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ARTIFICIAL INTELLIGENCE AND FINANCE: A REVIEW AND RESEARCH AGENDA

INTELLIGENZA ARTIFICIALE E FINANZA: ANALISI E PROSPETTIVE FUTURE

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ABSTRACT

The rapid development of artificial intelligence (AI) in financial matters has sparked the intention of financial managers and academic researchers. Through hybrid review (bibliometrics citation and content analysis), we analysed 892 articles between 1992 to March 2021. Based on this review, we first present a taxonomy of AI in finance. Second, we identify the following 10 research stream in the literature: (1) AI and the stock market, (2) AI and Trading Models, (3) AI and Volatility Forecasting, (4) AI and Portfolio Management, (5) AI and Performance, Risk, & Default Valuation, (6) AI and Bitcoin, Cryptocurrencies, (7) AI and Derivatives, (8) AI and Credit Risk in Banks, (9) AI and Investor Sentiments Analysis, (10) AI and Foreign Exchange Management. Third, we identify influential aspects of literature. Finally, we posit future research questions to extend the literature.

Keywords: Artificial Intelligence; Finance, Machine Learning, Bibliometrics Citation Analysis; Digitalization

SINTESI

Il rapido sviluppo dell'intelligenza artificiale (IA) in materia finanziaria ha scatenato la curiosità dei financial manager e dei ricercatori accademici. Attraverso la revisione ibrida (analisi bibliometrica e analisi dei contenuti), abbiamo analizzato 892 articoli tra il 1992 e marzo 2021. Sulla base di questa analisi, presentiamo innanzitutto una tassonomia dell'Intelligenza Artificiale nella finanza. In secondo luogo, identifichiamo i seguenti 10 filoni di ricerca in letteratura: (1) IA e mercato azionario, (2) Modelli di intelligenza artificiale e trading, (3) IA e previsione della volatilità, (4) IA e gestione del portafoglio, (5) IA e performance, rischio, e fallimento, (6) IA e Bitcoin, criptovalute, (7) IA e derivati, (8) IA e rischio di credito nelle banche, (9) IA e *Sentiment* degli investitori, (10) IA e gestione dei tassi di cambio. In terzo luogo, identifichiamo aspetti influenti della letteratura. Infine, proponiamo una tabella di marcia evidenziando possibili future aree di ricerca.

Parole chiave: Intelligenza artificiale, finanza, Machine Learning, Analisi Bibliometrica delle citazioni; Digitalizzazione.

INTRODUCTION

Artificial intelligence (AI) is a field of computer science that creates intelligent machines capable of cognitive human tasks such as reasoning, learning, taking action and speech recognition (Frankenfield, 2021).

Being the core driver of the technology revolution of the 21st century, AI can be considered the new "energy paradigm." Andrew Ng, Professor of Computer Science at Stanford University believes that "AI is the new electricity... just as electricity transformed every industry one hundred years ago, so will AI" (Buchanan, 2019).

Progress in computer science and the digitisation phenomenon have fostered AI opportunities in every sector, particularly in financial services. Specific applications are found in risk management including credit risk, fraud, and bankruptcy detection; asset management inclusive of portfolio management and corporate performance evaluations; banking, and algorithmic trading.

AI generates several benefits in the financial industry. It encourages automation of manufacturing processes which enhances efficiency and productivity. Secondly, machines are immune to human errors and psychological factors, thus ensuring accurate and unbiased predictive analytics and trading strategies. AI is also employed in monitoring systems to prevent frauds or systemic financial crisis through alert signals in case of unusual market activities. AI significantly accelerates banks task facilitating lending decisions and automating compliance.

However, AI is not merely a tool for business or financial purposes. It should be regarded as a conceptual framework able to innovate obsolete modus operandi and establish new business processes.

In this paper, we review the literature on Artificial Intelligence in finance.

The paper is organized as follows. In chapter 1, we give an overview of Artificial Intelligence, its history, main applications, and we lay out our research questions. In chapter 2, we define our three-fold methodology. Chapter 3 presents the results of our research. A future research agenda is discussed in chapter 4.

