised learning models (Rouf et al., [2021](#)) are used to forecast the asset prices and returns given past performance history. Some unsupervised learning methods, such as clustering and principal component analysis, are used in identifying relations that are not easily discernible from financial data (Verbeeck et al., [2020](#)). Based on behavioral psychology, reinforcement learning aims at achieving a long series of rewards when choosing certain actions, which is appropriate for dynamic portfolio rebalancing. The interaction between ML and finance is evident in some research showing the efficiency of ML-based models Mirete-Ferrer et al. ([2022](#)) over other ones regarding forecasting possibilities and portfolio efficiency.

Equities, bonds, commodities, and real estate have been conventional instruments of investment for a long time and are often considered the building blocks of the investment portfolio (Mundi & Kumar, [2023](#)). Such assets are deemed to be stable, with special emphasis on the previous year's performance and the presence of regulation authorities that ensure the relative stability of the market (Ferreira & Sandner, [2021](#)). However, the period of the financial disasters during the past decades has shown that the traditional asset classes are highly risky and so the clients have started looking for some more classes of investment. Cryptocurrencies are also reactive to conventional assets with low correlation, providing diversification and hedging potential (Almeida & Gonçalves, [2022](#)). The problem is to create models that could fully integrate the two types of assets, as they are fundamentally different in characteristics and behavior in the market.

The use of bibliometric analysis is a crucial part of the research as it offers information on publication and citation behaviors together with patterns and networks in a specific study area (Mejia et al., [2021](#)). In this analysis of the scholarly literature, co-authorship and co-occurrence analysis have revealed this field's key authors and keywords. Even bibliometric analysis as a method represents the changes in data science and available data processing techniques (Raban & Gordon, [2020](#)). Recent advances in bibliometric software like VOSviewer and CiteSpace (Kemeç & Altınay, [2023](#)) have made it possible to represent large and intricate datasets in a way that makes it easier to understand the results and, consequently, the extended applicability of bibliometric analysis. These tools help to visualize the configurations of the research fields, search for seminal works, and discover trends in the discussions, offering an introduction to the academic conversation (Wales et al., [2021](#)).

This analysis is expected to fill existing gaps by analyzing the literature on using machine learning to attain optimal portfolios that include cryptocurrencies and other conventional financial assets (Sabry et al., [2020](#)). Consequently, this work aims to contribute to the landscape of the existing academic knowledge by defining tendencies, works that leave a significant impact, and the gaps in the research in the specified fields, which will be useful for researchers and practitioners. The application of ML in portfolio optimization will help improve the current financial analysis problem to open new opportunities for more effective investment management in the conditions of the contemporary dynamically developing market (Mirete-Ferrer et al., [2022](#)). As a result of the methodical and extensive review of this body of literature, this study aims to contribute to mapping the directions for developing new ideas and investigations in this rapidly evolving area.

2 Methodology

The present study aims to underscore the application of machine learning in achieving an optimal portfolio that incorporates both cryptocurrencies and traditional assets by conducting bibliometric analysis. It is a quantitative study that intricately applies mathematical and statistical techniques to derive meaning from the bibliometric data Donthu et al. ([2021](#)); thereby presenting a big picture of the domain under consideration. This bibliometric analysis uses a sensemaking approach to rigorously decipher and map the huge unstructured cumulative research (Lim et al., [2024](#)). Donthu et al. ([2021](#)) highlighted that a bibliometric analysis that includes both performance analysis and science mapping show its true potential, unlike those involving one another. Donthu et al. ([2021](#)) and Palmatier et al. ([2018](#)) suggest that bibliometric analysis can have three types of subjects of inquiry; a domain, a methodology, or a theory.

2.1 Selection of Research Database

With the emergence and availability of scientific databases, collecting big data to conduct bibliometric analysis has been made easier (Donthu et al., [2021](#)). For this study, data has been retrieved from the Scopus database, one of the largest databases consisting of publications from 1788 to the present (Singh et al., [2021](#)).

2.2 Search Strategy

When deciding on the keywords to extract data, it must be considered whether the selected search terms effectively reflect the scope of the study. (Donthu et al., [2021](#)). This research initially employed the keywords “MACHINE LEARNING” and “PORTFOLIO OPTIMIZATION”. Further, they were refined to include “TRADITIONAL ASSETS” and “CRYPTOCURRENCIES”.

2.3 Finding Relevant Materials

Determining if the finalized bibliometric data focuses on the domain under consideration and does not deviate from the objectives is important. That is the prime reason the bibliometric data is subject to cleaning i.e., addressing the duplicates, removing the studies with missing data, and excluding the irrelevant ones. Moreover, data screening depends on the objectives of the study. (Donthu et al., [2021](#))

2.4 PRISMA Framework

This study encompasses the Preferred Reporting and Items for Systematic Reviews and Meta-Analysis (PRISMA) Framework. It encompasses 4 phases of systematic literature review; identification of studies, screening of records, eligibility based on inclusion/exclusion criteria, and the finally included records.

- **Identification:**
Initially, 916 records were identified from the Scopus database using the aforementioned search terms. At this step, fifteen duplicates were identified and removed. These words not only appeared in the keywords but also in the titles and abstracts.
- **Screening:**
After removing duplicates, the remaining 901 publications were subject to the screening stage. Here, 3 records were excluded as they were not fulfilling the inclusion criteria of document type. The pie chart shows that 66 papers are articles, 42 studies are conference papers, and only 2 are from book chapters.
- **Eligibility:**
After that, 898 records were analyzed for their eligibility. Based on missing information and irrelevance, several publications were excluded.
- **Included:**
Eventually, 110 records were included for further analysis i.e., performance analysis and science mapping.

