

A Bibliometric Analysis of Hedging in Commodity Derivatives Using Machine Learning.

Bhagya Shree Tiwari¹, Nishant Kumar², Kaushal Kishore Shukla³

¹Research Scholar, Department of Management, FMS, University of Lucknow, Lucknow, India

²Associate Professor, Department of Management, FMS, University of Lucknow, Lucknow, India

³Principal, Faculty of Commerce, Shri Jai Narain PG College, Lucknow, India

Abstract

The adoption and institution of AI in risk management started in the late 90s, but its active application in hedging started appearing around 2000. Besides that, its ingress in commodity derivatives was spotted two decades ago. Commodity derivatives markets are designed to manage the price risk associated with fluctuations in commodity prices. With this view, the study is conducted to review the penetration of Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in hedging or hedging effectiveness in commodity derivatives. This research presents a bibliometric analysis (BA) of 126 documents published in the Scopus database from the year 2000 to 2025 using science mapping and network approaches. The analysis was conducted utilizing the Biblioshiny (RStudio) and VOSviewer software. The review explores the foundation and evolution of various themes, the key conceptual and intellectual structures that are being developed with the help of AI/ML in hedging mechanisms, as well as future research trajectories. After analysis, it has been concluded that the dynamic daily hedging model, distributional reinforcement learning, deep quadratic hedging in commodity derivatives, the use of AI and ML models in cross hedging, and working on the conceptual framework and mechanisms behind these models to make them more transparent and authentic in the eyes of retail investors are the major gaps to be addressed. The study examines the literature of hedging in commodity derivatives using ML and AI and will be useful to academicians, policymakers, and operational risk management professionals.

Keywords: Hedging, Commodity Derivatives, Machine Learning, Artificial Intelligence Bibliometric analysis, Science mapping

1. INTRODUCTION

The history of derivative trading in commodities goes back thousands of years. Clay tablets collected from Mesopotamia way back in 1750 BC have derivative contracts written on them. Aristotle has mentioned derivative contracts in the story of Thales. Expecting a bumper olive crop in the next harvesting season, Thales entered into an agreement with oil mill owners by paying an advance deposit to use their mills during the harvest season for pressing oils—equivalent to a modern-day forward contract (Rajib, 2014). In India, the origins of the commodity derivatives market can be traced back several millennia, with references to such trading systems appearing in ancient literature like Kautilya's Arthashastra. But the organized trading in commodity derivatives began with the Bombay Cotton Trade Association Ltd. in the

year 1875. Subsequently, the Gujarati Vyapari Mandali was established in 1900 to conduct derivatives trading for groundnut, cotton & castor seed. The value proposition provided by the commodity derivatives exchange of India is as follows: 1. Risk hedging (Price, quality & quantity risk), 2. Price discovery, 3. Warehouse receipt finance, 4. Offers a new asset class, 5. Innovative derivatives contract on assets like weather, carbon, water, etc.

As shown globally (Figure 1), on the basis of the number of contracts, agricultural products are traded most in the commodity derivatives market and are rising year by year. Followed by contracts on industrial metals and energy products, which are rising, whereas there is a decline in the number of contracts for precious metals. Nevertheless, when it comes to notional value (Figure 2), energy products dominate the market, trailed by agricultural products, industrial and precious metals.

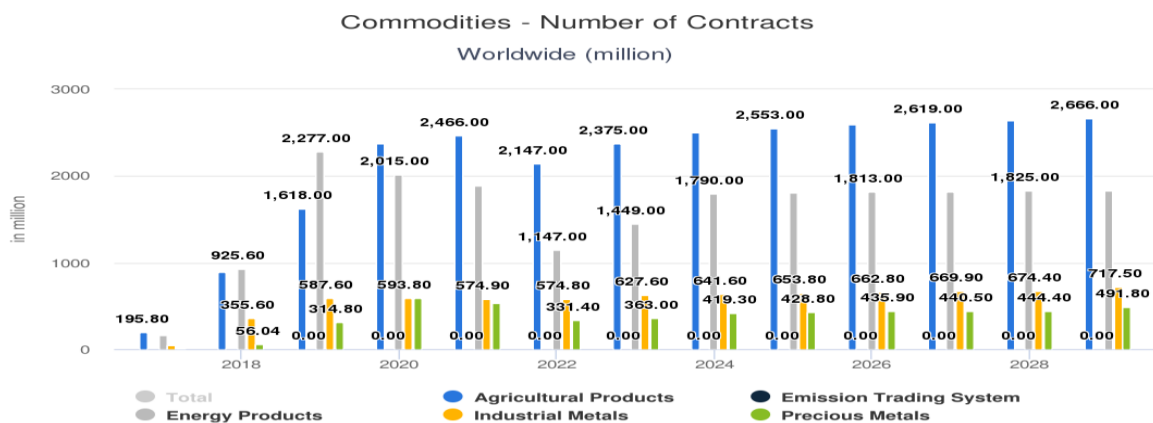


Fig.1. Source: Statista market insights (<https://www.statista.com>)

In India, the regulatory framework permits the use of derivatives primarily for mitigating price risk. However, the terms "hedge" or "hedging" are not explicitly defined in the RBI's exchange regulations (Rajwade, 2010). John Hull, in his book "Risk Management for Financial Institutions," has argued that a hedge is "a trade designed to reduce risk; the goal of a hedging program is to reduce the risk, not to increase expected profit." The concept of hedging revolves around the idea

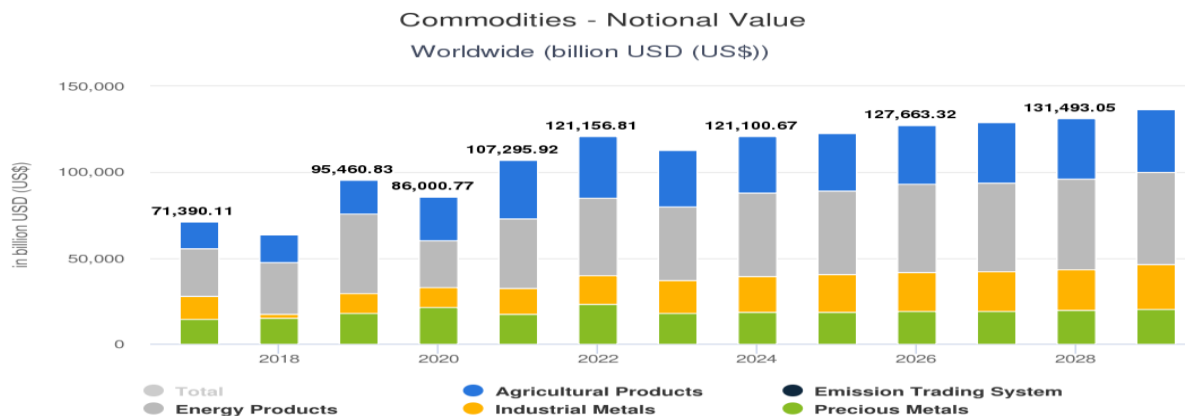


Fig.2. Source: Statista market insights

(<https://www.statista.com/outlook/fmo/commodities/agricultural-product-derivatives/worldwide>)

of taking counterbalancing positions in the market to mitigate potential losses from adverse movements in asset prices (Loso Judijanto, 2024) Modern Portfolio Theory (MPT), introduced by Harry Markowitz in 1952, is one of the foundational theories in finance that supports the use of hedging as a risk

management tool. MPT posits that investors can optimize the expected return of their portfolios for a given level of risk through diversification across different assets (Markowitz, 1991). By constructing a well-diversified portfolio, unsystematic risk, which is specific to individual assets, can be reduced. However, systematic risk, which affects the entire market, cannot be eliminated through diversification alone, and this is where hedging becomes relevant (Judijanto, 2024). Hedging has expanded beyond traditional asset classes overtime and includes more complex instruments and strategies. Advances in financial engineering, algorithmic trading, and the introduction of complex derivatives have resulted in the development of advanced hedging techniques. The application of machine learning (ML), artificial intelligence (AI), deep learning (DL), and neural network (NN) models are a few of them. ML, DL, and NN are the branches of AI that are aiding financial institutions in managing risks and implementing hedging strategies, such as for hedging against market volatility and assessment of price volatility (Khatri, 2024).

Based on insights from various stakeholders (intermediaries and end users), Figure 4 illustrates the segments of derivatives trading and workflow that AI will affect over the next five years starting 2023.