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CHAPTER 1- A TAXONOMY OF ARTIFICIAL INTELLIGENCE IN FINANCE

1.1 OVERVIEW OF ARTIFICIAL INTELLIGENCE, HISTORY, ROLE IN FINANCE

The term “Artificial intelligence” was first coined by John McCarthy in 1956 during a conference at Dartmouth College to describe “thinking machines” (Buchanan, 2019). Synthesizing the literature, AI is a sub-field of computer science that enables software and machines with human problem-solving and decision-making abilities. AI-driven devices are “intelligent” because they learn from experience, just as humans do.

Achievements in AI go hand-in-hand with achievements in computer engineering and information technology (“History of Artificial intelligence: the definitive guide,” 2021).

Before 2000, the lack of storage capability and low computing power prevented any progress in the field. As a result, governments and investors lost their interest and AI fell short of financial support and funding in 1974-1980 and again in 1987-1993. These periods of funding shortage are also known as “AI winters.”

In the last ten years, AI has rapidly developed thanks to progress in computing technology and the advent of Internet of Things (IoT).

The digitization process of manufacturing and the rising availability of big data extend the range of applications of intelligent machines, thus encouraging the fourth industrial evolution (Industry 4.0) and spurring the global economy forward.

On a macroeconomic level, the global GDP is likely to increase by up to 14% by 2030 (PricewaterhouseCoopers [Pwc], 2017). Companies expect a positive impact on productivity and profitability overall. The automation of routine tasks and personalization of products and services lead to competitive edge, cost reduction in the production process, and customer relationship revolution enabled by large data insights and IoT (Pwc, 2018).

North America and China are the leading investors in the field and will benefit the most from AI-driven economic returns. Europe and Emerging markets in Asia and South America will follow with moderate profits owing to fewer and later investments (Pwc, 2017). AI will affect labour markets as well. The demand for high-skilled employees is expected to increase, while the demand for low-skilled jobs is likely to decrease because of automation. The resulting higher unemployment rate, however, should be offset by new job positions.

AI solutions are deployed in every major industry, especially in finance. Under the recent surge of Fintech, the financial industry is witnessing a profound transformation. Granted that financial institutions rely heavily on big data and process automation, they are in a "unique position to lead the adoption of AI" (Pwc, 2020).

Intelligent devices in finance are used in the following areas:

- Fraud detection: to prevent illegal behaviour like money laundering or credit card fraud. Algorithms are trained on historical payment data to capture client's financial behaviour. The system sends a warning signal as soon as it detects unusual spending patterns (Buchanan, 2019);
- Algorithmic trading and high-frequency trading: to automate trading and enhance market activity and efficiency compared to trading markets dominated by humans;
- Portfolio management: to accurately predict asset prices, market future performance with AI-driven instrument;
- Credit decision based on credit scoring or credit approval models through which banks decide whether the borrower has access to a loan based on his financial history;
- Bankruptcy prediction to forecast financially troubled firms and prevent actual default on time;
- Risk management to make informed credit evaluations based on market participants' risk profile. On top of that, aggregated consumer credit risk may contribute to forecasting systemic risk and avoid future financial crises according to Zhang et al, (2019).
- Behavioural analyses through sentiment analysis to predict asset performance based on investors or market agent's sentiment (Kim & Kim, 2014).

AI is also applied in regulatory compliance to automate administrative tasks such as reporting and accounting using machine learning and natural language processing. AI innovates business models and radically changes customer relationship towards the era of digital finance. Customized finance and automation of process result in service efficiency and cost-saving.

1.2 RESEARCH QUESTION AND PURPOSE

The objective of this thesis is to answer the following research questions.

1. What is the taxonomy of artificial intelligence in finance?
2. Which are the dominant research streams in the literature on the topic: Artificial intelligence in finance?
3. Which are the influential aspects of literature, such as key methods, articles, authors, countries, institutions, theories, frameworks, and networks?
4. Which are the future research directions to extend the literature?