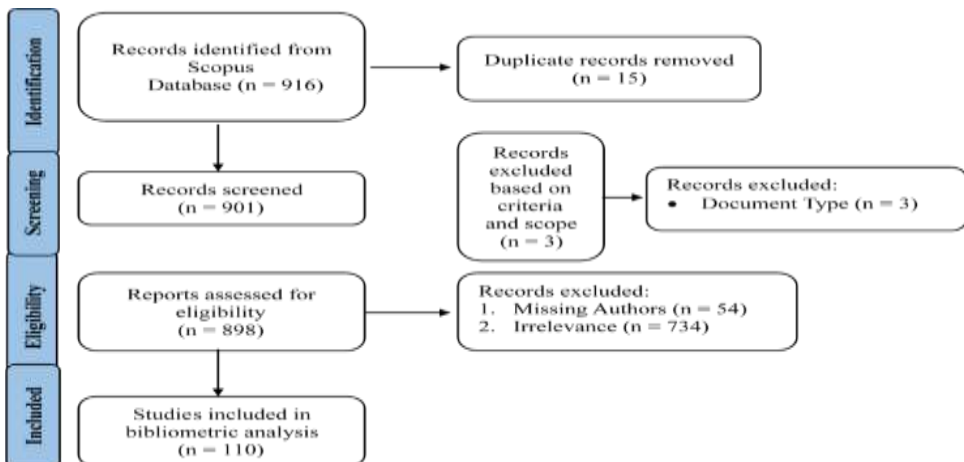


Figure 1: PRISMA framework

2.5 Tool Selection for Science Mapping

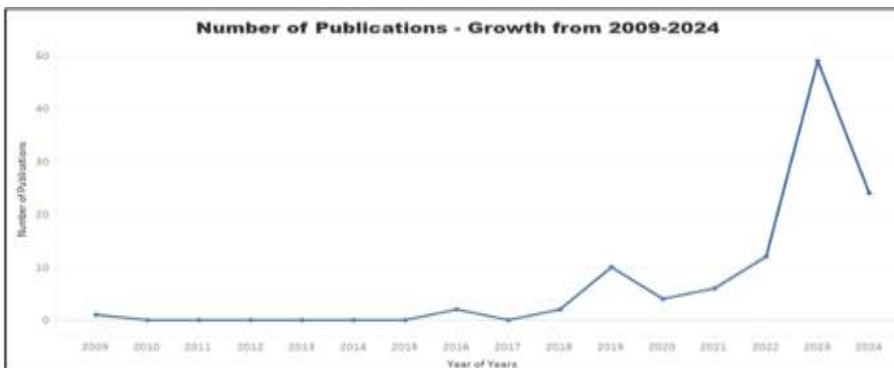
The present study targets the domain of portfolio optimization through machine learning techniques. (Palmatier et al., [2018](#)). Tableau has been used for performance analysis to prepare publication growth and citation growth charts. In order to conduct science mapping, this bibliometric analysis leveraged the text-mining skills and insightful two-dimensional map-producing capabilities of VOSviewer 1.6.19. According to Qudah et al. ([2023](#)), it is the most suitable software that creates maps by employing mathematical methods to visualize the raw network data. Using VOSviewer, the scient metric techniques applied include co-authorship analysis (author-wise) and co-occurrence analysis (all keywords) was conducted.

2.5.1 Performance Analysis

Performance analysis evaluates the extent of contribution that components of research have given to this field (Donthu et al., [2021](#)). This type of descriptive analysis is the attribute related to bibliometric studies. Irrespective of science mapping performance analysis can be ascertained in most of the studies as it is a generalized method used by different studies to present the performance of different elements of the research body. The most promising measures that give comprehensive results are a number of publications representing the competence of the researcher. furthermore, the performance measure of citation is useful to measure the influence and significance of the researcher in the field of academic literature. This is how performance analysis acknowledges the significance of diverse elements in the field of research.

- **Growth of Publication**

The growth of the publications' number over the year is considered an important indicator of the expanding development and interest within a specific research field. The number of publications is relatively low in the early growth phase from 2009 to 2015 which is considered as the foundational phase of the research area. During these years, initial concepts have been explored by the researchers with developing methodologies. After that, the year 2016 and then 2019 showed higher growth. From the year 2021, till the year 2023, the growth of the publications increased. The increases till the year 2023, are attributed to several factors such as enhanced research funding advanced technology with greater collaboration across institutions as identified. The graph provides insight into more timely and critical topics related to the growth of the research criteria and publications per year.

**Figure 2: Growth of the Number of Publications over the years**

- **Growth of Citations:**

From the year 2009 till the year 2015, the growth in the number of citations of the published articles was consistent and quite low. However, from the year 2015, in the year 2016 the

number of citations of the published articles has increased a little, and then again reduced in the year 2017. This is followed by indicating steady increase in the recognition and impact of the published articles during this period. In between the time frame of 2018-2019, the growth has been a positive and increased way, whereas in the year 2020, it declines from 200 citations to about 60–70 citations from the published articles. The surge attributed as identified from the graph contributed to significant advancements and breakthroughs with the research that garnered widespread attention. However, sudden growth is identified in the year 2021, with 250 citations in the year followed by a decline in the year 2022, in the citations, to the number of citations similar to the year 2020. In the year 2023, approximately 90 citations. This graph provides a trend in a number of citations highlighting the periods of both stability and volatility including external and internal factors affecting academic research.