In the last few years, BA has been incredibly popular in business research (Donthu, 2021). This study attempts to conduct BA of hedging in commodity derivatives using ML and AI. BA is an analytical technique that is often employed in systematic literature reviews—it involves the quantitative analysis of academic works (Lim, 2023). BA extracts data from scholarly databases (Scopus, Web of Science, Dimensions, etc.) and utilizes computational algorithms and quantitative techniques in specialized software packages like Bibliometrix in R, VOSviewer, etc. to process, structure, examine, and present bibliometric data in an objective manner (Kraus, 2022). The methodology consists of performance analysis, science mapping and thematic analysis (Cobo et al., 2011).

Numerous scholars have conducted specialized BA across diverse fields (Kim, 2021). Including the derivative market, the Indian commodity derivatives market, managerial finance, foreign exchange hedges, AI, ML and DL in finance, etc. But the ambiguous findings strengthen the argument for re-examining and reviewing how AI & ML-based hedging with commodity derivatives has evolved over the past two decades, its anticipated direction, and the obstacles it's currently facing. This study may prove valuable for academics, industry experts, participants in commodity derivatives markets, risk managers, and policymakers.

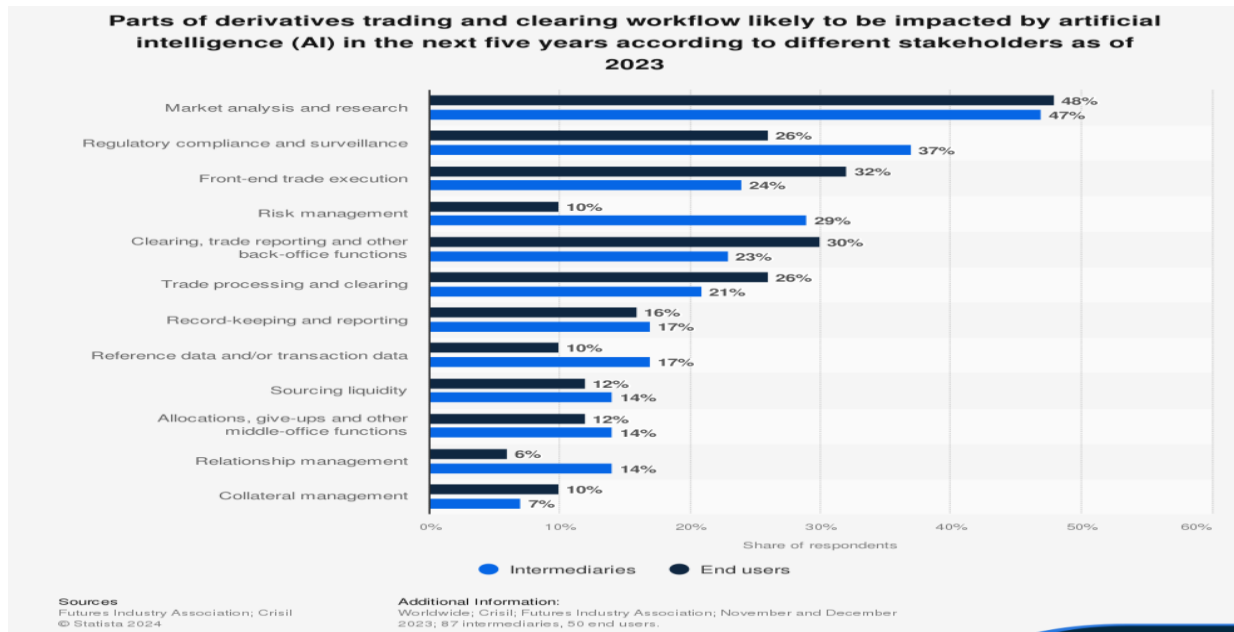


Fig.3. Source: Future industry association, Crisil © Statista 2024

The study enables to identify leading journals, prominent researchers, emerging trends, current research topics, collaborative efforts, countries at the forefront of research, and influential institutions. By examining this comprehensive overview of research conducted since 2000, a well-informed scientific perspective on the subject matter can be duly formed.

This study investigates majorly three questions pertaining to the MA & AI-based hedging with commodity derivatives, focusing on articles published between 2000 and 2025. These are:

RQ1. How the evolution of ML based hedging through commodity derivatives has occurred during the last two decades?

RQ2. What future trajectory may be observed in ML based hedging through commodity derivatives?

RQ3. What may be the challenges and limitations of ML based hedging in commodity derivatives?

2. Literature Review

The review literature on commodity derivatives so far offers valuable insights into price discovery, energy markets and financial market linkage, the connectedness of commodities to traditional assets and the commodity market. The topic has been researched in different dimensions, but this paper focuses specifically on examining it through the lens of AI and ML integration in hedging with CD.

A compilation of past reviews on the “Bibliometric analysis of hedging with commodity derivatives” research.

Author(s) (year)	Review type	Major Thrust Area and Research focus
Anas, et al. (2024)	Bibliometric review	Review of safe haven and hedge assets
Subeesh vk and Liya k k, (2024)	Bibliometric review	An analysis of articles published in the derivative market.
Judijanto, L., et al. (2024)	Bibliometric review	The development of hedging strategies in investment.
Khatri, K. (2024)	Thematic review	Integration of Artificial Intelligence in Pricing and Hedging Strategies for Currency and Credit Derivatives

Biju, A.K.V.N., et al. (2024)	Bibliometric review	Examining the research taxonomy of artificial intelligence, deep learning & machine learning in the financial sphere
Subeesh, v.k. and liya, k.(2024)	Bibliometric review	Articles published in the derivative market - influential researches, subjects and issues.
Prashant Sharma, et al. (2023)	Bibliometric review & content analysis	Price Discovery in Financial Securities.
Jędrzej B. et al., (2023)	Meta-analysis	Commodity futures optimal hedge ratios in the academic literature mostly overlaps with the 80–125 threshold.
Gairola G. and Dey K. (2023)	Bibliometric review	Price discovery and hedging in financial assets and commodities.
Filho, J.F.D.S., and Ogasavara, M.H.O. (2022)	Bibliometric review	Foreign exchange hedge applied as a strategy to protect against the foreign exchange risk
Pandey, R.P.(2022)	Bibliometric review	focusing world CD market
JohnW.Goodella, (2021)	Bibliometric review	Artificial intelligence and machine learning in finance
Kim, J.S. (2021)	Bibliometric review	Journal of Derivatives and Quantitative Studies
Jerome J.K., et al. (2021)	Meta-analysis	Analyzing firm value effects of corporate financial hedging
Baker, H. K., et al. (2021)	Bibliometric review	The Journal of Futures Markets.
Koutha, S. J., & Rao, D.(2017)	Thematic review	Review of origin and development, role of Exchanges, Regulatory mechanism, Performance of commodity market of India and Commodity Risk Management.

When considered as a whole, the assessments that currently exist on DL, NN, AI, and ML in hedging are typically not specific; they are presenting several facets separately rather than all at once. To the best of knowledge, none of the study has covered the BA of applications of ML, AI, DL, and NN in hedging in commodity derivatives. In this review, a holistic and inclusive perspective is used, offering a detailed overview of how AI and ML are being adopted and implemented for hedging in commodity derivatives.

3. Methodology

This section describes the sampling, data gathering, and analysis methods used to conduct the study. Mainly three analytical techniques are utilized in this study: performance analysis, science mapping and manual content analysis. The first one evaluates the output of various research entities, such as individual researchers, academic institutions, and nations or regions. The second one examines the interrelationships among research entities and the conceptual framework of a given field. The third approach analyzes the content of documents published in the last 5 years with a minimum of 20 citations per article on scholarly databases.

3.1: Bibliometric Techniques and Rationale

To answer first **RQ1**, a combination of performance analysis and thematic evolution along with two interconnected techniques: Co-citation analysis (investigating the past) and bibliographic coupling (the current status) is employed. By utilizing these approaches, productivity (number of articles published each year), influence (number of citations per year), and the publication patterns and evolutionary trajectory within the field of study are uncovered.

To study future trajectory **RQ2**, the thematic map of the network approach is used. This analyze the keyword co-occurrence frequencies facilitated the identification of emerging research themes within the discipline. This technique provides valuable insights into evolving areas of study and potential future research directions.

To answer our final **RQ3**, we use content analytics of the scholarly databases that we have extracted to identify the challenges and constraints within the field of research.

