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Examining the research taxonomy of artificial intelligence, deep learning & machine learning in the financial sphere—a bibliometric analysis

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Abstract

This paper surveys the extant literature on machine learning, artificial intelligence, and deep learning mechanisms within the financial sphere using bibliometric methods. We considered the conceptual and social structure of publications in ML, AI, and DL in finance to better understand the research's status, development, and growth. The study finds an upsurge in publication trends within this research arena, with a bit of concentration around the financial domain. The institutional contributions from USA and China constitute much of the literature on applying ML and AI in finance. Our analysis identifies emerging research themes, with the most futuristic being ESG scoring using ML and AI. However, we find there is a lack of empirical academic research with a critical appraisal of these algorithmic-based advanced automated financial technologies. There are severe pitfalls in the prediction process using ML and AI due to algorithmic biases, mostly in the areas of insurance, credit scoring and mortgages. Thus, this study indicates the next evolution of ML and DL archetypes in the economic sphere and the need for a strategic turnaround in academics regarding these forces of disruption and innovation that are shaping the future of finance.

Keywords Bibliometric analysis · Deep learning · Machine learning · Artificial intelligence · Conceptual structure · Social structure

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1 Introduction

For a long time, the concept of machines and computers being able to replicate human thoughts and carry out informed decisions could only be perceived in theory. Emerging technology breakthroughs such as artificial intelligence (AI), robotics, the Internet of Things, big data analytics, and machine learning (ML) techniques have empowered machines to act by analogy with humans. The concepts of artificial intelligence, machine learning, and deep learning (DL) are particularly gaining a significant foothold in the financial ecosystem, capturing the research community's interest.

Industry 4.0, with its multi-faceted technologies, has been transforming the industrial and economic fabric across the world (Rai et al. 2021). From being just a figment of imagination in sci-fi movies and novels, technological advancements such as artificial intelligence, deep learning, and machine learning have come a long way in harnessing the cognitive functions of humans. This sphere of revolutionary technology has permeated a wide range of scientific, technological, business, industry, and government fields.

The roots of AI date to a 1955 Dartmouth Summer Research Project Proposal dedicated to enabling machines to simulate human intellect, thereby handling complex tasks (McCarthy et al. 2006). Amidst differing standpoints on a universal definition, AI stands for the development of the computer from being merely an instrument simulating human intelligence to its attaining intellectual and self-learning processes. Encompassed in artificial intelligence, ML and DL techniques have grown to become the most promising branches of modern technological revolution (Huang et al. 2020).

ML refers to a broad discipline that focuses on the automated usage of data and algorithms without being explicitly programmed. Humans learn to perform a task through experience and practice, whereas machine learning algorithms know to complete a task through additional data and multiple models. For instance, algo trading uses a computer programme that follows a defined set of instructions (an algorithm) to place a trade. The trade through algo can generate profits at a speed and frequency that is impossible for a human trader. These algorithms independently detect complex patterns within the available data and uncover befitting combinations among variables to model accurate and precise predictions (Sarker 2021). However, conventional machine-learning techniques were limited in processing raw data in their raw form. ML systems were only considered part of AI systems in the early years, but now ML has become more autonomous (Gogas & Papadimitriou 2021).

Deep learning is a subset of machine learning that refines the existing structural framework of ML. DL incorporates representation learning which discovers and models various patterns and trends needed for detection or classification from unstructured datasets (Lecun et al. 2015). It is based on an artificial neural network where algorithms are structured in multi-processing layers, thereby helping to learn complex tasks (Bachouch et al. 2021). These networks replicate human intelligence into their processes, thereby eliminating more manual human intervention.

Initially developed in computer science, the applications of ML and DL have been used to formulate trend and pattern predictive tasks, image processing, audio-visual recognition, and even complex classification and extraction functions (Chai & Li 2019). Soon these techniques were assimilated into diversified fields such as physical and life sciences, medicine, energy economics, finance, and operations management (Chiroma et al. 2020; Chai et al. 2013; Ghoddusi et al. 2019; Schmidt et al. 2019).

The immense capability of ML and DL in identifying, processing/analysing, forecasting, and even formulating explanatory models based on complex, large-scale data is transforming the financial systems (Li & Tang 2020; Wall 2018). OECD 2021[1] substantiated that the deployment of AI and its assisted technologies in finance is expected to drive the competitive advantages of financial firms by increasing the quality of services and products offered to consumers. With the escalating volume of data and persistent growth in computational power and storage, conventional hedge funds and banks, as well as emerging fintech service providers, have begun deploying these machine algorithms in their regular activities (Carbonneau & Godin 2021; Xu et al. 2020; Yeh & Chen 2020).

The ML techniques have been predominantly used for risk evaluation of customer credit scores and risks along with loan and insurance underwriting (Bee et al. 2021; García et al. 2019; Wen et al. 2021). Its application in producing predictive analytics has been widely employed in exchange rate forecasts (Zheng et al. 2019), in stock markets (Srivastava et al. 2021; Yin et al. 2021), while Sevim et al., (2014) have used it in macroeconomic predictions and forecasts. Further, ML-based algorithmic trading models monitor and analyse real-time data to detect patterns, thereby giving traders a distinct advantage over the market average (Gómez Martínez et al. 2018). It is noted that the increasing transactional events and customer participation in the financial environment makes it vulnerable to security threats. This makes financial fraud detection one of the surging domains for applying the ML/DL mechanisms (Trompeter et al. 2013; Zhang & Trubey 2019).

The studies of Ala'raj et al. (2021), Li et al. (2020), and Song et al. (2017) elucidate how ML/DL models also ignite the application of AI and ML implementation across areas of the financial sphere of financial modelling, sentiment inferences, portfolio management etc. However, Butaru et al. (2016) observed that the increased utility of these algorithmic models in their conduct of activities also calls for a more customised approach to supervision and regulation by financial institutions. Hence, more care and control are required to ensure accuracy while using these technologies.

We understand that the continuing adoption of ML and DL techniques over traditional econometric models necessitates an academic summary of the existing plethora of literature on the financial ecosystem. The significant volume of information across various disciplines makes it necessary to have an updated literature set and upcoming research fronts. A comprehensive bibliometric analysis will help us investigate the development track characteristics and disclose statistical patterns across the prevailing theoretical underpinnings (Borgman & Furner 2005; Wang et al. 2018). We understand that a bibliometric analysis is helpful in the present situation to synthesise the existing knowledge on the applications of ML, DL, and AI in the finance streams.

The prominent reason to use bibliometric analyses here is that they furnish quantitative analysis of articles published in a particular area of scientific research (Baker et al. 2020; Blanco-Mesa et al. 2017). In addition to that, they provide helpful insights into document type, dispersal among countries/territories, distribution of institutions, geographical distribution of authors, most active authors and their research interests or fields, co-authorship network, and global/local cooperation (Donthu et al. 2020). Moreover, the deployment of advanced bibliometric methodologies using advanced software and packages is helpful for obtaining an unbiased picture of the literature conclusion on a topic (Aria & Cuccurullo 2017). Also, the scientific mapping based on bibliometric methods and applications allows

[1] https://www.oecd.org/finance/financial-markets/Artificial-intelligence-machine-learning-big-data-in-finance.pdf

us to investigate from a statistical point of view, the applications of AI-based and ML/DL methods in the financial discipline.

In this paper, through a bibliometric mapping, we analyse why financial institutions should focus on ML and AI techniques and why they need to reach a standard set of governance practices. In addition to these, we aim to address the following aspects/objectives: Firstly, we analyse the growth pattern and developmental trends of machine learning and deep learning literature in the financial domain. Secondly, we identify authors, research institutions, and journals contributing to the scientific output in the AI/ ML/ DL areas. Subsequently, we synthesise the analytical findings to provide an overview of the scientific landscape and the relationship between various "actors" through network analysis. Thirdly, we analyse the conceptual and social structure of the literature published in applying ML, DL, and AI in finance to provide an overview of existing foundations of research and a prediction for future research. Finally, we identify the existing research gap prevailing in the area and provide future research agenda through a thematic mapping approach.

To accomplish these self-appointed tasks, we conducted a bibliometric analysis based on the widely used database Web of Science, covering the period from 1992 to 2022. We generated a bottom-up clustering of academic articles using network analysis tools such as VOSviewer and RStudio(packages: bibliometrix and biblioshiny), which led us to identify the most prominent clusters of keywords based on the research in ML and AI in finance. Also, we analysed the documents based on the conceptual and social knowledge structure of articles published in journals in the selected period.