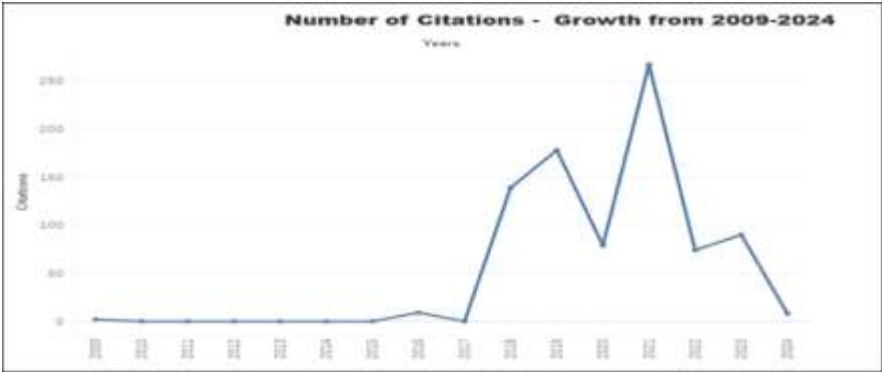


Figure 3: Growth of the Number of Citations over the years

- Number of Publications Per Document Type**
In the current study, 110 papers are selected. There are different categories of papers that have been selected. Categories include conference papers, articles, and book chapters. Performance analysis helps to identify the selected papers from each category



Figure 4: Number of Publications per Document Type

- Top Cited Authors and Authors with Highest Publications**
Another analysis is being conducted on the top cited authors of the study and the authors having the highest publications. They are arranged in descending order. Top cited authors are mentioned on the top being the most productive authors while the number of citations

decreases as we move down the list. These are the list of authors of the study that are highly cited in the academic literature. On the contrary, there is a list of the authors having the highest publications named Al Janabi M.A.M who contributed a lot to the dynamic research field and is one of the authors having the highest publications among all other authors in the study.

Top Cited Authors		Authors with Highest Publications	
Authors		Authors	
Ben G.-Y., El Karoui N., Lim A.E.B.	146	Al Janabi M.A.M	3
Chen W., Zhang H., Mehrotra M.K., Jia L.	134	Cao X., Li S.	2
Ma Y., Han R., Wang W.	115	Yao X., Zhang N.	2
Ta V.-D., Liu C.-H., Tedesco D.A.	78		
Venkat Y., He X., Liu S., Xu G.	66		

• Top Keywords

The keywords of article are distinctive as they help to signify what the researcher thinks are the most important words in the paper. In the current study, four keywords are very prominent in the study. In the above table, keywords are mentioned in the ascending order being less influential than the most influential ones. Portfolio optimization is the word that has the highest count in the study as the study is related to portfolio optimization with machine learning and machine learning is the second most noticeable word. Keywords help to analyze the prospect and the theme of the research.

Top Keywords	
Keywords	
financial markets	40
investments	41
machine learning	68
portfolio optimization	73

2.5.2 Science Mapping

Science mapping is another measure used in performance analysis to study the association between different elements of research (Donthu et al., [2021](#)). The main concern of the analysis is the intellectual independence and systematic correlation of research components. The process for science mapping constitutes citation and co-citation analysis, co-word analysis, bibliography combination/coupling, and analysis of co-authorship. These types of techniques when inter-relate with analysis of networks and graph theory become influential in offering the bibliometric structure in the field of research.

• Co-authorship Analysis

Scholars have found that research is now a communal process, indicated by the growing significance of the co-authorship analysis (Agahi et al., [2022](#)). The main reason co-authorship analysis is important in bibliometric studies is that it reveals both the structure and personal relationships between scholars (Koseoglu, [2016](#)). In the area of machine learning, portfolio optimization, traditional assets, and cryptocurrency, awareness of such synergistic effects can go a long way in developing this field. When it is applied as a measure of collaboration, it is extremely useful to determine how researchers from very different fields that do not necessarily follow the same way of thinking are coming together to solve one or another problem. Hence, by analyzing the co-authorship networks, one can identify key researchers in a particular area of research (Ullah et al., [2022](#)). These scholars, as pointed out by the centrality measures in a network, are highly connected and play a role in the production of new

knowledge. Many-pair co-authorship plots are a method of depicting the intellectual structure in a defined domain. It can also reveal new research fields by analyzing groups of authors that work together and can follow the dynamics of research themes in time. Out of 557 top-cited authors, 9 authors have collaborated in research for at least one research publication as was indicated by the VOSviewer output. The network visualization as presented by Figure 1 shows the link among 9 authors known as co-authorship. This relationship indicates the collaboration that authors have in conducting relevant studies on the application of machine learning in achieving an optimal portfolio that incorporates both cryptocurrencies and traditional assets.