3.2: Bibliometric Search & Data collection

Data is acquired from the Scopus database, as it has the most comprehensive coverage of peer-reviewed research in finance as compared, for instance, to the Web of Science (JohnW.Goodella, 2021). The data was retrieved from the Scopus database (2025) by using its source search functionality. The key search terms "hedging" OR "hedging effectiveness" OR "commodity derivatives" AND ("machine learning" OR "artificial intelligence" OR "deep learning" OR "neural network" OR "AI" OR "natural language processing") were employed for the period between 2000 and 2025, yielding 516 documents. Subsequently, the data were extracted from Scopus and refined using specific domain, language, document type, and source type. The final dataset comprises 126 articles. The VOSviewer (van Eck, 2010) was employed for co-citation & bibliographic coupling and Bibliometrix of Rstudio for descriptive and network approach analysis.

Bibliometric Data Extraction: Search criteria & article selection.

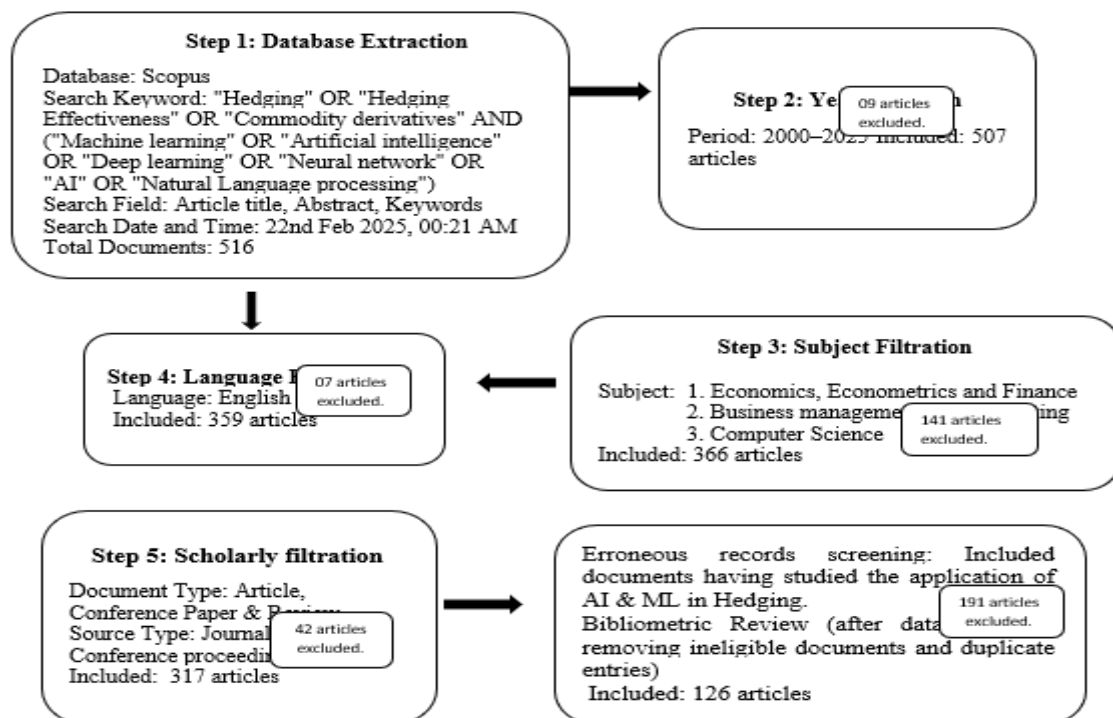


Figure 4. author compilation

4. Findings and conclusion

4.1. The evolution of ML & AI based hedging through commodity derivatives (RQ1) -

In 1985, Spencer Star authored "Expert system for foreign currency hedging," which documented ongoing efforts to construct a system (Information systems applications—Decision support systems) capable of making hedging strategy decisions to mitigate foreign exchange risk. Notably, the database contained no source information for this article. A decade later, in 1996, research emerged on computational approaches to option pricing and portfolio optimization utilizing neural networks. However, in the year 2000, the first scholarly investigation into hedging derivative securities with neural networks was conducted, but in commodity derivatives, the first research was done by Radosław Puka, Bartosz Łamasz & Marek Michalski (in collaboration) on crude oil in the year 2021. But the entry of ML & AI in commodity derivatives begins with price forecasts for gold futures (Chunmei, 2009) in 2009, followed by price volatility, commodity price forecasting, return prediction, and statistical arbitrage.

Figure 5 illustrates the publication pattern of AI and ML studies in hedging using commodity derivatives, correlating the number of articles with their publication years. The graph reveals that AI and ML applications in hedging are relatively recent, beginning in 2000.

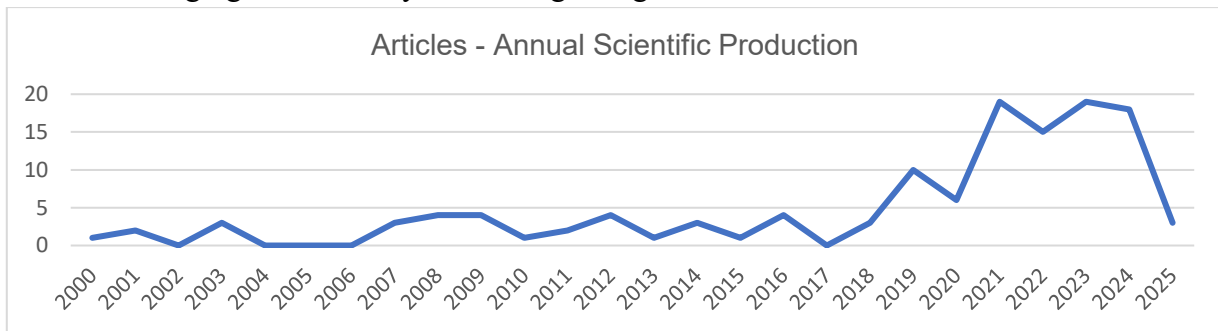


Fig.5. Publication trend of AI and ML Research in Hedging using CD. Source: Authors' compilation (2025) based on Scopus.

However, research in this field has seen significant growth in recent years, coinciding with the advent of the fourth industrial revolution and advancements in financial markets. The most productive years for publications were 2023 and 2021 (19 articles each), followed by 2024 (18 articles), 2022 (15 articles), and 2019 (10 articles). This ascending trajectory is expected to continue into 2025, with 3 articles already published by early February of the year.

a) Top authors and countries of AI and ML research in hedging with commodity derivatives.

The top authors and countries in AI and ML research in hedging, at the time of authorship, are presented in Table 1. Based on the number of citations, Ramazan Gencay and René Garcia emerge as the most impactful and influential authors in AI and ML research in hedging, with 282 citations, followed by Chao Ning and Fengqi You with 268 citations each. In terms of number-of-publication productivity (Fig. 6), Chen Juan, Minami Kentaro & Imajo Kentaro are the most productive authors with four publications. Among countries, the USA has the most intellectual contributions in AI and ML research in hedging (53 publications), with the highest number of citations (453), followed by China (NP–74, TC–320) and Switzerland (NP–12, TC–226). In terms of production over time (fig. 7), China (74 publications) leads the top 10 countries, followed by the USA (NP 53), the UK (NP 51), and Canada (NP 29).

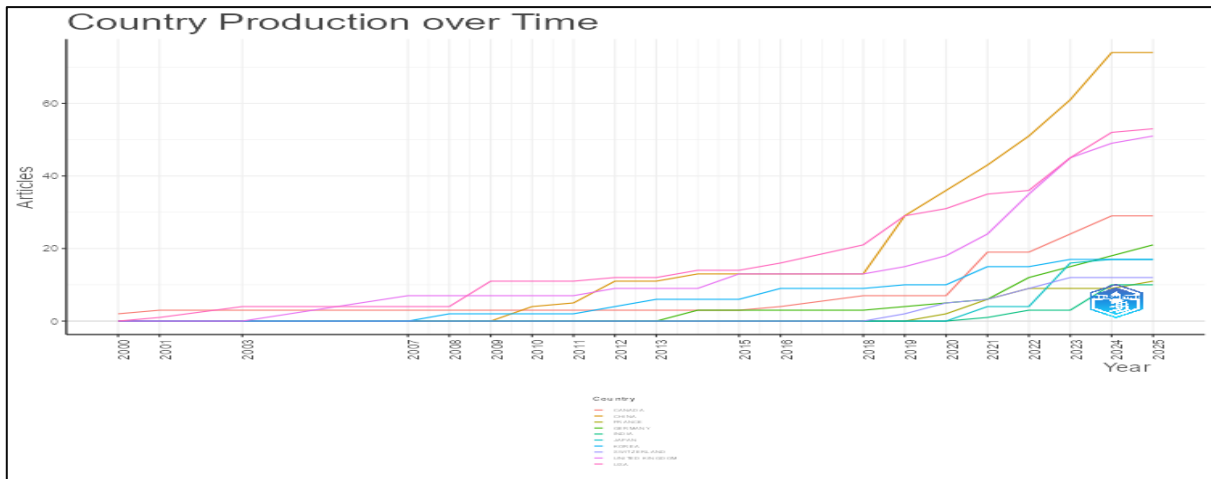


Fig.6. Number of country’s publication productivity of AI and ML Research in Hedging using CD. Source: Authors’ compilation (2025).