Our bibliometric analysis showed gaps in studies related to the failures of ML and AI in finance, which is to be addressed by the academicians. Interestingly, it was noted that the USA and China are among the countries with the most significant number of publications in ML and AI. Next, it was noted that ML and AI tools have wide applications in various fields of finance such as banking, credit scoring, insurance underwriting, insurance fraud risk management, algo trading, etc. We were surprised to note that presently ML is even used in the Environment Social and Governance (ESG) scoring initiatives by the ESG-score providers. If using ML and AI is a successful venture, we can expect to see a phenomenal application of these technological algorithms for ESG scoring in the future by the score providers and financial asset issuers. Because the world is looking to reach Sustainable Development Goals (SDG) set by the United Nations, it is only natural that business firms are now looking for green initiatives, and sustainability reporting is their core agenda.

The rest of the study is articulated as follows. Section 2 deals with the literature review, and Sect. 3 introduces the methodology used in the research. A statistical summary of research findings is reported in Sect. 4. Section 5 offers research directions toward an outlook for the future. Finally, Sect. 6 ends this paper with some vital conclusions.

2 Literature review

ML and AI technology have immense applications in finance. In this section, we focus on the theoretical underpinnings of ML and AI applications and present a conceptual, methodological, and thematic development of different domains of finance which use ML and AI mechanics.

We are not the first to review on the applications of AI and ML in finance. For example, Ghoddusi et al. (2019) reported the achievements and limitations of existing machine-learning literature. They identified the current gaps and offered suggestions for future research. The term Machine Learning (ML) was introduced by Arthur Samuel while working for IBM in 1959, mainly to describe the pattern-recognition tasks delivered. The literature suggests its usage in economic and financial areas. For instance, Agarwal et al. (2019) examined the evolution, adoption, implementation, and future opportunities of leveraging artificial intelligence (AI) for successful strategy implementation in finance. In the opinion of Gogas & Papadimitriou (2021), the terms AI and ML are often abusively interchanged for several reasons such as trending, funding, or even unknowingly creating confusion to the readers. Still, a general rule of thumb is that if the system acts without intervention, then it is possibly AI. If the system classifies or forecasts through learning, then it is ML.

The OECD report[2] asserts that AI and ML have more comprehensive applications such as asset management, algorithmic trading, credit underwriting, or blockchain-based finance, enabled by abundant available data and affordable computing capacity. The OECD Business and Finance outlook[3] also stated the reasons for the demand for AI and ML over dependability in financial services. The significant usage of AI technology focuses on automation to improve the efficiency of human actions and reduce errors. Additionally, we found that AI is exceptional at repetitive tasks, and it rarely makes mistakes. Hence, due to the phenomenal growth of big data in finance, AI and ML technologies are booming in financial services.[4]

We found that academia has supported or rejected the positive and negative directions for using AI and ML in emerging finance disciplines. However, we acknowledge that the camp of positive literature on ML and AI in finance is far greater than the literature about the negatives of these advanced technologies. First, we discuss the literature that has proved the success of using AI and ML in finance. As regards the positive directions of ML and AI, for example, Ghoddusi et al. (2019) asserted that the ML has been widely used for predicting energy prices (crude oil, natural gas, and power), demand forecasting, risk management, trading strategies, data processing, and analysing macro/energy trends. Eletter et al. (2010) suggested that artificial neural networks are a successful technology used in loan application evaluation of commercial banks. Fethi & Pasiouras (2010) proposed that AI methods outperform the traditional techniques for assessing bank efficiency and performance. Castelli et al. (2016) proposed an artificial intelligence system for building a model for predicting service quality. Chakroborty (2017) examined the applications of robotics in finance, such as quarterly report and balance sheet preparation.

While comparing ML applications with the traditional econometric models, Ma & Lv (2019) suggested that ML and AI applications are more valuable than conventional econometric humanistic models in finance. They also examined the efficiency of financial credit risk prediction using internet finance driven by machine learning models. They found that AI and ML are more efficient in prediction than traditional econometric and regression tools. In the same vein, Ghodselahi & Amirmadhi (2011) suggested that artificial intelligence has led to better performance of credit-scoring models. Furthermore, these views are supported by Chow (2017), and Addo et al. (2018) who found that machine learning

[2] https://www.oecd.org/finance/artificial-intelligence-machine-learning-big-data-in-finance.htm

[3] https://www.oecd-ilibrary.org/finance-and-investment/oecd-business-and-finance-outlook-2019_af784794-en

[4] https://hackernoon.com/why-ai-blockchain-make-sense-5k4u3s6l

methods were successful in learning the relationship between the company's current state and its fate.

For credit risk assessment and prediction, Aithal & Jathanna (2019) compared algorithms such as Support Vector Network, Neural Network, Logistic Regression, Naive Bayes, Random Forest, and Classification and Regression Trees (CART). They found that the most suitable algorithm is Random Forest algorithm, which can predict credit risk of banks with the highest accuracy. Additionally, Bao et al. (2019) concentrated on integrating unsupervised and supervised machine learning algorithms for credit risk assessment. They proved that integration effectively improves the performance of credit scoring models.

For credit risk management, Zhu et al., (2019)worked on improving the accuracy of forecasting the credit risk of SMEs in supply chain finance with an enhanced hybrid ensemble machine learning approach created by incorporating two classic ensemble ML approaches such as Random Subspace (RS) and Multi Boosting. In another study of the same type, Bussmann et al., (2021) proved that the AI model can be used in credit risk management and measuring the risks that arise when credit is borrowed by employing peer-to-peer lending platforms.

In auditing and accounting, Davenport (2016) worked on analysing the role of audit analytics, AI, and cognitive technologies in the field of auditing. The objective of these initiatives was to set accountants free from grunt work. However, findings showed that there are challenges of ML and AI in the fields of accounting and auditing. Cho et al. (2020) said that machine learning in accounting/auditing research and practice also raises concerns about potential bias and ethical implications. But Ding et al. (2020) positively observed that machine learning was superior to manual managerial estimates in financial service data structures.

In derivatives and hedging, Hutchinson et al. (1994) demonstrated that a neural network is an excellent algorithm to approximate the market's option pricing, function of products, and hedging. In the same vein, Tan, (1995) found that a neural network model is the best for stock forecasting. This was supported by Saad et al. (1995) who indicated that networks such as Time Delay, Recurrent, and Probabilistic Neural Networks are feasible for predicting the stock market. Based on predictions of stock prices using genetic programming, Kaboudan, (2000) proposed a possibly profitable trading strategy. However, Choudhry & Garg (2008) showed that the hybrid GA-SVM system outperforms the stand-alone SVM system.

Reddy (2018) suggested using ML techniques such as Support Vector Machine (SVM) to predict stock prices for large and small capitalisations. Vijh et al. (2020) shared similar views, indicating that ML models efficiently predict stock closing prices. Lee et al. (2019) found that investment strategies using machine learning techniques based on financial network indicators successfully predicted the global stock market using big data. In the same line, Khan et al. (2020) made predictions using machine learning algorithms on social media and financial news information, as this data can change investors' behaviour. Gadey et al. (2020) found that ML methods are successful in predicting Bitcoin prices in the crypto market. Goodell et al. (2021) suggested that deep learning networks are used to learn option pricing models from the derivative markets and could be trained to mimic option pricing traders specialising in a single stock or index.

When we speak about the efficiency of ML and AI models for short-term or long-term predictions, Ta et al. (2018) examined whether AI and ML prediction models performed effectively in short-term forecasts with high accuracy and return. However, they found that in short-term prediction, the linear regression model outperforms the support vector regression model. The findings of Alessandretti et al. (2018) suggested that state-of-the-art machine learning algorithms outperform standard benchmarks and are capable but ultimately simple algorithmic mechanisms can help anticipate the short-term evolution of the cryptocurrency market. In continuation, Jidong & Ran (2018) identified that the XG Boost model is effective in predicting coefficients, and the dynamic weighting can improve the performance of multi-index or factor stock selection strategy in line with the optimum portfolio models of Fama–French factor modelling.

The neural network learning module provides an interface to various commercial databases for fraud detection and estimation and has a comfortable graphical user interface. The synthetically generated credit card data and an auto-associative neural network model of ML show very successful fraud detection rates (Aleskerov et al. 1997). The ML and AI models are favourably successful with a baseline Logit model, especially in predicting fraud cases (Lin et al. 2003).