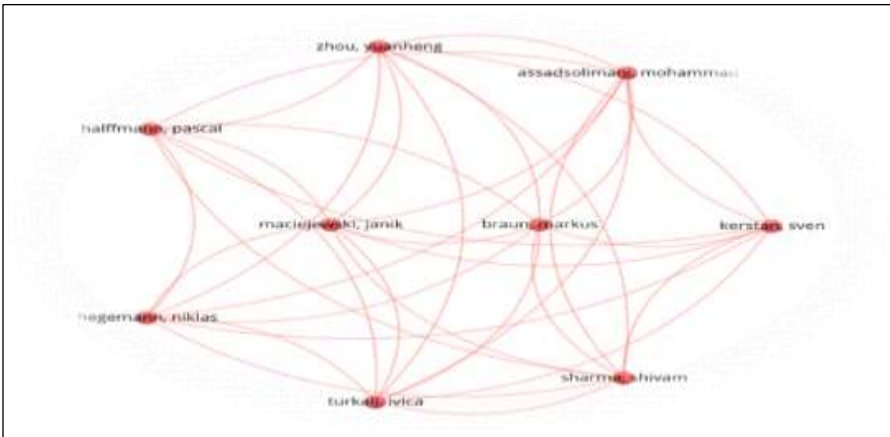


Figure 5: Co-Authorship Analysis-Network Visualization

Every node equals an author, and the connections between the nodes are based on co-authorship. The thickness of the edges represents the level of interaction between the co-authors; the thicker the edges of the authors, the more often they collaborated. The authors who published the most articles in the identified network are Maciejewski, Janik, Braun, Markus, and Kersten; Sven seems to be the most active author in this field. The interconnected components are not separated and shaded differently, indicating that the graph represents a single dense community without prominent sub-communities. It could also mean that all the authors are members of the same research team, or are preoccupied with related research activities. The identified authors such as Maciejewski, Janik and Braun, Markus indicate that they are probably prolific and influential in their research area.

The scholars' central status enables them to narrow the gap between researchers and become catalysts encouraging knowledge exchange and cooperation. This connection of the network indicates that there is plenty of space for cooperation and interdisciplinary study. Less connected authors, i.e., are located more towards the peripheral area of the network, like Turkalj and Ivica, may find it more productive to collaborate with authors in the center of the network. For this reason, central authors might act as some of the main knowledge and innovation brokers within the given research area. Such collaborations with multiple authors increase the dissemination of the research findings and may contribute to new ideas for further research.

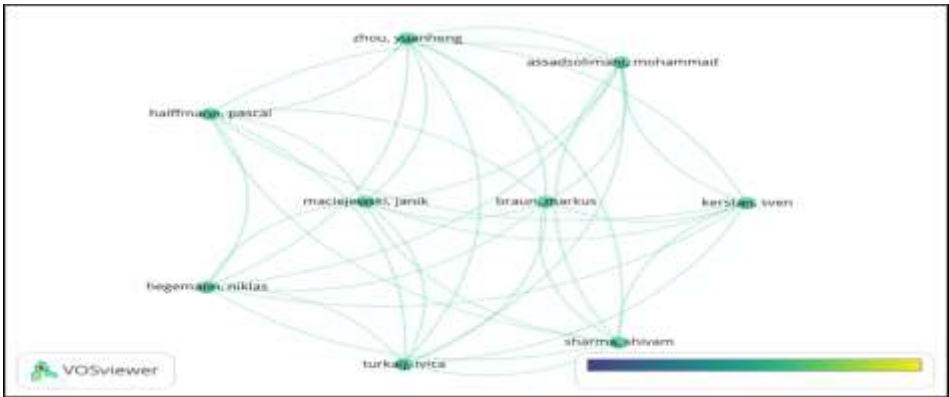


Figure 6: Co-Authorship Analysis-Overlay Visualization

The overlay visualization presented by Figure 2 is important as it introduces the time dependency aspect in the co-authorship analysis. It presents the changes within the collaboration network for researchers and demonstrates equal proportions of actively collaborating over a long period and the newly emerging collaborators in the field (Guo et al., 2019). Kerstan, Sven, Sharma, Shivam, and Assadsolimani, Mohammad are some of the authors who have appeared more in the past few years, pointing out their increasing relevance in the field. The collaboration network is plotted based on the number and date of the publications, with older collaborations represented in blue while recent ones are represented in green to yellow. Overall, all the collaborations are depicted in lighter intensities suggesting that they are active in recent research. The figure depicts that the trend is slowly shifting towards lighter shades for the central authors which supports the assumption that the field is growing and newer researchers are coming up to contribute significantly to this area.