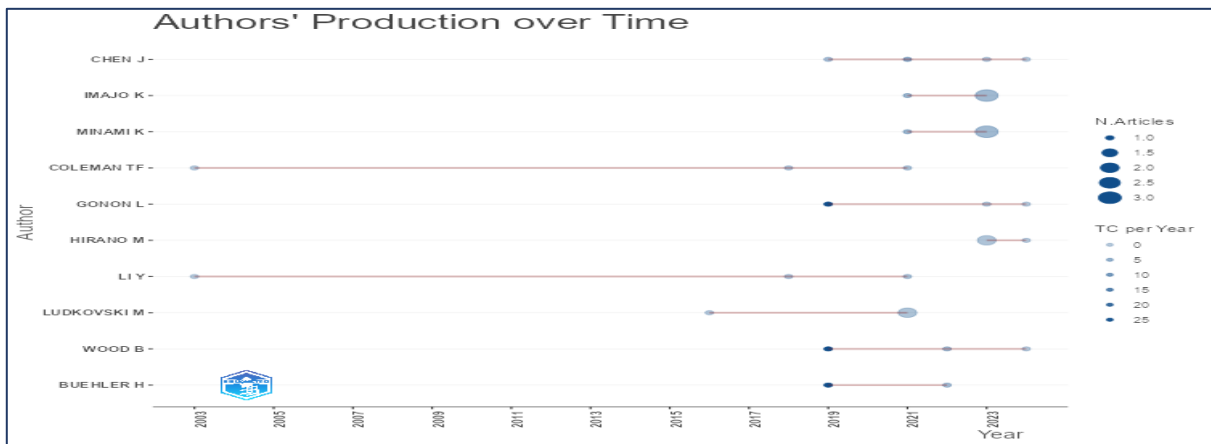


Fig.7. Number-of-publication productivity of AI and ML Research in Hedging using CD. The figure displays top ten productive authors over time. In the hierarchy of authors, those who have published more recently occupy the upper echelons, while earlier contributors are situated at the bottom. Nodes represent the yearly publication frequency. Figure 7’s line traces the trajectory of each author’s scholarly journey, illustrating when their work began, continued, and ended throughout the years. Source: Authors’ compilation (2025).

Table 1. Top authors and countries of AI and ML research in hedging with commodity derivatives.

TC	Author	NP	TC	Country	NP
282	Gençay R	2	453	USA	53
268	Ning C	1	320	China	74
268	You F	1	226	Switzerland	12
206	Teichmann J	2	178	United Kingdom	51
201	Buehler H	2	138	Germany	21
201	Wood B	3	93	Belgium	4
191	Gonon L	3	68	Canada	29
147	Qi M	1	68	South Korea	17

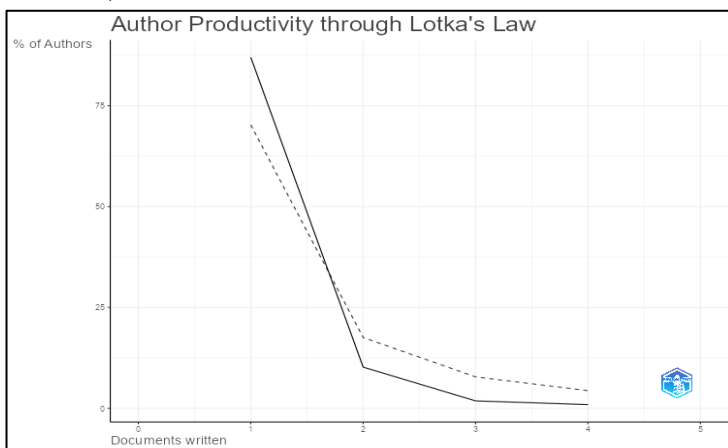
135	Garcia R	1	58	Sweden	9
122	Gammerman A	2	46	Cyprus	3
122	Vovk V	2	16	Singapore	9
110	Chen S-S	1	11	France	11
110	Gupta A	1	9	Tunisia	8
110	Kar Ak	1	6	Finland	1
110	Nanavati B	1	4	India	10
110	Singh V	1	3	Brazil	1
110	Singhania M	1	3	Hong Kong	1
102	Yao H	2	2	Japan	17
100	Huang Q	1	2	Lithuania	1

Note(s): TC = total citations. NP = Number of publications. The research constituent (i.e., author, country) appear according to total citations in this table.

b) Author's productivity on AI and ML research in hedging through Lotka's Law

As shown in Figure 8 and Table 2, the study assessed how well Lotka's bibliometric law fit the assessment of the author's productivity. According to law, about 60% of researchers in a given field will publish one article, while 15% will produce two, 7% will contribute three, and merely 6% of authors will produce more than ten articles. The analysis indicates that 87% of the authors have contributed one article, 10% (33 authors) have published two, and only 2% (6 authors) have contributed 3 articles. The highest author productivity is four (1%) articles.

In contrast to Lotka's expectation of 60%, above 60% of writers that study AI and ML in hedging have only one publication. Additionally, writers with two, three, and four publications, respectively, deviate from the expected by 5%. The conclusion is that the literature on AI and ML in hedging does not follow Lotka's law, as results show a deviation from it.



No. Articles	No. Authors	Frequency (%)
1	281	0.86996904(87%)
2	33	0.10216718(10%)
3	6	0.01857585 (2%)
4	3	0.00928793 (1%)

Fig.8. and Table 2. Shows the Author's productivity through Lotka's Law. Source: Authors' compilation (2025).

c) Top institutions in AI and ML research in hedging with CD

With ten publications, the University of Waterloo (fig. 9) is the most productive university worldwide in AI and ML research in hedging. Jiangsu University (China), Technical University of Munich (Germany), University of Sfax (Tunisia), Guangxi University (China), and National Central University (China) came

next with six, five, five, and four publications, respectively.

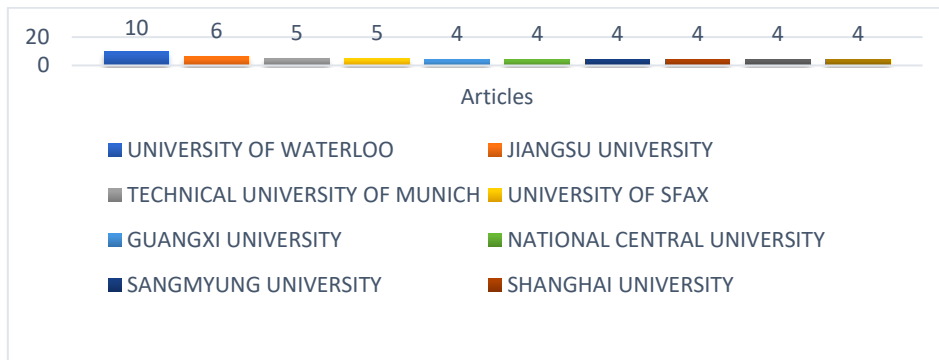


Fig. 9. Top institutions in AI and ML research in hedging using CD. Source: Authors' compilation (2025).

d) Top journals for AI and ML research in hedging with CD

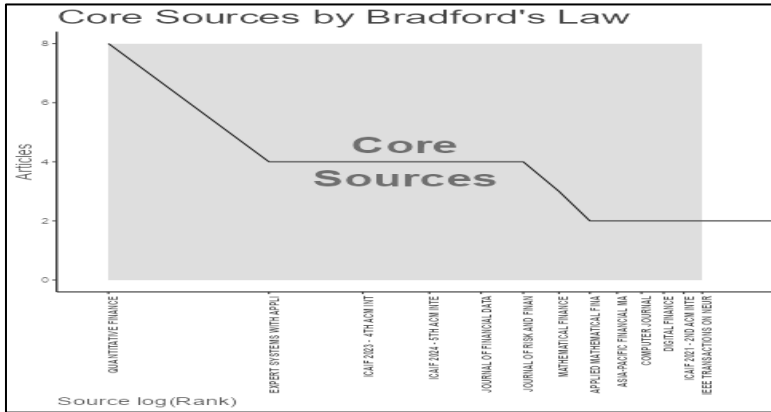
Bradford's Law and source impact are used to identify the key journals that publish AI and ML in hedging literature. Bradford's Law deals with how literature is distributed within a particular field (Summers, 1983). As per source impact, the top journals in the said field are presented in Table 5. In terms of citations, Quantitative Finance & Computers and Chemical Engineering are the two most influential journals, with 374 and 268 citations, respectively. However, in terms of publications, Quantitative Finance & Expert Systems with Applications are the two most productive journals, with 8 and 4 publications.