In addition, Kaal (2019) observed that the performance of hedge funds, which has been on the leading edge of fintech users, had tremendously improved and employ big data, AI and ML algorithms in prediction and estimation, trade execution, and back-office functions. Moreover, Bloomberg (2019) reports that AI and ML can systematically help stock and derivative trading strategies in any upcoming trade by enabling an "if/then" thought process. ML models are used in credit scoring to predict borrowers' defaults with superior forecasting accuracy than standard statistical models (e.g., logic regressions), especially when limited information is available (Albanesi and Vamossy 2019).

From the literature analysis, we understand that Agarwal et al. (2009), and Gogas & Papadimitriou, (2021) studied the usage and applicability of ML and AI in finance disciplines. We acknowledge that the work of Hansen & Borch, (2021) revealed the uncertainty of the ML and AI models. But everyone using it aims to reduce uncertainty through ML techniques and this is empirically and theoretically significant from the past literature. We understand the ML is getting adopted by financial analysts because an explosion of market data has necessitated new approaches to comprehend an increasingly uncertain future.

With automated trading (Mackenzie 2018) orders to buy or sell financial assets have risen dramatically. Human brains are incapable of predicting and assessing the large amounts of data involved. For instance, Mattli (2019) reports that in the USA, the Financial Industry Regulatory Authority "monitors on average about 50 billion market events, quotes, cancellations, and trades a day across equities, options, and a few other markets". Moreover, this kind of explosion of data accounts for the heavy demand for ML- and AI-based algorithms in the industry, despite some criticisms levelled against them.

3 Methodology

3.1 Rationale behind bibliometric analysis in ML and AI

This section justifies using a bibliometrics analysis in ML, AI, and DL across financial research. Over a period, social science research has witnessed much bibliometric research in all disciplines using bibliometric programmes (Aria & Cuccurullo 2017; Ellegaard & Wallin 2015). The relevance of bibliometric analysis highlights the development trajectory and the scientific research tendencies in a particular research field (Mourao & Martinho 2021). Besides, bibliometrics provides a structural analysis of the past literature over a period, identifies the shifts in the boundaries of disciplines and detects the most prolific scholars and institutions (Crane 1972). Besides the classical production-centred bibliometric methods, scientific mapping provides a spatial representation of research themes and disciplines (Morris & van der Veer Martens 2009; Yan 2014). It charts the structural and dynamic progression of the defined terms and the research area. It also partitions the various elements of research, such as documents, authors, journals, and words into groups, thereby scrutinising them under distinct structures (Docampo & Cram 2019).

For synthesising this knowledge, the conceptual, intellectual, and social structures need to be identified to determine the interrelationships of the concepts within the domain (Aria & Cuccurullo 2017). These structures centralise the relationship between themes and keywords. Analysing the co-occurrence of words within the document helps us understand the concepts behind these words (Nasir et al. 2020; van Eck & Waltman 2014). Bibliometrics attempts to derive the scientific literature's structural patterns and research trajectory. It studies the fundamental research work, which serves as the foundation for deducing the interrelationship among the most influential citations (Goswami & Agrawal 2020). This set of structural groups also reflects the intellectual connections among significant contributions of the researchers. Creating such bibliometric maps and networks help researchers evaluate the collective state of the art and identify hotspots in the respective research field (van Eck & Waltman 2014).

3.2 Software and visualization tools

Several visualisation tools for bibliometrics have been developed, and here we employ two frequently used tools: VOSviewer and the R-tool Bibliometrix via Biblioshiny. They are software tools for building and depicting networks based on bibliometric data. They represent the body of the literature in a tangible way using diverse techniques such as quotation analysis, bibliographic coupling, or keyword co-occurrence analysis, among others, making it possible to visualise the progress of the field along with improving the readability of analysis results (Gaviria-Marin et al. 2019). Some of the methods adopted in this research study include the co-occurrence analysis, factorial analysis using Multi Correspondence Analysis (MCA), and multiple collaboration networks. These illustrate the inner association among the research documents and visualise them in different ways, such as clustering and dynamic timeline. We have used the modularity-based clustering algorithm suggested by Blondel et al. (2008) and Newman & Girvan (2004) to identify various linkages among the concepts of machine learning, deep learning and finance.

3.3 Data retrieval and search strategy

The literature dataset used in this paper is obtained from the Web of Science (WoS), one of the widely used bibliographic repositories in academics (Falagas et al. 2008). The choice of the database was because the WoS database gathers and allows easy access to a wide range of multidisciplinary scientific studies with recognised scientific relevance (Fetscherin & Heinrich 2015; Li et al. 2018), providing the necessary data to achieve the objectives of the present study. In addition, the data available in the WoS database are the most used to assess the academic impact of scientific production at various levels of aggregation, such as institutions, journals, and individuals (Birkle et al. 2020). Research documents were collected by creating and iteratively testing different queries using the *"topic"* search option.

A simple search using the search terms associated with the domain was applied using the Boolean operator *'OR': ("AI" OR "artificial intelligence" OR "machine learning" OR "deep learning" OR "robotics") AND ("finance" OR "finance*manag*")*. The search

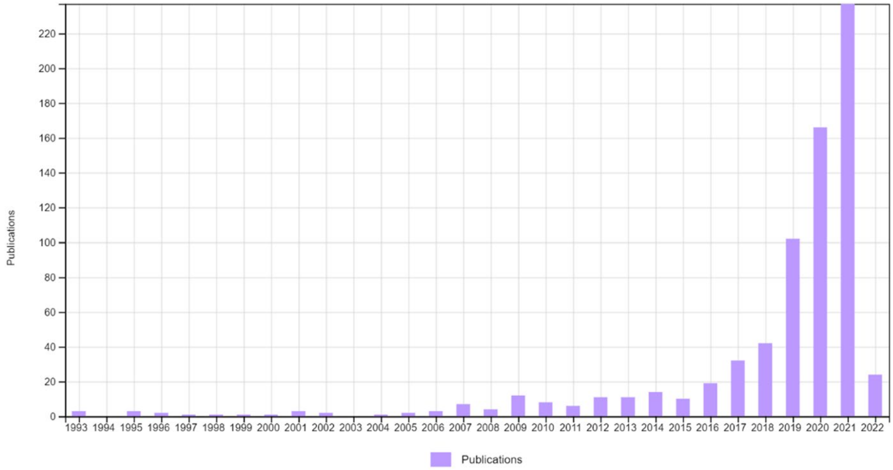

Fig. 1 Publications from 1993 to 2022. *Note:* In the volume of publications from 1993 to 2021, we can see a hike in 2019, 2020, and 2021 showing a phenomenal growth

covered the publications indexed in the Social Sciences Citation Index (SSCI) from 1993 to 2022. After manual refining based on WoS categories and Publication titles, the retrieved data were summed up to 723 publications. The number of papers published each year during the respective sample period is plotted in Fig. 1. A clear upward trend of publications can be spotted during the period, with a sharp increase from 2017, implying the substantially increased interest from academicians.

4 Results—scientific performance profile

4.1 Journal distribution and the top research articles

Table 1 reports a list of journals according to their number of ML and DL research publications on finance. In terms of total citations, *Expert Systems with Applications* and *the European Journal of Operational Research* are the two most influential journals, with 1174 and 842 citations, respectively. However, in terms of publications, *Expert Systems with Applications* and *Sustainability* are the two most productive journals, with 34 publications individually. *Quantitative Finance* and *Journal of Behavioral and Experimental Finance* are at the top of the list regarding publication productivity and citation count in finance-specific journals.

We also found that a significant percentage of premier journals are receptive toward ML/DL research in finance, suggesting an ensuing growth in the respective literature. However, we can note a passivity in research articles' concentration in the finance-classified journals compared to the other disciplines in which related themes are studied. This stipulates a more significant research potential in using these algorithmic machine models in the financial domain.