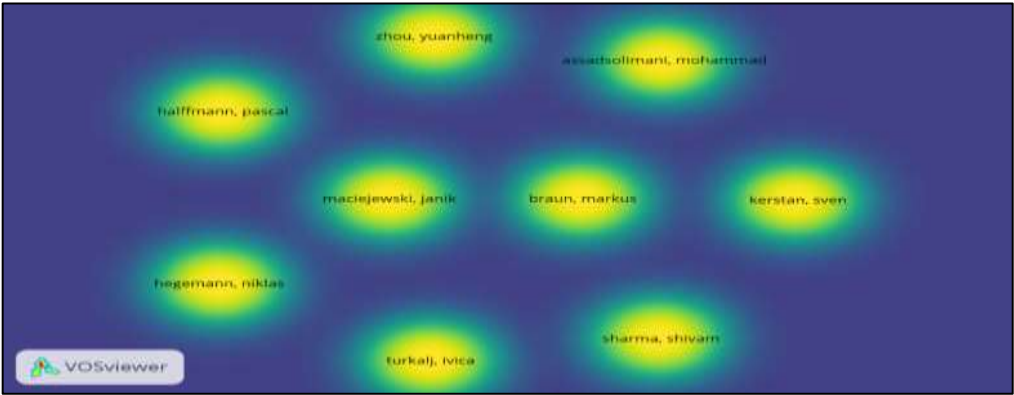


Figure 7: Co-Authorship Analysis-Density Visualization

In the density visualization, shown by Figure 3, there are several dense regions seen as areas with high density as represented by shades of color. These clusters are generally regions that are probable to possess more nodes, and in relativity to co-authorship, they signify a group of scholars with high tendencies to collaborate (Guo et al., 2019). The brightest points, correspond to passing to a yellow color, suggesting that the authors therein indicated share the most connections and compose the greatest number of co-authorship pairs. Changing shades from green to yellow exemplifies different levels of collaboration intensity. The green single-colored areas imply that the various personnel have a low frequency of interaction with each other, and the yellow single-

colored areas imply a high frequency of interaction among them. This gradient is useful in quickly deciding exactly which researchers or groups of researchers are more tightly wound or simply more important in the network for their collaborative work. Researchers from the institutions situated in or close to the yellow zones can be regarded as major actors or the most pivotal figures in their spheres or the given set database. The positioning of names such as Zhou, Yuanheng, Assadsolimani, Mohammad, Halfmann, Pascal, Maciejewski, Janik, Braun, Markus, Kerstan, Sven, Hegemann, Niklas, Turkalj, Ivica, and Sharma, Shivam in the same color zones implies that these people belong to the same or related research groups. Because of these dynamics, it is possible to identify key researchers, prospects for cooperation or voids in the network that would benefit from the establishment of a connection with other researchers.

- **Co-occurrence Analysis:**

- Keywords are phrases or nouns that represent the subject of interest of a publication (Majumder et al., [2023](#)). The bibliometric data shows there were 751 keywords in this research. To recognize research trends of the application of machine learning in achieving optimal portfolio, the keyword co-occurrence method was analyzed using VOSviewer. The keyword co-occurrence method, often used in bibliometrics makes it easier for scholars to recognize research trends (Ding et al., [2001](#)). It involves assessing how often keywords appear together in literature to identify relationships between them. Therefore, it reveals how concepts relating to a certain research field are associated, revealing key areas of interest and new directions in research.

Five clusters were obtained that had dissimilar thematic connections. These clusters are the result of keyword co-occurrence and give different narratives on the application of machine learning in finance. This particular type of cloud map shows the frequencies of the words appearing in the articles and the connections between the keywords. In this network, each term is shown as a circle where the circle's size is proportional to the number of publications where it is used. Every circle is related to an area of terms grouped according to clusters, and the length of the curved lines symbolizes the approximate connection between the keywords. The thickness of these lines is representative of the extent of the relationship between two sets of topics or keywords. Figure 6 presents all the clusters obtained.

Cluster 1: “Utilization of Machine Learning for Portfolio Optimization in Investment Decision Making”

The Green Cluster is associated with portfolio selection, artificial intelligence, machine learning, deep learning, the mean-variance model, investment, and decision-making. The keyword ‘portfolio optimization’ emerges as the most recurrent one being used, appearing 73 times, with a strength of 417. A link between two keywords signifies their co-occurrence connection. According to the VOSviewer manual, the total link strength represents the number of times two keywords occur in the index together. This keyword is most associated with the term “Investment” as it occurred 41 times and has a strong correlation to portfolio management and investment strategies. “Machine learning” and “Deep learning” appeared 68 and 23 times respectively, which shows the increasing significance of AI and advanced analytics in investment decision-making. The term “Decision making” occurs slightly more rarely – 9 times, but connects both portfolio optimization and Machine learning, pointing to its importance in the context of investment decisions. ‘Portfolio management’ is also present but is used less frequently, it indicates a wider range of activities connected with managing investment portfolios. Lastly, cryptocurrency was used only once with the name of prediction. It came only once in keywords but there were 5 topics where it appeared.

Table 1: Cluster 1 Keywords

Keywords	Occurrences	Total Link Strength
Portfolio optimization	73	417
Machine learning	68	363
Investment	41	327
Deep learning	23	176
Decision making	9	86
Portfolio management	8	74

Optimization of portfolios using machine learning methods has attracted much interest among researchers in the current times. Machine learning in the financial context has been a trend in the recent past with a systematic literature review of the recent progress of machine learning and deep learning in the financial sector in multiple areas, including stock exchange, investment portfolio, and financial crises (Economics). There are prior papers where researchers have attempted to incorporate simple machine learning models like LSTM and CNN-BiLSTM with conventional portfolio optimization techniques like Markowitz's mean-variance (MV) and Hierarchical Risk Parity (HRP) for improvements in portfolio improvements (Chaweewanchon & Chaysiri, [2022](#)).

Cluster 2: “The Role of Deep Learning and Reinforcement Learning in Finance”

The blue cluster depicts keywords: Portfolio management, Reinforcement learning, Deep learning, and Decision making. “Reinforcement learning” can be considered significant because of its strong connections with the other keywords. “Deep learning” remains as one of the most shifting keywords in frequency and with high connectivity; proving as one of the most vital concepts in advanced analysis and forecasting. “Decision making,” as a concept, has a moderate frequency of appearance but remains closely interconnected, demonstrating its importance in the context of investment decisions and interaction with reinforcement learning as well as deep learning. “Portfolio management” while being used less often, indicates fairly constant relevance with moderate interconnectivity proving that it remains an essential part of a wider process of managing and building effective investment portfolios.