The data illustrated in Figure 10, Table 3, & Table 4, revealed that each of the three zones accounted for roughly 33% to the total of 126 articles. Zone 1 contained the minimum sources (13), which increased threefold in zone 2 to 33 and further expanded to 41 in zone 3. This distribution pattern aligns with Bradford's law, which posits that a limited number of core journals contain most articles, and zones should have a relatively equal distribution of articles.

Table. 3. Journal rankings based on core sources of Bradford's law. Source: author's elaboration.

Sources	Rank	Freq.	CF	Zone
Quantitative Finance	1	8	8	Zone 1
Expert Systems With Applications	2	4	12	Zone 1
ICAIF 2023 - 4th ACM International Conference On AI In Finance	3	4	16	Zone 1
ICAIF 2024 - 5th ACM International Conference On AI In Finance	4	4	20	Zone 1
Journal Of Financial Data Science	5	4	24	Zone 1
Journal Of Risk And Financial Management	6	4	28	Zone 1
Mathematical Finance	7	3	31	Zone 1
Applied Mathematical Finance	8	2	33	Zone 1
Asia-Pacific Financial Markets	9	2	35	Zone 1
Computer Journal	10	2	37	Zone 1
Digital Finance	11	2	39	Zone 1
ICAIF 2021 - 2nd ACM International Conference On AI In Finance	12	2	41	Zone 1
IEEE Transactions On Neural Networks	13	2	43	Zone 1

IEEE/IAFE Conference On Computational Intelligence For Financial Engineering, Proceedings (CIFER)	14	2	45	Zone 2
Insurance: Mathematics And Economics	15	2	47	Zone 2



Zone	Number of Journals	%	Number of Articles	%
Zone1	13	15%	43	34%
Zone2	33	38%	42	33%
Zone3	41	47%	41	33%
Total	87		126	

Fig.10. and Table 4. Top journals for AI and ML research in hedging using CD as per Bradford’s Law. Source: Authors’ compilation

NP	Source	h_index	g_index	m_index	TC
8	Quantitative Finance	7	8	0.875	374
1	Computers And Chemical Engineering	1	1	0.143	268
2	IEEE Transactions On Neural Networks	2	2	0.08	153
1	Journal Of Econometrics	1	1	0.038	135
2	Computer Journal	2	2	0.105	122
1	International Journal Of Information Management Data Insights	1	1	0.25	110
1	IEEE Transactions On Pattern Analysis And Machine Intelligence	1	1	0.143	100
1	Applied Soft Computing Journal	1	1	0.143	98
4	Journal Of Financial Data Science	3	4	0.429	92
4	Expert Systems With Applications	3	4	0.167	83

Table 5. Source Impact. Source: Authors’ compilation. Note(s): TC = total citations. NP = Number publication

e) Top articles for AI and ML research in hedging with CD

The top 10 cited articles on AI and ML research in hedging are presented in table 6 and table 7 (as per global and local citation). Ning C, 2019 is the most impactful and influential article with the highest number of citations in Scopus (268), followed by Buehler H, 2019 with 189 citations. In respect to local citation Buehler H, 2019 with 31 lead the table followed by Garcia R, 2000 with 12 local citation.

Sr. No.	articles	DOI	TC
1	Ning C, 2019 Computers And Chemical Engineering.	10.1016/j.compchemeng.2019.03.034	268

2	Buehler H, 2019, Quantitative Finance	10.1080/14697688.2019.1571683	189
3	Gençay R, 2001, IEEE Transactions On Neural Networks	10.1109/72.935086	147
4	Garcia R, 2000, J. of Econometrics	10.1016/S0304-4076(99)00018-4	135
5	Gammerman A, 2007, Computer Journal	10.1093/comjnl/bxl065	115
6	Singh V, 2022, Int. J. Inf. Manage Data Insights	10.1016/j.jjime.2022.100094	110
7	Qi Y, 2019, IEEE Transactions On Pattern Analysis And Machine Intelligence	10.1109/TPAMI.2018.2828817	100
8	Zhu Q, 2019, Applied Soft Computing Journal	10.1016/j.asoc.2019.105739	98
9	De Spiegeleer J, 2018, Quantitative Finance	10.1080/14697688.2018.1495335	93
10	Chaudhuri K, 2009, Adv Neural Inf Process System - Proc Conf		79

Table 6. Authors' compilation. Note(s): TC = total citations.

Local Citations	Document	DOI	Year	Global Citations
31	Buehler H, 2019, Quant Finance,	10.1080/14697688.2019.1571683	2019	189
12	Garcia R, 2000, J Econometrics,	10.1016/S0304-4076(99)00018-4	2000	135
12	Kolm Pn, 2019, J Financial Data Science,	10.3905/jfds.2019.1.1.159	2019	49
9	Cao J, 2021, J Financial Data Science,	10.3905/jfds.2020.1.052	2021	36
8	Murray P, 2022, Proc. Acm. Int. Conf. AI Finance, ICAIF	10.1145/3533271.3561731	2022	12
7	Carbonneau A, 2021, Quant Finance,	10.1080/14697688.2020.1806343	2021	20
5	Amilon H, 2003, J Forecasting,	10.1002/for.867	2003	55
4	Carbonneau A, 2021, Insurance: Mathematics And Economics,	10.1016/j.insmatheco.2021.03.017	2021	21
3	Imaki S, 2023, J Financial Data Science,	10.3905/jfds.2023.1.125	2023	7
2	Chen F, 2012, Intell System Account Finance Management,	10.1002/isaf.336	2012	14

Table 7. Source Impact. Source: Authors' compilation.

f) Knowledge foundations of AI and ML literature in hedging through co-citation analysis

Co-citation analysis reveals the semantic relationships between co-cited references, which illustrate the body of knowledge in a topic (Donthu, 2021). Of the 4704 cited reference, Fig. 11 displays the co-

citation map of references that are cited at least three times by articles, of which only 59 meet the threshold in the review corpus. Broadly, co-citation analysis of co-cited references shows that research on AI and ML in hedging has six fundamental categories, i.e. cluster 1 (Red): **long short-term memory, neural computation powering deep hedging**, cluster 2 (Green): **valuation & pricing of options and volatility**, cluster 3 (Blue): **deep reinforcement learning and reinforcement learning approach**, cluster 4 (Yellow): **deep learning, stochastic volatility, method for stochastic optimization**, cluster 5 (Purple): **multilayer feedforward networks, neural networks and optimal delta hedging**, cluster 6 (Aqua): **machine learning and Gaussian processes**. Interestingly, The most foundational clusters, it turns out, are related to deep hedging and long short-term memory, neural computation that underpins deep hedging (red nodes), options valuation and pricing (blue nodes), deep learning, stochastic volatility, and stochastic optimization technique (yellow nodes).

On examining these clusters in greater detail reveals that the six core clusters combine to create three overarching foundational clusters. 1. Deep hedging using neural networks, 2. Stochastic volatility, pricing & valuation of options, 3. Machine learning, deep learning, deep reinforcement learning & Gaussian processes. These broad core clusters serve as the knowledge bases for AI and ML in hedging research in CD.