1.3 ASPECTS OF AI STUDIED IN FINANCE

Table 1 summarizes the aspects of Artificial Intelligence studied in finance with exemplary studies. AI is an ensemble of intelligent technologies able to recognise patterns, anticipate future events, make rational decisions based on given information, and communicate with other people (Kavlakoglu, 2020).

To guarantee a clear understanding of the topic, we explain the main terminology used in this paper.

We can think of machine learning, deep learning, and neural networks (NNs) as one the subfield of the other. Machine learning (ML) is a subfield of AI, deep learning is a subfield of machine learning, and NN is the underlying structure of deep learning (Delua, 2021a). For instance, the core operating unit of ML is the algorithm: a set of rules to follow to solve a mathematical problem (Financial Stability Board, 2017). These algorithms enable the computer to automatically "learn" from training data how to solve a problem through repeated simulation. In other words, machine learning teaches the computer how to perform a task based on experience without programming it. This method is extremely valuable because the same algorithm can be used for various objectives (e.g., stock prediction or speech recognition) based on the type of training data (Financial Stability Board, 2017). Machine learning is divided into four sub-categories:

- Supervised learning: a learning method based on "labelled" input data. For example, data labelled as bankrupt will teach the algorithm the rules to classify firms as bankrupt. The process is supervised because we already know the correct answer and can correct the algorithm in case of errors. Supervised learning can be further divided into (Delua, 2021b): (1) *classification* problem that deals with categorical data. Mselmi, Lahiani, & Hamza, (2017) adopt this approach to classify default and non-default firms. Support vector machines (SVM), Naive Bayes (NB), decision trees and random forest are the most common classifiers; (2) *regression* problems that predict numerical data like stock prices (e.g., linear regression, logistic regression);

- Unsupervised learning: utilizes unlabelled data as input. The algorithm detects hidden patterns in the dataset through (1) *clustering*, a data mining technique that "clusters" similar variables together (e.g., K-means) or (2) *association*, a learning approach that identifies correlation among items. It is often used in shopping apps or websites to suggest customers items correlated with their purchase (Delua, 2021c);
- Reinforcement learning is a machine learning method that rewards and punishes the algorithm based on its behaviour.
- Deep learning: is a form of machine learning that analyses data "in-depth" through "hidden layers," made up of artificial neural networks.

Deep learning is an evolution of both supervised and unsupervised learning methods because it self-learns how to analyse unstructured data to draw out underlying features (Delua, 2017). Artificial neural networks, henceforth ANN, represent the basic structure of deep learning. By mimicking the biological neural system, ANNs simulate human reasoning and decision process. They comprise an input layer for data entry, one or more hidden layers for information processing, and an output layer where the system makes the decision (IBM Cloud Education, 2021). ANNs with more than three layers are called deep neural networks. Nodes (or processing units) connect each layer and assign weights to input variables based on their significance within the dataset. As data passes from layer to layer, the network "calibrates" the correct weight through learning rules (Frankefield, 2020). Rules determine the type of the neural net: backpropagation neural networks solve problems by going backwards from output to input, the opposite happens for feed-forward neural networks.

In Table 1 we categorize the articles based on the aspect of AI studied.

Many research papers use AI as a predictive instrument for forecasts and future estimates of stock prices, performance, volatility.

In 23 out of 110 papers, AI is employed in classification problems and warning systems to detect credit risk, frauds and corporate or banks performance. This aspect of AI classifies firms into two categories based on qualitative and quantitative data. The categories may vary according to classification and data type. For example, we may have distressed or non-distressed, viable-nonviable, bankrupt-non bankrupt, or financially healthy-not healthy, good-bad, fraud-not fraud. Despite the name changing, the principle remains the same. Warning systems follow the same criteria. After analysing customers' financial behaviour and classifying potential fraud issues in bank accounts, alert models signal to the bank unusual transactions.