Table 2: Cluster 2 Keywords

Keywords	Occurrences	Total Link Strength
Deep learning	23	176
Decision making	9	86
Reinforcement learning	11	76
Portfolio management	8	74

In the case where the Reinforcement learning algorithm is used for portfolio management the most common application is the trading of cryptocurrencies. It has been established that using on-chain data to improve reinforcement learning-based systems for managing portfolios of cryptocurrencies results in better returns for on-chain crypto portfolios than previously established benchmarks (Sen, [2023](#)). Applying ideas such as the Squeeze-and-Excitation of the Neural Network Architecture and the Soft Thresholding Functions could enhance the capability of reinforcement learning algorithms in recognizing contemporary information in financial settings resulting in efficient portfolio management techniques (Cui et al., [2022](#)). Deep reinforcement learning was applied to simulate the market condition and S&P 500 stocks in the work of (Kovácsnai et al., [2021](#)), results show that portfolio choices could be improved to above-average markets by utilizing the model. Further, Huang et al. adopted deep reinforcement learning to improve the investment decision in investment portfolio management with the turnover rate in the stock market and with excess returns (Dong et al., [2021](#)).

Cluster 3: “Advanced Strategies in Portfolio Selection: Leveraging Artificial Intelligence”

The red cluster portfolio selection, constrained optimization, stock prediction, stock portfolio, artificial intelligence, and optimizations. Portfolio selection emerges as a prominent theme, appearing 13 times and exhibiting a strong total link strength of 92, indicating its centrality and close association with other keywords. Optimizations follow with 9 occurrences and a total link strength of 73, suggesting its significance but slightly lesser interconnectedness than Portfolio selection. Additionally, Artificial Intelligence appears rarely, with 6 occurrences and a total of 57 link strength, indicating it is also quite relevant to the given set of keywords. Based on these results, it can be concluded that Portfolio selection and Optimizations can be considered as important keywords, which might suggest that these are the points of interest or the frequent topics in the sample, though the relevance of Artificial Intelligence seems to be slightly lower.

Table 3: Cluster 3 Keywords

Keywords	Occurrences	Total Link Strength
Portfolio selection	13	92
Optimisations	9	73
Artificial Intelligence	6	57
Investment	41	327

Studies suggest that AI strategies such as the Risk-balanced Deep Portfolio Constructor (RDPC) maximize returns with risks, such as using the hard attention mechanism that replicates good pairs trading (Luo et al., 2023). To handle the non-linear correlation between assets, (Zhao et al., 2023) propose a policy network based on self-attention mechanisms and reinforcement learning to model different assets that perform well in any given dataset. Moreover, market segment selection for profitable portfolios and constructing portfolios with ideal profiles using AI algorithms, which are superior to conventional ways in terms of profits, are also referred to by (Zhao et al., 2023). These studies combined suggest the ability of AI to aid portfolio selection decisions by dealing with risk, non-linearity, uncertainty, and profit optimization.

Cluster 4: "Investment and Financial Markets: Integrating Neural Networks for Advanced Analysis"

The yellow cluster is associated with keywords investment, neural networks, and financial markets. The most frequent word is Investment, which is used 41 times and has a link strength totaling 327, pointing at the role of this concept and its strong connection to others. In the same way, financial markets stand out and is used most frequently; it is mentioned 40 times and has a total link strength of 323, demonstrating its importance and connectedness. In contrast, "neural networks" is cited 12 times while its link strength is 94, while it is less often used than other key terms, its connection strength indicates significant relations to the others' ideas. Thus, it is evident that Investment and Financial markets act as main themes, while Neural networks are prominent but belong to the group of more detailed and specific themes.

Table 4: Cluster 4 Keywords

Keywords	Occurrences	Total Link Strength
Financial Markets	40	323
Investment	41	327
Neural Networks	12	94

Neural networks have become one of the most vital technologies in the financial markets, demonstrating a deep impact on investment plans (Kutsurelis, 2012). There are also many neural network models that have been proposed and tested for stock market prediction applications, including DQN and LSTM, which has further revealed that with the help of these techniques, effective excess return could be achieved for a management company (Fan & Peng, 2022). Also,

some works have compared the application of neural networks with conventional methods such as multiple linear regression analysis, where studies have established the workability and the possibilities of using neural networks in forecasting various stock market indices with a reasonably high probability of accuracy (Maknickienė & Sabaliauskas, 2019).

Cluster 5: “The Role of FinTech in Reshaping Asset Allocation Strategies”

Purple cluster deals with Asset allocation, fintech, and performance. Asset allocation appears 7 times, and its link strength is 39. Therefore, it is moderately present and linked with other keywords. Fintech occurred 5 times with a link strength of 27; this signifies that as much as it is not as common, it still links to other forms in the network in some way. Comparing the keywords, Performance, in particular, has lesser occurrence, only 4 times, but has a total link strength of 34, suggesting that though not very frequently used, it is impactful. Thus, the keyword of Asset allocation is looked for most frequently, and it is the most connected keyword in this set, while the keywords of Fintech and Performance are looked for with slightly less frequency and take less central place in the keyword network.