The top globally cited publications on AI and ML research in finance are presented in Table 2. The study by Das & Chen (2007) can be regarded as a highly influential one with the highest number of citations (495), followed by that of Fischer & Krauss (2018) with 423

Table 1 Journal distribution with the publication note

Publication outlet	Number of articles	TC	Publication outlet	Number of articles	TC
Expert systems with applications	34	1174	Decision support systems	9	351
Sustainability	34	169	Mathematics	8	48
IEEE access	28	159	Economic computation and economic cybernetics studies and research	7	19
Computational economics	22	105	Journal of enterprise information management	7	37
European journal of operational research	16	842	Journal of intelligent & fuzzy systems	7	23
Quantitative finance	12	80	Complexity	6	23
Journal of behavioral and experimental finance	11	88	Financial innovation	6	28
Journal of forecasting	10	115	Journal of international financial markets institutions & money	6	25
Technological forecasting and social change	10	52	Knowledge-based systems	6	132
Applied soft computing	9	467	Technological and economic development of economy	6	182

Note: Table 1 reports the number of journals and articles published in ML and AI in finance and citations

Table 2 Top 10 cited articles on the applications of AI/ML/DL mechanisms in finance in terms of total citation

Title	*Journal*	*Authors*	*Total citation*	*Year of Publication*
Yahoo! for Amazon: Sentiment extraction from small talk on the web	Management Science	Das, Sanjiv R.; Chen, Mike Y	495	2007
Deep learning with long short-term memory networks for financial market predictions	European journal of operational research	Fischer, Thomas; Krauss, Christopher	423	2018
A deep learning framework for financial time series using stacked auto-encoders and long-short term memory	PLoS ONE	Bao, Wei; Yue, Jun; Rao, Yulei	296	2017
Solving high-dimensional partial differential equations using deep learning	Proceedings of the national academy of sciences of the UNITED STATES Of AMERICA	Han, Jiequn; Jentzen, Arnulf; Weinan, E	268	2018
A comparative assessment of ensemble learning for credit scoring	Expert systems with applications	Wang, Gang; Hao, Jinxing; Ma, Jian; Jiang, Hongbing	244	2011
Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy	International journal of information management	Dwivedi, Yogesh K.; Hughes, Laurie; Ismagilova, Elvira; Aarts, Gert; et al	222	2021
Deep Direct Reinforcement Learning for Financial Signal Representation and Trading	IEEE transactions on neural networks and learning systems	Deng, Yue; Bao, Feng; Kong, Youyong; Ren, Zhiquan; Dai, Qionghai	204	2017
Business data mining—a machine learning perspective	Information & management	Bose, I; Mahapatra, RK	202	2001
A comparative survey of artificial intelligence applications in finance: artificial neural networks, expert system and hybrid intelligent systems	Neural computing & applications	Bahrammirzaee, Arash	200	2010
Machine learning models and bankruptcy prediction	EXPERT SYSTEMS WITH APPLICATIONS	Barboza, Flavio; Kimura, Herbert; Altman, Edward	196	2017

Note: Table 2 reports the top ten papers that have more citations and shows the contributors of those papers and the journal name citations. Research articles catering to a holistic understanding of artificial intelligence fall under the list of Cioffi et al. (2020), Dwivedi et al. (2021), and Goodell et al. (2021). Further scrutiny of the top-cited publications revealed the increasing usage of deep learning frameworks for financial time series and financial signal representation (Bao et al. 2017; Deng et al. 2017). The research on credit scoring and bankruptcy prediction has also attracted significant scholarly attention (Barboza et al. 2017; Wang et al. 2011). Noteworthy articles involving the broader application of ML/DL mechanisms can also be found in research themes such as forecasting stock price index (Kim & Won 2018), statistical arbitrage (Krauss et al. 2017) and even business data mining (Bose & Mahapatra 2001).

4.2 Country share and research institutions

Figures 2 and 3 visualise the country-wise strength of publications in terms of Frequency of production and Citation count, respectively. Regarding the country-wise strength of publications, we have the USA at the top with a frequency of output of 355 articles, followed by China with 294, and the UK with 147 articles. Various countries such as Taiwan (91), South Korea (82), Canada (81), Spain (69), and India (65) are also seen to make remarkable contributions to the literature set. Thus, this demonstrates the global dissemination of the domain of artificial intelligence along with machine learning and deep learning techniques in the financial discipline.

The deliberation on total citations received from other researchers lists the United States of America (2925) at the top place, followed by China (1591), and Germany (966). However, considering their average citation value, Germany (966–38.64) surpassed China (1591–12.73). Similarly, we have Singapore (201–25.12), Netherlands (227–28.38), Brazil (249–24.90), and Turkey (330–27.50), which received low total citations but high average article citations value. This evidence shows that, though these countries published a lower number of articles, their quality earned them significant citations worldwide.

We have the Chinese Culture University with the highest number of articles (19), followed by the Korea University and the Toronto University with identical record counts (13). Among the top 20 institutions, there is a significant presence of Chinese universities or institutes such as the Chinese Culture University, Hefei University of Technology, Seoul National University and City University Hong Kong, contributing a significant volume of publications on AI, ML, and DL techniques. We also have the Pennsylvania State University, University of Washington, Arizona State University, and various other universities based in the USA with gradually rising research studies. Various distinguished institutions from the United Kingdom have also made the list of the top institutions. This institutional categorisation thus reveals China and the USA as fervent producers in this field of study, thereby substantiating the country-wise strength in frequency of production and citation count (Fig. 4).

4.3 Top authors

Table 3 identifies the top 15 productive and cited authors in this specific research area. Each of the 15 most active authors has contributed at least three research papers in the area. Lin Swu Jane ranks first with a contribution of 10 articles, followed by Hsu Ming Fu, authoring nine papers, both with an H-index of 5. Several other authors, such as Lee J (6), Creamer German G (4), Hansen Katrine B (4), and Kim Hyeongjun (4) too, have made considerable additions to the respective literature. However, we have various authors on the

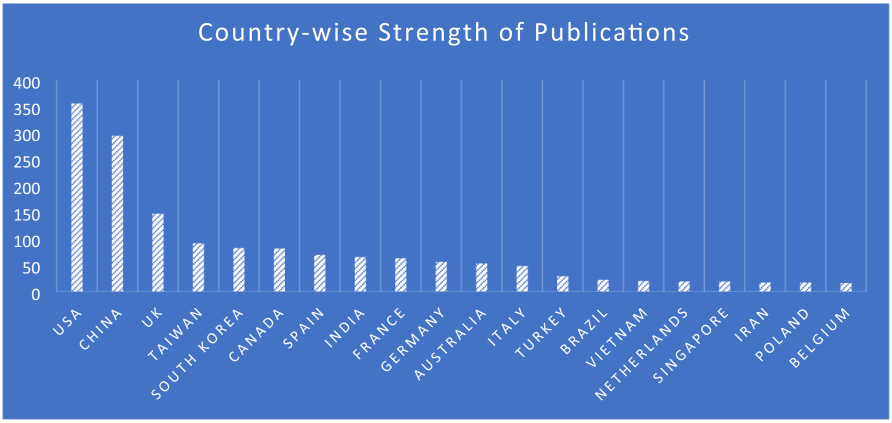

Fig. 2 Country-wise strength of publications in terms of frequency count. *Note:* Fig. 2 shows the top countries in terms of publications on the theme of ML and AI in finance; we can see that the USA and China dominated compared to other countries

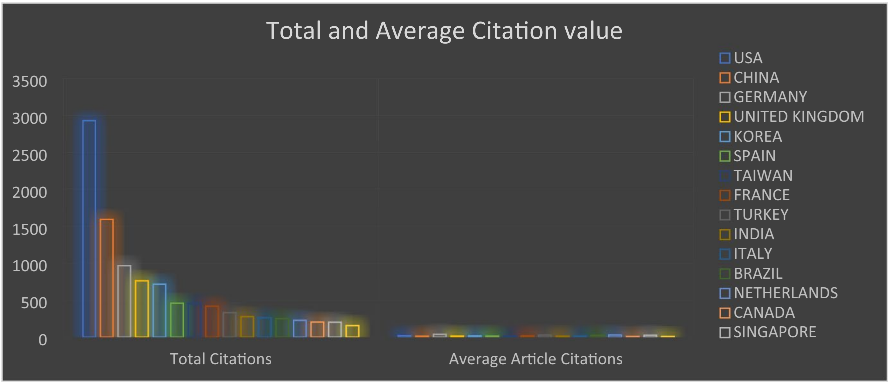

Fig. 3 Country categorisation on citation count. *Note:* Fig. 3 shows the citations of countries, the USA, China and Germany are top in citations

list regarding authors' citation count. With a citation count of 515 for three articles, Sanjay R Das had the most cited publication, followed by Li Bin with a total citation count of 154. The remaining list of highly cited authors coincides with the initial productive authors. These differing ranks may mean that the scope or repercussion of specific articles over other works is particularly significant in this research arena.