14 articles employ text mining and data mining language recognition, i.e., natural language processing, as well as sentiment analysis. This may be the starting point

of AI-driven behavioural analysis in finance. Among others, trading models and algorithmic trading are further popular aspects of AI widely analysed in the literature. Finally, interest in Robo-advisory is growing in the asset investment field. Minor aspects of AI discuss the modelling capability of algorithms and traditional machine learning and neural networks.

Table 1. AI aspects studied in prior literature.

AI Aspects	n. of articles	Authors(s) / Years
Predictive/ forecasting systems	39	Jones, Johnstone & Wilson, 2017; Yang, Platt & Platt, 1999; Sun & Vasarhelyi, 2018; Gepp, Kumar & Bhattacharya, 2010; Dunis, Laws, & Karathanasopoulos, 2013; Qi, & Maddala, 1999; Reboredo, Matías & Garcia-Rubio, 2012; Fernandes, Medeiros & Scharth, 2014; Wanke, Azad & Barros, 2016; Wanke et al., 2016; Le & Viviani, 2018; Parot, Michell & Kristjanpoller, 2019; Moshiri & Cameron, 2000; Nag & Mitra, 2002; Rodrigues & Stevenson, 2013; Chen et al., 2013; Trinkle & Baldwin, 2016; Dixon, Klabjan & Bang, 2017; Law & Shawe-Taylor, 2017; Pichl & Kaizoji, 2017; Vortelinos, 2017; Lahmiri & Bekiros, 2019; Sabău Popa et al., 2021; Zhang, Chu & Shen, 2021; Houlihan & Creamer, 2021; Caglayan et al., 2020; Bekiros & Georgoutsos, 2008; Dunis, Laws & Sermpinis, 2010; Sermpinis, Laws & Dunis, 2013; Heston & Sinha, 2017; Loukeris & Eleftheriadis, 2015; Abedin et al., 2019; Bucci, 2020; Jones & Wang, 2019; Episcopos, Pericli & Hu, 1998; Booth, Gerding, & McGroarty, 2015; Tashiro et al., 2019; Kim & Kim, 2014; Papadimitriou, Goga, & Agrapetidou, 2020
Classification / detection / early warning systems	23	Altman, Marco, & Varetto, 1994; Coats & Fant, 1993; Khandani, Kim, & Lo, 2010; Jones, Johnstone & Wilson, 2017; Jones, Johnstone & Wilson, 2015; Butaru et al., 2016; Varetto, 1998; Feldman & Gross, 2005; Jagric, Jagric & Kracun, 2011; Lu, Shen & Wei, 2013; Jiang & Jones, 2018; Huang & Guo, 2021; Deku, Kara & Semeyutin, 2020; Corazza, De March & Di Tollo, 2021; Kumar et al., 2019; Durango-Gutiérrez, Lara-Rubio & Navarro-Galera, 2021; Loukeris & Eleftheriadis, 2015; Mselmi, Lahiani & Hamza, 2017; Holopainen & Sarlin, 2017; Renault, 2017; Le & Viviani, 2018; Lahmiri, 2016; Xu, Zhang, & Feng, 2019
Big data Analytics / Data mining / Text mining	14	Houlihan & Creamer, 2021; Huang & Kuan, 2021; Abdou et al., 2020; Kanas, 2001; Durango-Gutiérrez, Lara-Rubio & Navarro-Galera, 2021; Wanke et al., 2016; Lu & Ohta, 2003; Li et al., 2020; Kamiya, Kim & Park, 2018; Renault, 2017; Heston & Sinha, 2017; Xu & Zhao, 2020; Yin, Wu & Kong, 2020; Xu, Zhang, & Feng, 2019;