Table 5: Cluster 5 Keywords

Keywords	Occurrences	Total Link Strength
Asset allocation	7	39
Performance	4	34
Fintech	5	27

According to the bibliometric research of FinTech, which exhibits the year-wise publication trend of financial technology in recent years (Garg et al., 2023). It also focuses on the expansion of financial inclusion and diverse approaches to advanced digital measures of financial innovation, including the introduction of new products of financial engineering (Khurana, 2023). This suggests that asset allocation within the area of funds can come under various forms of financial engineering. The development of FinTech does not only work on the asset allocation approaches but also affects the accounting and auditing patterns, thereby demonstrating that it has the ability to work on other research disciplines and contribute to the improvement of different professional asset management techniques. Each of these collective findings stresses the essential function of FinTech in the reform of asset management portfolios and financial industry practices, giving directions for future studies and applications for the field.

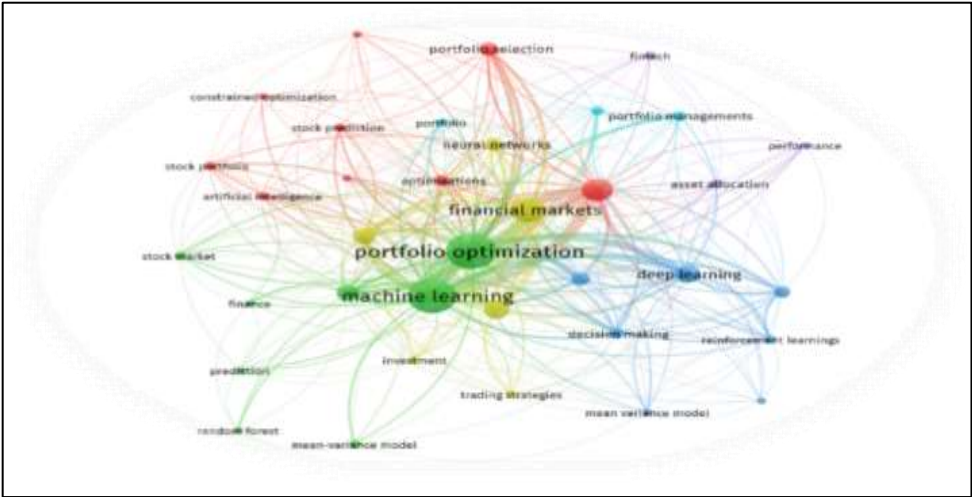


Figure 6: Co-Occurrence Analysis

3 Discussion

The findings demonstrate valuable trends in the current pattern of synergy in portfolio optimization with cryptocurrency investments and other conventional stocks. The analysis of the co-authors within the top cited works mapped through the VOSviewer reveals that these authors collaborate closely, with the nine most cited authors fully connected. Such a level of collaboration is highly valuable, given that portfolio optimization is a multidisciplinary area of study and practice (Liesiö et al., [2021](#)).

Additionally, the network display indicates that there are key authors such as Maciejewski, Janik, and Braun as significant figures in this collaborative network. According to the extent of their productions and the core role in the identified works, they can be considered the key representatives of this research area. This centrality enables them to also take up the role of disseminating information and thus, can act as a link between researchers (Landherr et al., [2010](#)). Furthermore, the findings of the co-authorship analysis are in accordance with other research investigations, which have emphasized the fact that social networks are crucial in boosting the effectiveness and efficiency of research activities and innovation (Hou et al., [2008](#); Newman, [2001](#)).

Moreover, the co-authorship analysis also allowed the identification of the peripheral authors in this domain i.e., Turkalj and Ivica, as they do not seem to directly liaise with many of their fellow scholars. Peripheral authors could improve the citation rates/research visibility by interacting with more authoritative members of the field, thus becoming more involved in the strong communicative core (Young & Bunting, [2024](#)). This can be explained based on the previous literature showing that collaborations between the peripheral and central researchers can be highly beneficial for the former in terms of subsequent citation of the papers produced within the collaboration (Abbasi et al., [2011](#); Bozeman et al., [2013](#)).

This criterion shows that there is a strong connection between the authors in this field to suggest that the research on the application of machine learning techniques in portfolio optimization is a collaborative venture (Jun et al., [2021](#)). This weblike system helps transfer knowledge as well as the results of the research and stimulates further ideas (Carbone et al., [2012](#)). As described in the conceptual background, collaborative networks help solve multifaceted research questions since such a combination of expertise and views (Adams et al., [2005](#)). In the context of portfolio optimization, such collaboration is quite wonderful as it blends knowledge from the finance field with artificial intelligence and machine learning with data scientists' input, thus resulting in better and more creative solving approaches (Sutiene et al., [2024](#)).

Likewise, through the co-occurrence analysis, a set of 5 clusters has been distinguished, which characterized the field of research and pointed out the most popular themes. The first cluster focuses on the problem of portfolio optimization and decision-making with the involvement of machine learning and deep learning. This result supports earlier research on the combination of deep learning algorithms such as LSTM and CNN-BiLSTM with classical optimization processes to improve investment portfolios (Shah et al., 2022). Frequently used keywords such as 'Portfolio optimization,' 'Machine learning,' and 'Deep learning' provide a testament to the fast-growing importance of analytics within the area of finance (Mashrur et al., [2020](#)).