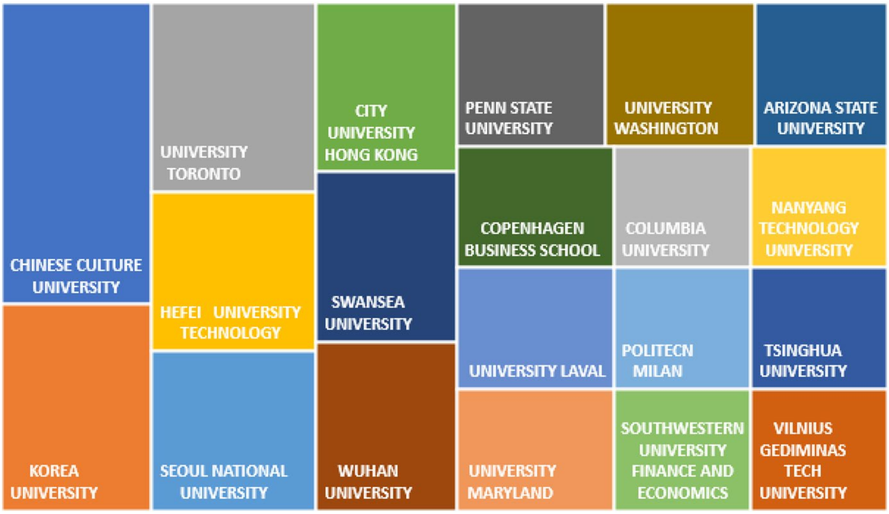

Fig. 4 Treemap on research institutions. *Note:* Fig. 4 shows the treemap of universities with publications in ML and AI. We drew the treemap based on user instructions of package bibliometrix. https://www.bibliometrix.org/ The treemap shows that the Chinese Culture University and Korea University are outperforming the others in publications on ML and AI

Table 3 Production by authors

Author	Number of documents	Total citations	H-index
Lin SJ	10	58	5
Hsu MF	9	54	5
Lee J	6	43	3
Creamer GG	4	65	2
Hansen KB	4	15	3
Kim H	4	16	2
Kumar A	4	43	2
Lee H	4	2	1
Lessmann S	4	43	3
Li B	4	154	3
Yang Y	4	28	3
Chang TM	3	19	3
Chen FH	3	26	2
Chen Y	3	28	2
Das SR	3	515	3

Note: Table 3 reports the top authors who published more papers with citations and corresponding H index

4.4 Keyword analysis

Keywords are the core of knowledge in academic studies as we can observe and identify the fields of research in development (Zhan et al. 2018). Keywords provide rapid access

Table 4 Top keywords

Keyword	Frequency
Machine learning	191
Artificial intelligence	101
Deep learning	57
Finance	44
Forecasting	23
Decision making	19
Big data	18
Risk management	18
Neural network	16
Credit scoring	15
Natural language processing	14
Sentiment analysis	14

Note: Table 4 reports the top keywords that have more repetitions by the authors

to scientific works and are highly effective in terms of bibliometric analysis when investigating the knowledge structure of scientific fields (Zhang and Trubey 2019; Vargas-Quesada et al. 2017). Table 4 represents the top keywords in the research documents. Clearly, Machine Learning, Artificial Intelligence, Deep Learning, Finance, and Forecasting are the chief research concerns within the literature. The network mapping and clustering of keywords represent the relationship between keywords in a set of publications via a network of associated co-words. Analysing or mapping the authors' keywords in the data frame can help to understand or aggregate the themes within the collection.

4.4.1 Keyword co-occurrence analysis

Initially, we explored a citation analysis using bibliometric data and identified the semantic similarity in a set of publications via a network of associated keywords. The keyword co-occurrence method has been widely applied in bibliometrics to help scholars grasp the research hotspots (Ding et al. 2001). We have obtained 10 clusters formed with different thematic linkages (Fig. 5). Our approach allowed us to systematise the exploitation of publications and limit the subjectivity associated with reviews, as underlined by (Kovács et al. 2015). We grouped the keywords into thematic clusters by setting the minimum number of keyword occurrences to 5. Out of the 2350 keywords found, 81 keywords met the threshold. For 81 keywords, we calculated the link strength among them, and the keywords with the greatest link strength were selected. Ten clusters were the outcome of the keyword co-occurrence, and each cluster showed us a different story on the applications of ML, AI, and DL in financial services.

Cluster #1 relates to the application of ML and AI in finance and portfolio management, such as data mining, financial forecasting, genetic algorithm, neural network, forecasting, stock price prediction, portfolio optimisation, random forest, random forests, support vector machine, text classification and text mining. Cluster #2 gives an overview of the usage of ML and AI in different areas of banking and credit risk management, which include banking, bagging, and prediction of bankruptcy, consumer finance, assessment of credit

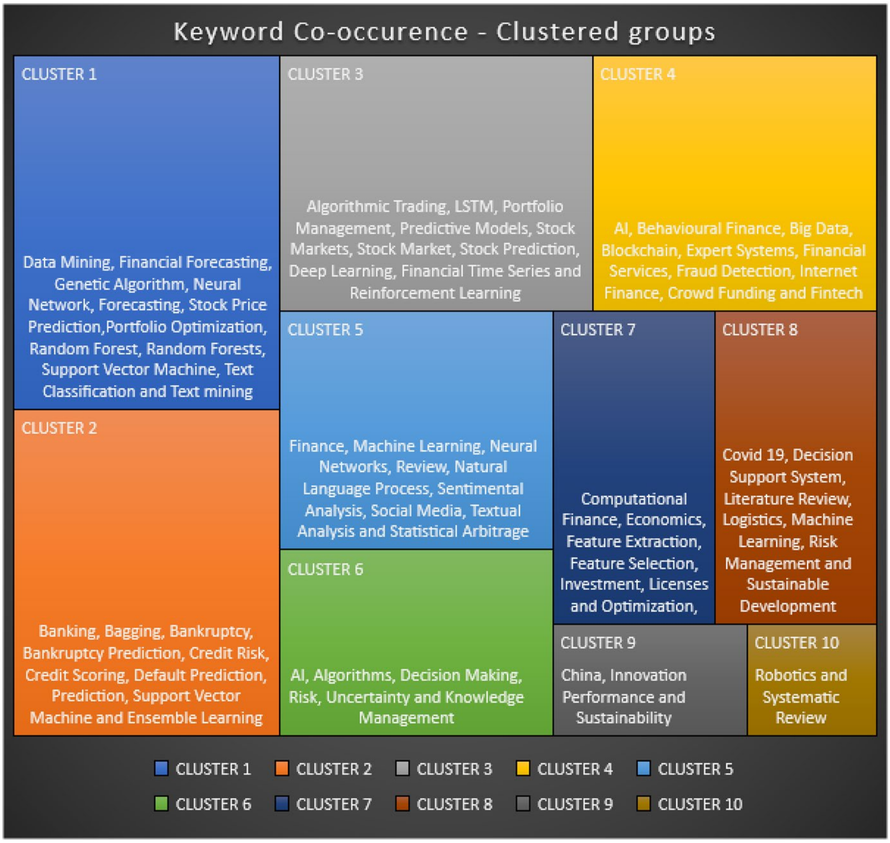

Fig. 5 Keyword co-occurrence analysis. *Note:* Fig. 5 reports 10 clusters that have been formed after analysing the data using the VOSviewer programme. Each cluster represents a theme that the authors have contributed from 1993 to 2022

risk and credit scoring, default prediction, prediction, support vector machine and ensemble learning.

Cluster #3 deals with making use of ML in the field of algorithmic trading, portfolio management, predictive models, stock markets, stock market, stock prediction, deep learning, financial time series, and reinforcement learning. Cluster #4 gives insights into applications of ML and DL in AI, behavioural finance, big data, blockchain, expert systems, financial services, fraud detection, and application of ML in predicting the success of crowdfunding and internet finance on fintech startups. In the trading process, finance, machine learning, neural networks, natural language process, sentimental analysis, social media, textual analysis, and statistical arbitrage are grouped under Cluster #5. Cluster #6 discusses AI, algorithms, and their use in decision making, identifying risk, overcoming uncertainty, and knowledge management using ML and DL. Next, cluster #7 deals more with the application of ML in computational finance, economics, feature extraction, feature selection, investment, licenses, and optimisation. Cluster #8 deals with literature review, examines the effects of COVID-19 and associated developments