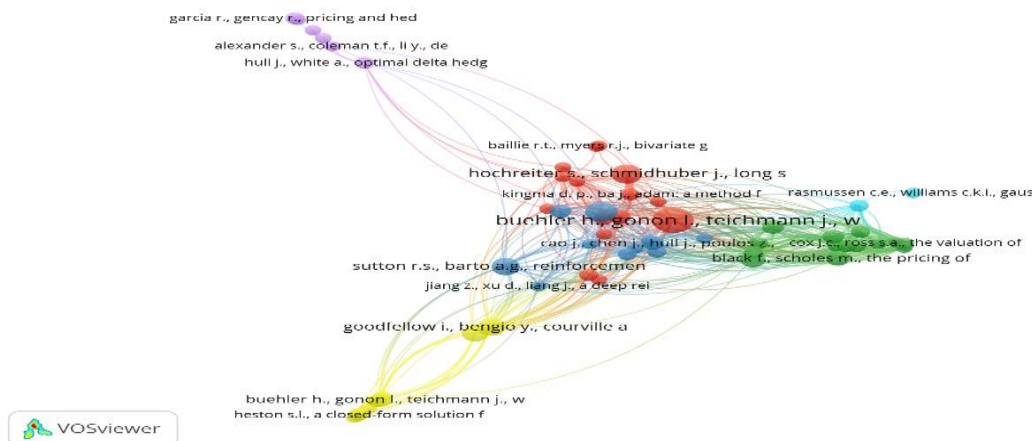


Fig.11. co-citation analysis using cited reference by articles on AI and ML in hedging using CD research. Note(s): Cited references are depicted as nodes. Thematic clusters of references are represented by different node colors, based on semantic similarity. Node size indicates the frequency of local citations. Co-citations are shown as links between nodes. The thickness of these links represents co-citation frequency. Nomological network of co-citation clusters. Notes: Co-citation cluster 1 (Red): Immersive technologies powering. Cluster 2 (Green): Identity and ownership. Cluster 3 (Blue): Concepts, challenges, and cluster 4 (Yellow): Frameworks. Cluster 5 (Purple): Current trends and future directions. 6 (Aqua): Consumer behavior and marketing.

g) The body of knowledge: Thematic clusters of AI and ML research in hedging through bibliographic coupling.

Expanding upon the basis of information established in the preceding section, this part has examined the thematic clusters: body of information regarding AI and ML in hedging. The bibliographic coupling analysis has been conducted using “Documents” as the unit of analysis, keeping the minimum number of citations of a document to “0” so that all articles in the corpus can be included for analysis. Bibliographic coupling captures recent, specialized, and groundbreaking knowledge. As a result, it draws attention to

works that are probably missed in co-citation analysis because they haven't got many citations yet (Donthu, 2021). Major themes of knowledge produced by AI and ML in hedging research are revealed in Fig. 12 and Table 8.

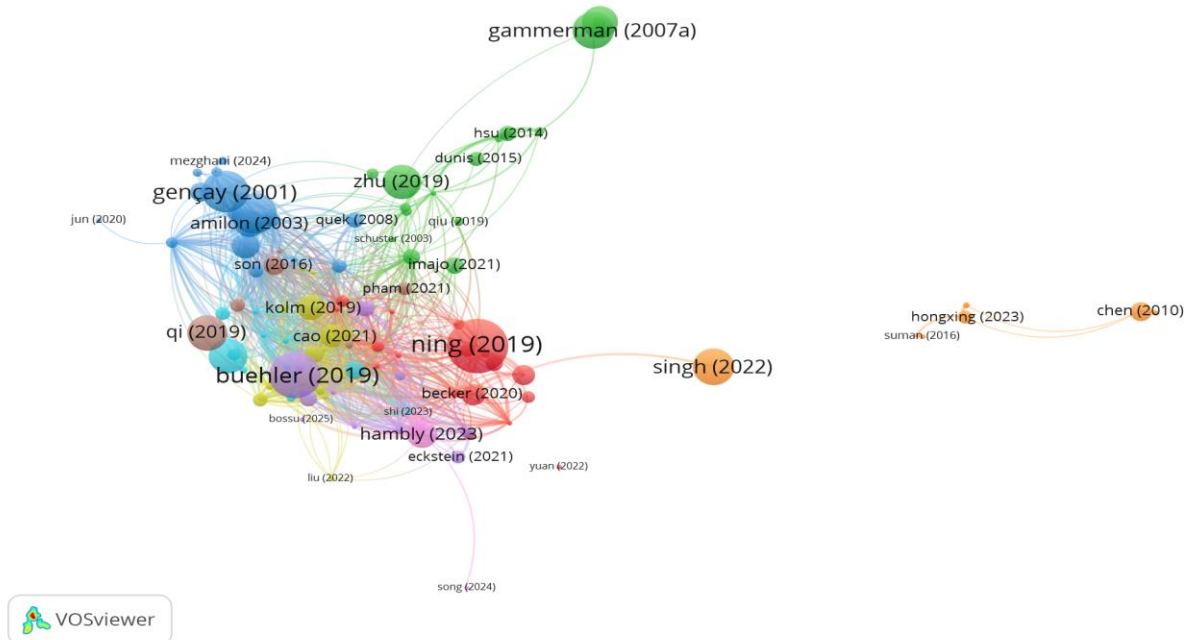


Fig.12. Bibliographic coupling using documents on AI and ML in hedging with CD research

Theme	Author(s)	Title	Citation
Deep learning models and hedging	Rettinger (2025)	Understand your decision rather than your model prescription: towards explainable deep learning approaches for commodity procurement.	0
	Agram (2024)	Deep learning for quadratic hedging in incomplete jump market.	1
	Dai (2022)	evaluation of deep learning algorithms for quadratic hedging	4
Management of commodity risk and Machine learning	Hu (2024)	A deep learning-based financial hedging approach for the effective management of commodity risks.	1
	Chen (2020)	Financial hedging in energy market by cross-learning machines.	4
	Zhu (2019)	A hybrid VMD–BIGRU model for rubber futures time series forecasting.	98
Forecasting price and hedging using multi-parametric models	Mezghani (2024)	Forecasting the impact of financial stress on hedging between the oil market and GCC financial markets.	4
	Mezghani (2023)		5

	Kumar (2021)	Forecast the role of GCC financial stress on oil market and GCC financial markets using convolutional neural networks. Predicting wheat futures prices in India.	4
Deeper hedging	Li (2024) Malekzadeh (2024) Cannelli (2023) Gao (2023)	Application of deep learning to option hedging strategy. Ex-DRL: hedging against heavy losses with extreme distributional reinforcement learning. Hedging using reinforcement learning: contextual k-armed bandit versus q-learning. Deeper hedging: a new agent-based model for effective deep hedging.	0 0 4 2
Robust Pricing and hedging	Limmer (2025) Lütkebohmert (2022) Gierjatowicz (2022)	Robust hedging gans: towards automated robustification of hedging strategies. Robust deep hedging. Robust pricing and hedging via neural stochastic differential equations.	0 12 5
Deep hedging	Hirano (2024) Hirano (2023) Shi (2023)	Experimental analysis of deep hedging using artificial market simulations for underlying asset simulators. Efficient learning of nested deep hedging using multiple options. Deep learning algorithms for hedging with frictions.	0 2 0
Currency risk hedging	Likitapiwat (2024) Naveed (2024) Hongxing (2023)	Weathering exchange rates: estimating the effect of climate change vulnerability on foreign currency hedging using a text-based approach. Assessing the nexus between currency exchange rate returns, currency risk hedging and international investments: intelligent network-based analysis. Connectedness between currency risk hedging and firm value: a deep neural network-based evaluation.	0 2 12
Deep hedging and Non-parametric	Ruf (2022) Chen (2023)	Hedging with linear regressions and neural networks.	12 3

machine learning models	Pham (2021)	Data-driven hedging of stock index options via deep learning. Multi-agent reinforcement learning approach for hedging portfolio problem.	11
Reinforcement learning	Hambly(2023)	Recent advances in reinforcement learning in finance.	58
	Song (2024)	Research on the dynamic hedging trading strategy for portfolios based on deep reinforcement learning.	0

Table 8. Bibliographic coupling using documents as unit of analysis on AI and ML in hedging using CD research. (Author’s compilation)

h) The evolution of AI & ML based hedging through Thematic Evolution technique of network approach.

Thematic evolution (Figure 13) depicts the literature's history over time, as well as the theme diagram. The title—topic trend and thematic map—is used to demonstrate the history and development of topics. This study splits the time period into time slices so that analysis can be performed for a certain point in time to capture the evolution of research throughout time. The cutting years are determined by economic events like the 2007-2008 financial crisis, Industrial Revolution 4.0, post-COVID-19, and recent developments, which are shown in Fig. 13. Time slice parameters are five points with the following cutting years: 2007, 2011, 2016, 2020, and 2023.

A set of keywords creates some clusters for each time, which are then displayed in two-dimensional thematic maps called strategic diagrams in six theme maps for the following Periods: 2000–2007, 2008–2011, 2012–2016, 2018–2020, 2021–2023, and 2024–2025, which were obtained from one of the top themes in each quadrant of the thematic map of thematic evolution.