Consequently, the second cluster focuses on deep learning and reinforcement learning in the field of finance, especially in portfolio management. Research has shown that, with the help of on-chain data, reinforcement learning algorithms are capable of surpassing the most fundamental benchmarks in the case of portfolio management for cryptocurrencies (Fang & Polukarov, [2023](#)). Likewise, the third cluster also deals with the application of artificial intelligence in portfolio

optimization, and as evident, the frequency of the keyword ‘artificial intelligence’ is lower compared to the others, but some investors are evidently aware of and interested in the possibilities of using AI for portfolio selection, albeit in the pioneering stage. Subsequent research should, therefore, persist in exploring AI’s capability to manage non-linear relations and other sources of volatility in the financial markets.

The last two clusters also refer to the application of the neural network in the financial market and the life-changing nature of FinTech in the way that firms perform and allocate assets. These conclusions corroborate the previous research that confirmed the efficiency of the neural network models and the increasing trend in FinTech publications and changes toward more efficient and technology-focused investment solutions (Fang & Polukarov, [2023](#); Tepe et al., [2021](#)). Altogether, the keyword co-occurrence analysis reveals the current state of research and gives some directions for future development, namely, the use of cryptocurrencies, the new methods of AI, and the usage of FinTech in the effective management of assets.

3.1 Conclusion

This research employed a bibliometric analysis to assess the literature regarding the use of machine learning (ML) in managing portfolios, focusing on portfolios that include cryptocurrencies together with conventional assets. Accordingly, by investigating the trends and patterns, focusing on the papers of various importance, key authors, and relations between themes in the literature, the research seeks to understand the intellectual structure and outline future research prospects. With the advent of digital finance and cryptocurrencies, scholars engage in developing novel ML-based approaches to portfolio optimization to tackle the new challenges and risks implied by various types of assets. This work presents the possibility of improving portfolio efficiency with the help of ML, pointing out important contributions and directions for future investigation and development in modern portfolio management. A systematic search of the Scopus database for records was conducted using keywords; ‘Machine Learning,’ ‘Portfolio Optimization,’ ‘Traditional Assets,’ And ‘Cryptocurrencies’. The PRISMA framework was utilized to identify, screen, and exclude irrelevant records. Then Tableau was used for performance analysis and VOSviewer for science mapping. Analysis of the publications and citations shows an increase in the number over the years. The relationship of authors was displayed by mapping techniques such as co-authorship and co-occurrence analysis.

3.2 Implications

This study has some implications. From a theoretical perspective, the four knowledge clusters identified shed light on the nomological networks, social patterns, evolutionary details, and research gaps. This work might have important implications for the assessment of the advantages and disadvantages of applying the machine learning approach in portfolios with crypto-assets and could be useful for the elaboration of reasonable regulations. Furthermore, through the visual representation of the academic background, the study can determine the research gaps that must be useful for the further analysis of particular machine learning algorithms, data aspects, and risk management concerning these combined portfolios.

From the practical perspective, the findings of this bibliometric analysis incorporating science mapping and performance analysis procedures, potentially make a significant contribution. It underscores the impact and productivity of researchers within the domain and highlights the extent of research. Analysts could use the findings to design strategies to build diversified and potentially high-return and possible-risk portfolios for investors and portfolio managers. One of the most attractive advantages of machine learning is its capacity for data analysis which can be used for the identification of the risks associated with the fluctuation of cryptocurrencies and the improvement of risk-managing instruments. The observations made within this research could be useful for enhancing the efficiency of trading with the help of algorithmic trading for

cryptocurrencies and other financial assets. Since cryptocurrency is becoming a regular practice, regulators will find themselves in need of such structures to maintain order in the market. Lastly, the investigation of investors' attitudes towards integrating cryptocurrencies with conventional assets may be used to establish what strategies could be useful in enlightening investors on the benefits and exigencies of integrating cryptocurrencies into the portfolio. This research can be at the cutting edge of this emerging field, defining the strategies and mechanisms that investors and institutions employ in this new investment environment.

3.3 Limitations and Future Directions

Bibliometric analysis is an efficient method used to summarize literature, but it has some limitations. Choosing a technique first and then seeking the bibliometric data according to the selected technique and choosing the relevant technique later after arranging the data is a challenge the researchers face during bibliometric analysis. The current study selected the latter technique as the former limits the choice of techniques that researchers utilize for the analysis. In future research, it is suggested to first decide on the technique for science mapping, such as co-authorship analysis, co-occurrence analysis, co-citation analysis, bibliographic coupling, etc., and then collect the required data.

Moreover, this study has only retrieved data from the Scopus database and this scientific database is not created solely for bibliometric analysis as a result there are always chances of errors that can impact the analysis as well as the results (Donthu et al., 2021). Another limitation of this study is that it used bibliometric data indexed only in Scopus and not the other databases. Hence, the studies not indexed in Scopus are left out. Future studies can extract bibliometric data from other databases such as the Web of Science. Furthermore, relevant studies are omitted that used diverse terminologies and expressions because of pointing out specific keywords and search terms in the study. This is how selection bias might bind the universality of our outcomes and not entirely exemplify the complete body of academic literature in the field. Additionally, in the field of research, only short-term predictions can be provided with the help of bibliometric studies therefore, researchers should circumvent making exaggerated assertions about the study and its effect in the distant future. Nevertheless, despite these limitations, the methodology of bibliometric analysis helps scholars handle large bibliometric datasets and assists in the creation of knowledge in all fields of research.

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