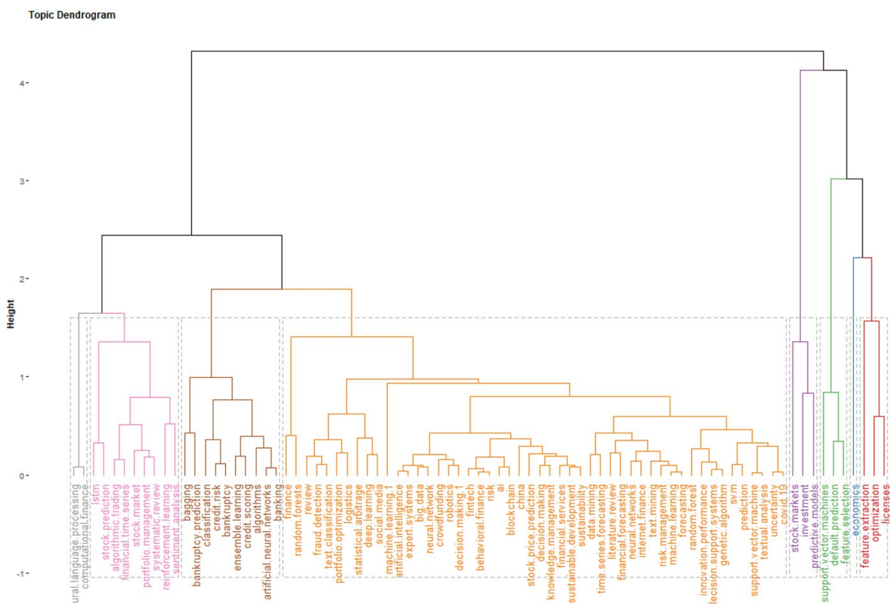

Fig. 6 Topic dendrogram. Note: Fig. 6 shows a topic dendrogram of ML and AI in finance, which exhibits the hierarchical relationship among the keywords generated from the article database

with ML, as well as ML's and DL's application in decision support systems, logistics, risk management, and sustainable development. Cluster #9 is centred on China's topics, innovation performance, and sustainability. Cluster #10 shows the usage of ML in robotics applications in financial services.

4.4.2 Keyword dendrogram

Another classificatory technique, the hierarchical cluster analysis using the dendrogram, is represented in Fig. 6. The topic dendrogram exhibits the hierarchical relationships among the keywords generated from the article database. This structure results from the iterative coupling of clusters according to similarity and grouping criteria (Leal et al. 2016). This 'clustering-on-clustering' method helps to assess the relationships among the granular keyword database. On traversing across, the dendrogram subsumes smaller clusters into larger ones until the entire database is covered.[5]

The graph structure shows us the central branch extensively enclosing the research areas connecting machine learning and deep learning techniques with various financial services. The dendrogram highlights the close relationship of machine learning with financial and time series forecasting, risk management, and data mining. The researchers are also seen to combine the artificial neural networks, which underscore the deep learning method with banking and credit-scoring activities. Similarly, branching relates algorithmic trading and long short-term memory, another neural architecture, to financial time series and stock

[5] https://ncss-wpengine.netdna-ssl.com/wp- content/themes/ncss/pdf/Procedures/NCSS/Hierarchical_Clustering-Dendrograms.pdf.

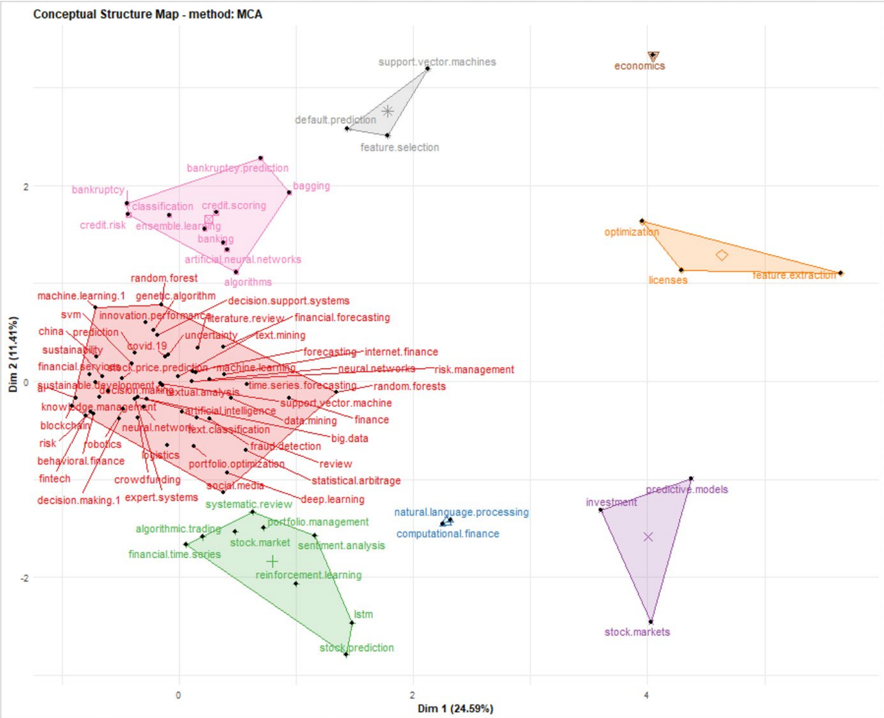

Fig. 7 Factorial analysis of conceptual structure map method: MCA of high-frequency keywords. *Note:* Fig. 7 shows the factorial analysis of the publications' themes. We can see that there are 6 clusters and each cluster consists of keyword mapping and conceived ideas of papers by the authors

prediction. Artificial intelligence is closely linked with expert systems, big data, and neural networks.

4.4.3 Conceptual structure map using factorial analysis

Figure 7 shows a conceptual mapping of keywords appertaining to factorial analysis. A Multi-Correspondence Analysis (MCA) methodology was adopted to present the extensive keyword dataset in a compressed form in a low dimensionality space. It forms an intuitive two-dimensional map describing the variability and the commonality in the database of keywords (Abdi & Valentin 2007). The proximity of words within the graph structure reflects the closeness and similarity with keywords at the central point, denoting the recent domains of study (Ding et al. 2001).

The clusters mentioned above are formed based on their homogeneity in the collection. The cluster in red tops the graph with a substantial collection of keywords relating to documents focusing on artificial intelligence, machine learning, neural network, robotics, finance, forecasting, and decision making. The classification in green signifies stock prediction, long short-term memory, algorithmic trading, and financial time series. The pink cluster represents artificial neural networks, credit risk, bankruptcy prediction, and credit scoring. The blue cluster is related to natural language processing

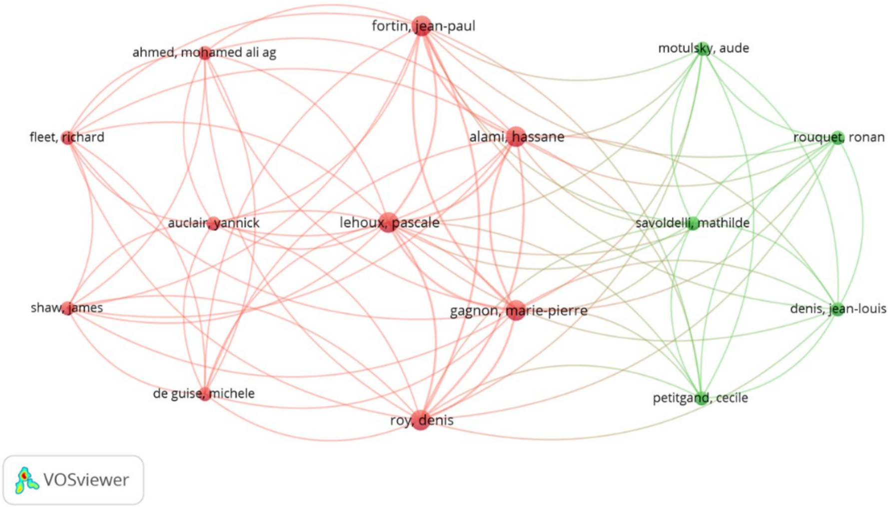

Fig. 8 Authors' collaboration network. *Note:* Fig. 8 shows the authors' collaboration network; we can see the collaboration links of authors from 1993 to 2021

and computational finance, whereas the violet classification combines predictive models, stock markets and investment. The smaller collections combine research areas on support vector machines, default prediction, and optimisation and licenses.

4.5 Social structure—collaboration network

To understand the social structure of in-depth collaboration, relationships between countries, institutions and authors, a pictorial representation of the collaborative network is framed. The circles in each network represent either countries, institutions or authors. In contrast, their size indicates the impact of the scientific production of each unit obtained by the number of article citations attributed. The lines between two circles means a collaborative relationship between two countries, institutions, or authors, and the thickness of the line indicates the cooperation intensity between these two analysed units. Units with similar colours form one cluster.