Algorithmic trading/ Trading models	12	Hendershott, Jones, & Menkveld, 2011; Chaboud et al., 2014; Scholtus, Van Dijk & Frijns, 2014; Kelejian & Mukerji, 2016; Frino et al., 2017; Kelejian & Mukerji, 2016; Litzenberger, Castura & Gorelick, 2012; Petukhina, Reule & Härdle, 2021; Jain, Jain & Khanapure, 2021; Gao, Liu & Wu, 2016; Frino, Garcia, & Zhou, 2020; Creamer, 2012;
Natural Language processing/ sentiment analysis	9	Kim & Kim, 2014; Wei et al., 2019; Calomiris & Mamaysky, 2019; Heston & Sinha, 2017; Renault, 2017; Heston & Sinha, 2017; Xu & Zhao, 2020; Yin, Wu & Kong, 2020; Houlihan and Creamer, 2021;
Artificial Neural Networks	8	Reber, 2014; Funahashi, 2020; Zhao et al., 2018; Jang & Lee, 2019; Sariev & Germano, 2020; Loukeris & Eleftheriadis, 2015; Heston & Sinha, 2017; Dunis, Laws, & Sermpinis, 2010;
Robo-advisory	7	Trippi & DeSieno, 1992; Rodrigues & Stevenson, 2013; Petukhina, Reule & Härdle, 2021; Tao et al., 2021; Loukeris & Eleftheriadis, 2015; D'Hondt et al., 2020; Creamer, 2012; Creamer & Freund, 2010;
Modelling	6	Fernandes, Medeiros & Scharth, 2014; Guotai, Abedin & E–Moula, 2017; Chen & Wan, 2021; Amelot, Subadar Agathee & Sunecher, 2021; Dunis, Laws & Sermpinis, 2010; Funahashi, 2020;
Machine learning	5	Rasekhschaffe & Jones, 2019; Kercheval & Zhang, 2015; Soleymani & Vasighi, 2020; Burggraf, 2021; Xu, Zhang, & Feng, 2019
Deep Learning	5	Culkin & Das, 2017; Dixon, Klabjan & Bang, 2017; Kim & Kim, 2020; Chen & Ge, 2021; Galeshchuk & Mukherjee, 2017
Digitalization / digital technology	1	Lu & Ohta, 2003

Note: The table shows the influential aspects of literature.

CHAPTER 2 – REVIEW METHODOLOGY

The methodology of this hybrid literature review consists of two important methods; (i) bibliometrics citation analysis, and (ii) content analysis (Bahoo, 2020; Bahoo, Alon, Paltrinieri, 2020a). Overall, the methodology section consists of three important steps: (i) article search strategy, articles screening and eligibility criteria, (ii) Analysis techniques. The detail of each step is given below. Figure 1 shows our methodology.