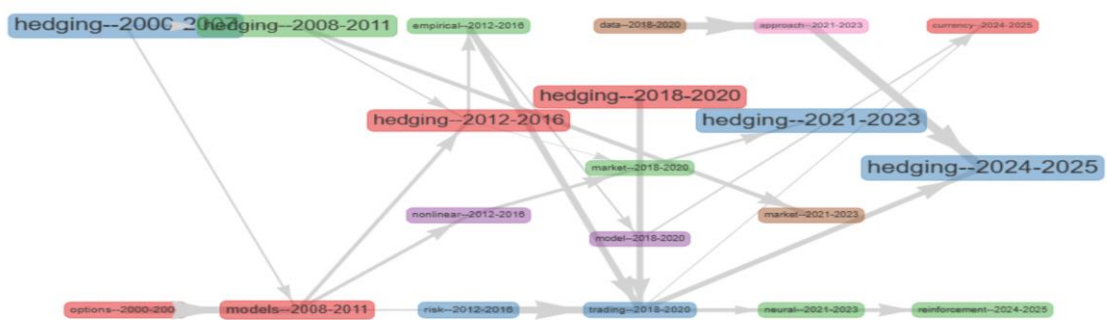


Fig.13. Thematic evolution of AI and ML in hedging with CD research. (Author’s compilation)

The time slice one (2000-2007) of the thematic evolution of AI and ML in hedging emerged with “hedging” with “options” contacts using neural networks of AI, followed by “Pricing”, “Derivatives”, and “Predictions”.

The second time frame in the thematic evolution of AI and ML in hedging is from 2008 to 2011. During this period “hedging”, “financial”, “risk” using different “models” of “neural” networks shifted from

emerging themes to motor themes and niche themes respectively.

On the Beginning of industry 4.0 in 2010, an intriguing thing is seen in the evolution of the theme in the third period (2012-2016). “Hedging”, with “neural” networks “models” become basic theme (previously in niche themes) of the study and it also evolve to use of “nonlinear” models in “hedging” as niche theme. However, “empirical”, “models”, were the motor research theme during the period. While “Risk” and “commodity” come up as emerging theme.

Compared to the preceding three eras, there are more clusters in the fourth (2018–2020) time slice. “Hedging” using “Deep learning” become the motor theme but “big data” in deep hedging were in mid of basic and motor theme. “Empirical”, “models” which were motor research topic in previous time slice becomes basic research theme during this period. Opinion-based pair “Trading”, and “Financial” “risk” with respect to hedging was niche themes.

The second-to-last phase of theme evolution is 2021–2023. “Hedging” using “deep learning” evolved to “reinforcement learning” in the motor theme along with the “deep neural” network framework. Robust Bayesian recourse emerged as the most potential area for study within the framework, but the “futures market” and “ML approaches” in hedging became basic themes with a moderate degree of relevance.

The last and most recent period of theme evolution is 2024–2025; in this time slice, “Hedging” using “Deep learning” shifted to the basic theme from motor themes (fifth slice). “Currency” risk hedging, “AI” in credit spread, deep learning approaches in “Commodity” price forecasting, procurement, and “Quadratic hedging” in derivatives emit as motor themes of the year. “Reinforcement learning” in hedging “strategies” unrolls to emerging/declining themes.

Analyzing each sub-period helps better grasp how the development of research themes on hedging with artificial intelligence and machine learning in CD has evolved over time. Figure 13 presents a Sankey diagram across six time periods, illustrating how these themes have shifted, with changes visualized through interconnected clusters. These flows indicate that themes either evolved from those in earlier periods, faded away as new ones took their place, or appeared alongside the rise of related topics. Each time period features a variety of keywords drawn from the titles of articles published during that specific timeframe.

4.2.Future trajectory (RQ2) of ML & AI based hedging through CD

This part continues with investigating thematic trends and future research trajectories using co-occurrence in AI and ML research in hedging with CD after building the foundations and themes identified by co-citation analysis (Fig. 11) and bibliographic coupling (Fig. 12 & Table 8) in the preceding section. Using author keywords, thematic map analysis is performed. This thematic map analysis of the network approach will reveal the important trends and patterns in the literature that are reported in Figures 14 & 15.

The graph consists of four quadrants. Themes that appear in the lower left corner are emerging or declining themes. These new ideas can emerge and advance the field of research, or they may fade. The terms “finance,” “AI,” “Knightian uncertainty,” “pricing,” and “random forest” may be found in this corner. These themes have previously been widely researched; their diminishing density Indicates a potential shift in study focus or increasing interest in other areas. Researchers can analyze the reasons for these patterns and investigate the evolving dynamics within these themes. The bottom right corner displays the fundamental or basic topics. The themes “financial risk management,” “DL,” “ML,” “reinforcement learning,” and “deep hedging” in the literature are less developed and of a high degree of relevance, indicating the need for additional research and development. Looking in-depth at the networks, it reveals

meaning they are frequently insufficient for addressing the highly specific constraints and idiosyncratic demands intrinsic to financial contexts. The complexity inherent in financial systems necessitates a careful balance between the flexibility of the model and the specific limitations of the domain.

3. A deep neural network framework using backward stochastic differential equations for option pricing and hedging faces a key limitation: its algorithm has a quadratic computational cost in relation to the number of timesteps (N). This makes it less efficient for large datasets; as the input size (n) doubles, the time it takes to run the algorithm increases by a factor of four (Chen, 2020). Future work may focus on redesigning the NN architecture to enhance computational efficiency.
4. The most of RL research centers on single-agent settings, while financial markets operate in multi-agent environments where agents' actions affect one another. In such multi-agent reinforcement learning (MARL) scenarios, modeling becomes more difficult and potentially less effective (Singh et al., 2022). Although deep RL has shown success under controlled conditions, its practical use in financial institutions remains limited. However, with the advancements in big data and AI platforms, future implementations are expected in areas like investment research, risk control, and wealth management.
5. The ML techniques used for price prediction, like support vector machines, boosting trees, and NN, particularly RNN and LSTM, struggle to grasp the internal connections of stock movements related to the lead-lag effects of events (or news) (Cheng, 2022). Most of these techniques rely on a single modality of data for predictions, potentially overlooking valuable information.

5. Conclusion

This research conducted a BA of hedging in CD using AI and ML literature, utilizing the Scopus database. The study encompasses performance analysis, which includes mapping the trend of annual scientific production, identifying relevant journal sources, examining author productivity, tracking country production over time, and highlighting top articles. It also explores thematic clusters, keyword connections, foundational knowledge, trending subjects, and the evolution of the topic over time and discusses the challenges and limitations within this field of study. Additionally, the study assessed the applicability of Bradford's and Lotka's bibliometric laws on ML-based hedging through CD literature.

The analysis uncovers the progression of AI and ML applications in hedging (Fig. 13), showing a shift from NN models to more advanced ML and DL models over time. Simultaneously, it maps out the body of knowledge through bibliographic coupling (Fig. 12 & Table 8), addressing topics such as the management of commodity risk and ML, price forecasting and hedging using multi-parametric models, DL models and hedging, deeper hedging, currency risk hedging, deep hedging and non-parametric ML models, and reinforcement learning.

Potential future directions of research in hedging in CD using AI and ML include examining the effectiveness between traditional econometrics model, AI and ML based model and the combination of both the models, dynamic daily hedging model in CD, distributional reinforcement learning, deep quadratic hedging in CD (Fig. 12. Bibliographic coupling, Fig. 13. Thematic evolution, Fig. 14. Thematic Map, Fig. 15. Thematic Map's network and table 8) the use of AI and ML models in cross hedging, and to work on the conceptual framework and mechanism behind these models to make them more transparent and authentic in the eyes of retail investors. By addressing these gaps, we can enhance the understanding of these ML and DL based models in hedging. There is a pressing need for additional research that

examines potential factors influencing the hedging effectiveness of commodity products in CD markets using AI and ML. This includes exploring how regulatory policies, geopolitical events, technological innovations, and market structures impact it.

In particular, we reviewed the literature on hedging in CD using AI and ML that can aid in decision-making for researchers, CD market participants, responsible investors, financial institutions, economic policymakers, and academia, enabling them to stay informed about current management studies and make appropriate decisions for further research ideas. There are some limitations in this study that it solely relies on data from the Scopus database for the years 2000 to 2025. Future researchers could also benefit from incorporating data from other sources as well.