4.5.1 Authors collaboration network

The co-author network is displayed in Fig. 8. Each node represents individual authors, and links among nodes represent the number of co-authored publications. The network shows definite collaboration among authors Hassane Alami, Pascal Lehoux, Yannick Auclair, Michèle de Guise, Marie-Pierre Gagnon, James Shaw, Denis Roy, Richard Fleet, Mohamed Ali Ag Ahmed, and Jean-Paul Fortin focusing on artificial intelligence. Similar collaboration among Hassane Alami, Pascale Lehoux, Jean-Louis Denis, Aude Motulsky, Cecile Petitgand, Mathilde Savoldelli, Ronan Rouquet, Marie-Pierre Gagnon, Denis Roy, and Jean-Paul Fortin can also be identified.

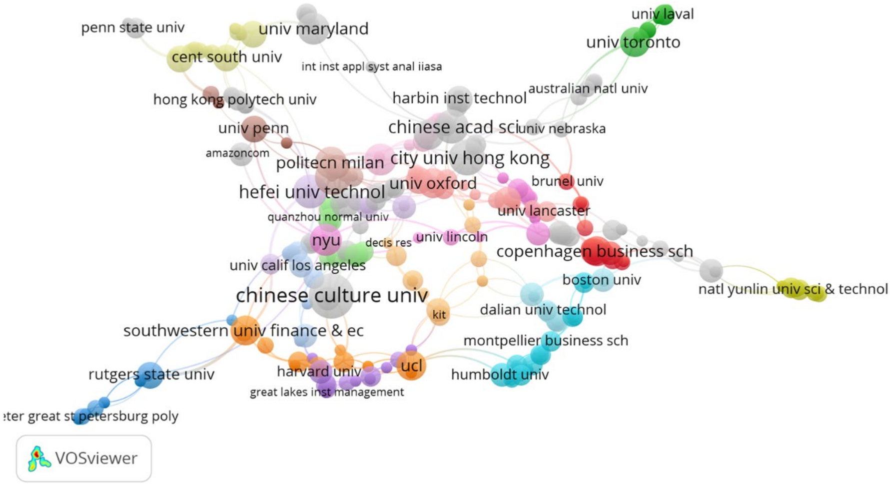

Fig. 9 Inter-institutional collaboration network. *Note:* Fig. 9 exhibits the institutional collaborations across universities in research relating to the usage of ML and AI in finance

4.5.2 Inter-institutional collaboration network

Figure 9 depicts the collaboration across institutional boundaries regarding this research area. Each circle represents an institution, the size of which depends on its weight. The number of collaborative publications determines the line thickness connecting these institutions.

Institutions from the USA and China dominate the network. The Chinese Culture University has been seen to corroborate works with the Chinese Academy of Science, City University of Hong Kong, Pennsylvania State University, and the University of Maryland. The research institutions under this cluster tend to collaborate with domestic organisations. A grouping of works across Southwestern University of Finance and Economics, Harvard University, and UCLA. Another cluster can be formed among Humboldt University, Montpellier Business School, Dalian University of Technology, and Boston University.

4.5.3 Country co-authorship network

Figure 10 sets out the international panorama of scientific production among various researchers. The size of circles represents the number of publications in the country, and the thickness of lines depicts the collaboration size. The pink cluster shows collaborative links among the United States, China, England, and Australia, representing authors affiliated with these countries. The United States plays a dominant role in transnational co-authorship linkages, closely followed by China and England as upcoming tier hubs. Other international researchers who collaborated the most with the United States researchers were from South Korea, Vietnam, France, and Spain. The blue cluster depicts the collaboration of China with Taiwan, France, and the United States, as well as, to a lesser extent, with the Netherlands and Spain. The yellow cluster is led by England, collaborating closely with Sweden, Netherlands, Venezuela, and several other countries.

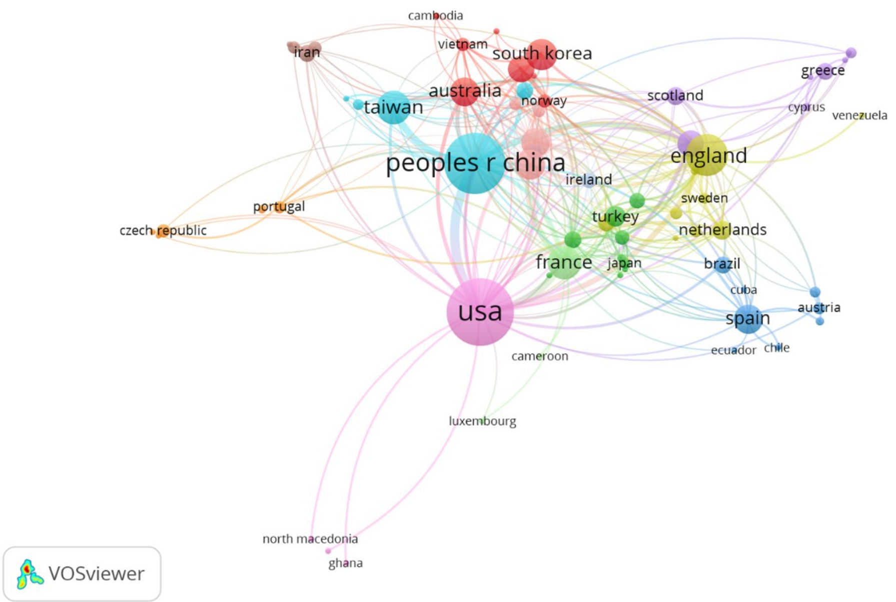

Fig. 10 Country co-authorship network. *Note:* Fig. 10 shows the co-authorship network of countries. The diagram clearly shows that the USA, China, and England have more link strength than other nations in the network

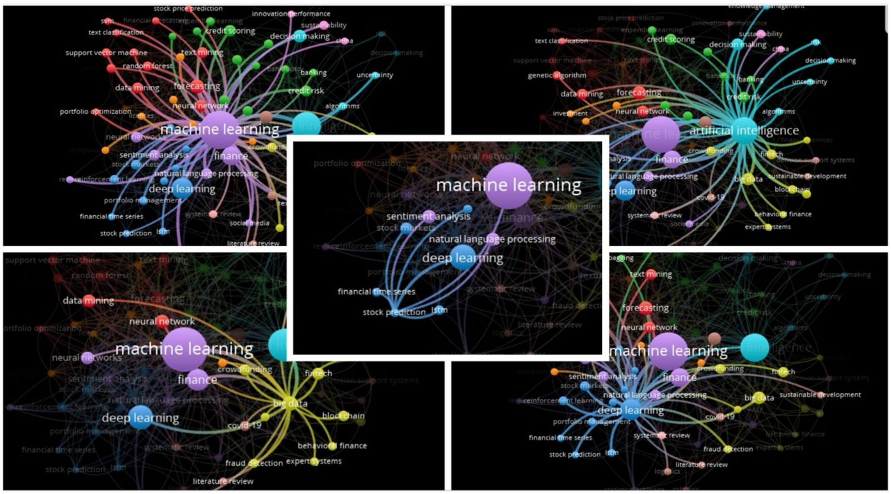

Fig. 11 Keyword coupling network. *Note:* Fig. 11 shows the thematic coupling of keywords; we can observe close linkage among the keywords

5 Keyword coupling

The author keyword coupling analysis (AKCA) is a method to visualise the studies using the keywords and understand the strength of those keywords. In Fig. 11, we can see the strength