References

1. Ajitha Kumari Vijayappan Nair Biju, A. S. (2023). Examining the research taxonomy of artificial intelligence, deep learning & machine learning in the financial sphere—a bibliometric analysis. *Quality & Quantity*, 58, 849–878. Retrieved from <https://doi.org/10.1007/s11135-023-01673-0>
2. Anas, M. E. (2024). A Bibliometric analysis of literature on hedge and safe haven assets. *Journal of Economic Surveys*, 2-s2.0-85212043339(09500804). doi:10.1111/joes.12677
3. Ben Hambly, R. X. (2023). Recent advances in reinforcement learning in finance. *Mathematical Finance*, 33(3), 437-503. Retrieved from <https://doi.org/10.1111/mafi.12382>
4. Chatnani, N. N. (2019). *Commodity markets and derivatives*. Cengage Learning india Pvt Ltd.
5. Chen, Y. a. (2020). Deep neural network framework based on backward stochastic differential equations for pricing and hedging American options in high dimensions. *Quantitative Finance*, 21(1), 45–67. Retrieved from <https://doi.org/10.1080/14697688.2020.1788219>
6. Chunmei, L. (2009). Price forecast for gold futures based on GA-BP neural network. *Proceedings - International Conference on Management and Service Science, MASS 2009*. doi:10.1109/ICMSS.2009.5302242
7. Dawei Cheng, F. Y. (2022). Financial time series forecasting with multi-modality graph neural network. *Pattern Recognition*, 121, 108218. doi:10.1016/j.patcog.2021.108218
8. Dey, G. G. (2023). Price discovery and risk management in asset class: a bibliometric analysis and. *APPLIED ECONOMICS LETTERS*, 30, NO. 17, 2320–2331. Retrieved from <https://doi.org/10.1080/13504851.2022.2096859>
9. Dey, G. G. (2023). Price discovery and risk management in asset class: a bibliometric analysis and research agenda. *APPLIED ECONOMICS LETTERS*, 30(17), 2320–2331. Retrieved from <https://doi.org/10.1080/13504851.2022.2096859>
10. Egghe, L. (1990). Applications of the Theory of Bradford's Law to the Calculation of Leimkuhler's Law and to the Completion of Bibliographies. *Journal of the American Society for Information Science*, 41, 469–92. Retrieved from [https://doi.org/10.1002/\(SICI\)1097-4571\(199010\)41:7<469::AID-ASII>3.0.CO;2-P](https://doi.org/10.1002/(SICI)1097-4571(199010)41:7<469::AID-ASII>3.0.CO;2-P)
11. Geyer-Klingenberg Jerome, H. M. (2021). Corporate financial hedging and firm value: a meta-analysis. *EUROPEAN JOURNAL OF FINANCE*, 27(6), 461-485. doi:10.1080/1351847X.2020.1816559
12. Geyer-Klingenberg Jerome, H. M. (2023). Corporate financial hedging and firm value: a meta-analysis. *Journal of Commodity Markets*, 30, 100276. Retrieved from <https://doi.org/10.1016/j.jcomm.2022.100276>

13. H. Kent Baker, S. K. (2021). Forty years of the Journal of Futures Markets: A bibliometric overview. *The Journal of Futures Markets*, 41(7), 1027–1054. doi:10.1002/fut.22211
14. Huber, J. C. (1998). The underlying process generating Lotka's Law and the statistics of exceedances. *Information Processing & Management*, 34(4), 471-487. Retrieved from [https://doi.org/10.1016/S0306-4573\(98\)00013-2](https://doi.org/10.1016/S0306-4573(98)00013-2)
15. Hull, J. C. (2018). *Options, Futures, and Other Derivatives*. Pearson India education services pvt. ltd.
16. Jędrzej Białkowski, M. T. (2023). Commodity futures hedge ratios: A meta-analysis. *Journal of Commodity Markets*, 30, 100276. Retrieved from <https://doi.org/10.1016/j.jcomm.2022.100276>
17. Jena, A. S. (2021). Lotka's law and author productivity pattern of research in law discipline. *Collection and Curation*, 41(2), 62–73. doi:10.1108/CC-04-2021-0012
18. JohnW.Goodella, S. W. (2021). Artificial intelligence and machine learning in finance :Identifying foundations,themes,and research clusters from bibliometric analysis. *Journal of Behavioral and Experimental Finance*, 32(100577), 2214-6350. Retrieved from <https://doi.org/10.1016/j.jbef.2021.100577>
19. K, S. V. (2024). Bibliographic coupling of documents: An analysis of articles published in the derivative market. *International Journal of Science and Research Archive*, 12(01), 3098–3110. Retrieved from <https://doi.org/10.30574/ijrsra.2024.12.1.1384>
20. Khatri, D. C. (2024, Jul-Dec). Integration of Artificial Intelligence in Pricing and Hedging Strategies for. *Library Progress International*, Vol.44 No.3, 722-730. Retrieved from www.bpasjournals.com
21. Kim, J. S. (2021). Thirty years of the Journal of Derivatives and Quantitative Studies: a bibliometric analysis. *Journal of Derivatives and Quantitative Studies*, 29, No. 4 , 258-279. doi:10.1108/JDQS-08-2021-0020
22. Kumar, S. (2015). *FINANCIAL DERIVATIVES*. PHI Learning.
23. Loso Judijanto, A. R. (2024). Bibliometric Review of the Development of Hedging Strategies in. *The Es Accounting and Finance*, Vol. 3(No. 01,), 35-51. doi:10.58812/esaf.v3i01
24. Markowitz, H. M. (1991, June). Foundations of Portfolio Theory. *The Journal of Finance*, Vol. 46, No. 2, 469-477. Retrieved 1991, from <https://doi.org/10.2307/2328831>
25. Naveen Donthu, S. k. (2021, April 25). How to conduct a bibliometric analysis: An overview and guidelines. *Journal of Business Research*, 133 (2021) , 285–296. doi:10.1016/j.jbusres.2021.04.070
26. Nidhi Desai, V. L. (2018). Using Bradford's Law of Scattering to Identify the Core Journals of Pediatric Surgery. *Journal of Surgical Research*, 229, 90–95. Retrieved from <https://doi.org/10.1016/j.jss.2018.03.062>
27. Prashant Sharma, G. A. (2023). Research on Price Discovery in Financial Securities: Trends and Directions for Future Research. *Journal of Risk and Financial Management*, 16(9). doi:10.3390/jrfm16090416
28. Purity Maina, B. G.-F.-D. (2024). Analyzing Trends in Green Financial Instrument Issuance for Climate Finance in Capital Markets. *Journal of Risk and Financial Management*, 17, 145. Retrieved from <https://doi.org/10.3390/jrfm17040145>
29. Rajib, P. (2014). *Commodity Derivatives and Risk Management*. delhi: PHI Learning Private Limited.
30. Rajwade, A. V. (2010). *currency exposures and derivatives*. Tata mcgraw hill education Pvt. Ltd.
31. Sascha Kraus, M. B.-C.-M. (2022). Literature reviews as independent studies: guidelines for. *Review of Managerial Science*, 16, 2577–2595. doi:10.1007/s11846-022-00588-8

32. Subhajit Pahari, A. B. (2024). A bibliometric analysis of digital advertising in social media: the state of the art and future research agenda. *Cogent Business & Management*, 11, No.1, 2383794. doi: <https://doi.org/10.1080/23311975.2024.2383794>
33. Summers, E. G. (1983). Bradford's Law and the Retrieval of Reading Research Journal Literature. *Reading Research Quarterly*, 19(1), 102-109. Retrieved from <https://doi.org/10.2307/747340>
34. van Eck, N. &. (2010). Software survey: VOSviewer, a computer program for bibliometric mapping", *Scientometrics*. 84 No. 2, 523-538.
35. Vinay Singh, S.-S. C. (2022). How are reinforcement learning and deep learning algorithms used for big data based decision making in financial industries—A review and research agenda. *International Journal of Information Management Data Insights*, 2(2). Retrieved from <https://doi.org/10.1016/j.jjime.2022.100094>
36. Weng Marc Lim, S. K. (2023). Guidelines for interpreting the results of bibliometric analysis: A sensemaking approach. *Global Business and Organizational Excellence*, 43, 17–26. doi:10.1002/joe.22229
37. Y. Li, S. W. (2021). A New Hybrid VMD-ICSS-BiGRU Approach for Gold Futures Price Forecasting and Algorithmic Trading. *IEEE Transactions on Computational Social Systems*, 8(6), 1357-1368,. doi:10.1109/TCSS.2021.3084847