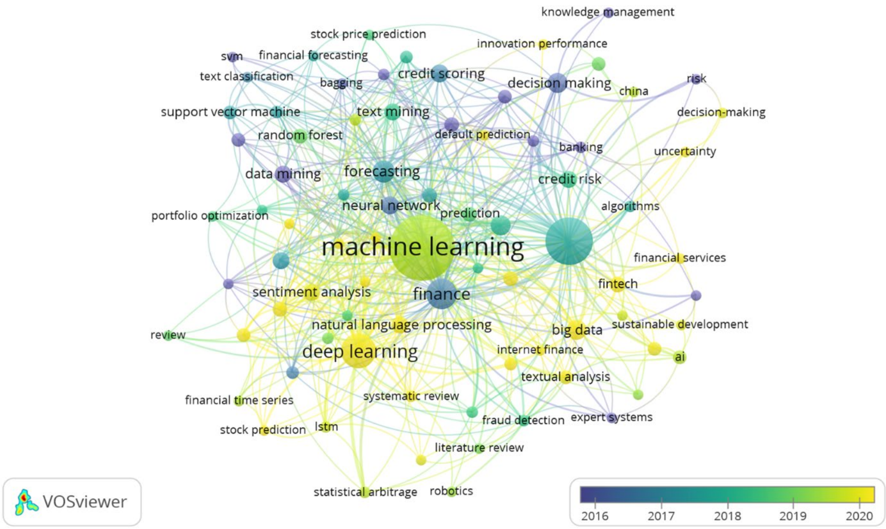

Fig. 12 Overlay visualization. *Note:* Fig. 12 shows the overlay visualisation of keywords and the conceptual mapping from 2016 to 2022. The colour yellow reflects the recent academic works of contributors. We easily distinguish machine learning, sentiment analysis, deep learning, sustainable development, NLP, and fintech

of the keywords in finance, such as ML, AI, DL, etc. The coupling shows the authors who have worked in ML and AI. The network can be interpreted based on the size of the label, and the weight of the item determines the circle of an item. The greater the weight of an item, the larger the title, and the rotation of the item. The colour of an object is determined by the cluster to which the article belongs. Here the process is more prominent in the case of ML, AI, and DL, which means that the authors who used these keywords are of most when they publish papers. The coupling network also shows the "between and among" association of keywords. For instance, in Fig. 11, the central network offers a coupling network of machine learning with associated keywords such as sentiment analysis, deep understanding, natural language processing, financial time series, and stock prediction. With this keyword, we can understand the story behind this research, such as the application of ML, DL, and natural language processing programmes in the financial time series data. Using these high-frequency data for sentimental analysis, an analyst can predict the stock market's future direction.

5.1 Overlay visualisation

To show the research trends of the documents more intuitively, Fig. 12 presents the overlay visualisation of keyword occurrences. Using average publications as the score, the colours represent the time-varying keyword occurrences from 2016 (in blue) to 2022 (in yellow). They initially focus on data mining, SVM, decision-making, and risk activities. The focus areas of research broadened towards finance, neural networks, default prediction, banking, and algorithms. The research frontiers have moved to various dimensions of machine learning, deep learning, sentiment analysis, big data, fintech, financial services, and sustainable development. The figure depicts the inculcation of AI and ML/DL techniques into various financial aspects, thereby transforming the fabric of the financial ecosystem.

6 Future research agenda

Our analysis found that academicians have conducted substantial research on the technicalities of machine learning as well as deep learning and their implications, but with a soft focus on the linkage between the usage of these algorithmic techniques by the financial industry and its repercussions through a critical perspective. The keyword analytics asserts that financial industries are widely using ML and DL methodologies for their own purposes such as fraud detection, prediction of account misstatements, prediction of success of crowdfunding, examining credit risks, algorithmic trading, social media analytics, customer analytics, supply chain finance, sentiments analysis, textual analysis, and portfolio optimisation. However, we could not find sensible empirical academic research depicting a critical outlook on the uses of machine learning and deep learning in finance.

Though big data and machine learning in finance are exciting areas, there is a danger of paying less attention to the reliability of the academic evidence (Subrahmanyam 2019). Furthermore, Brooks et al. (2019) questioned the utility and authenticity of machine learning and deep learning in their paper titled '*Financial Data Science: The Birth of a New Financial Research Paradigm Complementing Econometrics?*' published in *the European Journal of Finance*. A supportive argument in connection with this was raised by Hoepner et al. (2021), who suggested that classic machine learning approaches, such as neural networks, are suffering from inconsistency due to the lack of replicability, transparency, and traceability and, therefore, establishing causal inference is next to impossible. Hence, it is suggested that future research should adopt a more empirical approach to advance the design and efficiency of measuring the skills of these machine learning and deep learning algorithms to predict and forecast.

Due to the bottleneck of traditional statistical and data science predictive models, we propose a novel strategy based on machine learning to explore opportunities for machine learning in finance. We have tried to identify the possibilities of the technique of AI-based ML and DL in the financial scenario through insights derived from the thematic mapping of extant literature (See; Fig. 13).

7 Conclusion

It took digital evolution, an amalgamation of technology and mathematics, and the last decade for the world to be revolutionised by a fusion of technologies blurring the lines among the physical, digital, and biological spheres. Artificial intelligence and its subfields of ML and DL have transformed almost every industry worldwide, particularly the financial sector. The finance industry has witnessed the tremendous applications of these machine algorithmic models, from fraud detection, financial analytics, investment advisory services to algorithmic trading, Robo-advisory services, and loan underwriting.

The research carried out in this paper leads us to conclude that the scientific research related to ML and DL is growing exponentially with active institutional contributions by

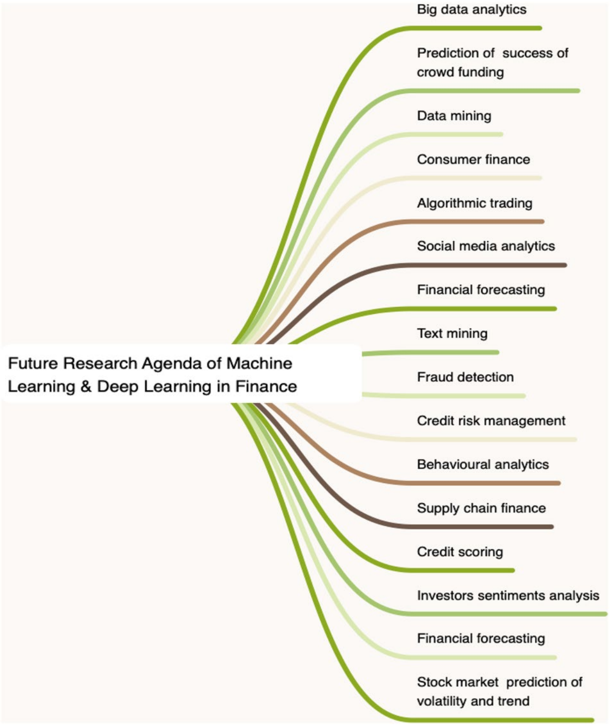

Fig. 13 A thematic approach to the scope of research opportunities of AI-based machine learning and deep learning in finance. *Note:* Fig. 13 shows a mind mapping of AI-based ML and DL in finance. We can see from the diagram the areas in which ML and AI are applied

the universities of China and the USA. Several authors, namely Lin Swu Jane, Hsu Ming Fu, Germen G. Creamer, Hansen Katrine B, and Sanjay R Das constitute the prominent names within the authors' network. In terms of research topics, prominent research fields relating to ML and DL in finance include data mining, portfolio optimisation, financial forecasting, algorithmic trading, computational finance, neural network, digital finance, fraud detection and assessment of credit risk, credit scoring, and currently it is seen relevant for ESG scoring as well. The evidence shows that AI and ML can help sustainability aspects, and sustainable investors process the use of voluminous data that hold essential information for ESG investing. In support, Sokolov et al. (2021) proposed an approach to automatically convert unstructured text data into ESG scores by using the advances in deep learning for natural language processing (NLP). However, we find a significant dearth of critical evaluation of the adoption of such mechanisms in the financial field. The unavailability of sufficient data leads to the usage of less reliable substitute dataset resulting in biases in measurement. In ML, even tiny discrepancies in data evoke major differences/gaps within the results. Also, neither the effectiveness nor its exceptional efficiency over existing analytical tools is queried, leading to ambiguity in its forecasting abilities.

Similarly, the artificial neural networks layered in the deep learning system have traceability and replicability issues making it a less than wholly reliable system. Moreover, the absence of governance over the technology adoption and usage of such technologies could turn detrimental later. Furthermore, the victims of these errors are the stakeholders using the outcomes of these analytics.

With scientific breakthroughs revolutionising the industry, it becomes essential to reinvent and restructure operating models within the financial sector. New analytics approaches and trends integrating the physical and digital worlds are necessary to thrive in this dynamic economic landscape. This broader appeal of machine learning and deep learning technologies across the financial domain certifies this as a promising field of research, opening the way to new investigations that make it possible to further the transfer of the knowledge generated, to facilitate and promote new research in the scientific community.

Finally, the finance domain contemplates an uncertain future that needs taming. We argue that these bibliometrics results point the same way as the uncertainties of ML suggested by Hansen & Borch, (2021). These automated financial service models are expected to be capable of absorbing uncertainty. But they also pose a reasonable chance of infiltrating new uncertainties because of the extensive usage of these models without critically essential supervision.

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Data availabilty The authors declare that the data will be available on reasonable request.

Declarations

Conflict of interest On behalf of all authors, the correspondent author states that this manuscript has not been published and is not under consideration for publication elsewhere. We have no conflicts of interest to disclose.

Concent to participate We do not harm human beings or animals during the process of research.

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