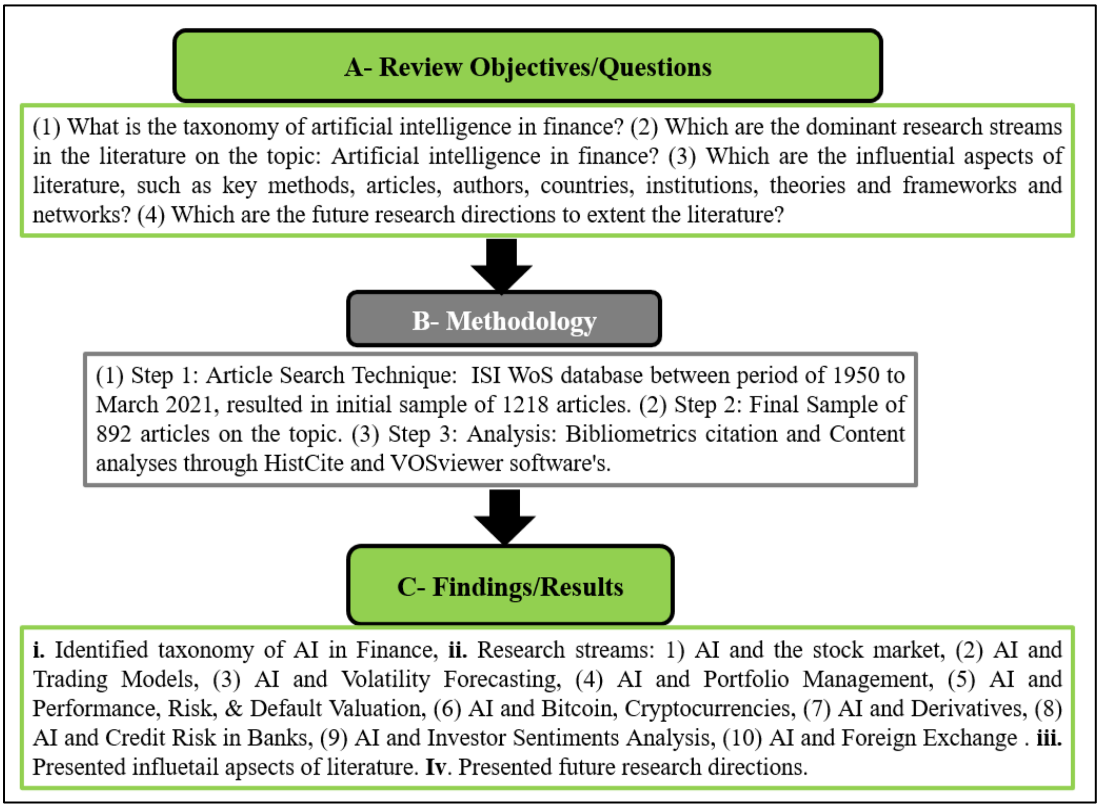

Figure 1. Method

2.1 STEP 01: ARTICLE RESEARCH STRATEGY

In this first step of the analysis, we decided to use Web of Science database to select the articles on the topic (Baho, Alon, & Floreani, 2021). Thus, we used the following keywords, combinations, and filters to collect citation data of articles.

Keywords for AI: "Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Neural Networks*" OR "Natural Language Processing*" OR "Algorithmic Trading*" OR "Artificial Neural Network" OR "Robot*" OR "Automation" OR "Text Mining" OR "Data Mining" OR "Soft Computing" OR "Fuzzy Logic Analysis" OR "Biometrics*" OR "Geotagging" OR "Wearable*" OR "IoT" OR "Internet of Thing*" OR “digitalization” OR “Artificial Neutral Networks” OR “Big Data” OR “Industry 4.0” OR “Smart products*” OR Cloud Computing” OR “Digital Technologies*.”

Keywords for finance: “Finance”

Filters: Subject Category: Finance, Economics, Business Finance, Business, Language: English, Type of papers: Articles

Period: 1950 to March 2021.

Initial Results: 1218 articles on the topic

2.2 STEP 02: ARTICLES SCREENING AND ELIGIBILITY CRITERIA

In the second step, two independent researchers have reviewed and studied title, abstract, and content of articles to exclude those not relevant. The criteria to include an article in the analysis is that, it should analyse any content AI in finance in a non-marginal and non-trivial way (Bahoo, Alon, & Paltrinieri, 2020a). Researcher discussed the conflicts regarding including the article in the sample, thus this process resulted in the final sample of 892 articles on the topic, AI in finance.

2.3 STEP 03: ANALYSIS TECHNIQUES

In the third step, we used the following bibliometrics and content analyses techniques to analyse the literature (Bahoo, Alon, Paltrinieri, 2020b); (1) bibliometrics co-citation analysis, (2) bibliometrics cartography analysis, (3) bibliometrics citation analysis, (4) bibliometrics co-authorship analysis, and (4) content analysis. The HistCite and VOSviewer software's are used for bibliometrics analysis. The detailed results are presented in Section 3.

CHAPTER 3 – FINDINGS AND REFLECTIONS

In this chapter, we report all the identified results to complete the research objective of this review. We identified the key journals, countries, methods, industries, theoretical frameworks and companies studied.

3.1 INFLUENTIAL ASPECTS OF LITERATURE

3.1.1. Publication Trend

Through HistCite software, we identify the publication trend per year on the topic, AI in finance. The publication trend is presented in Figure 2, which shows that the

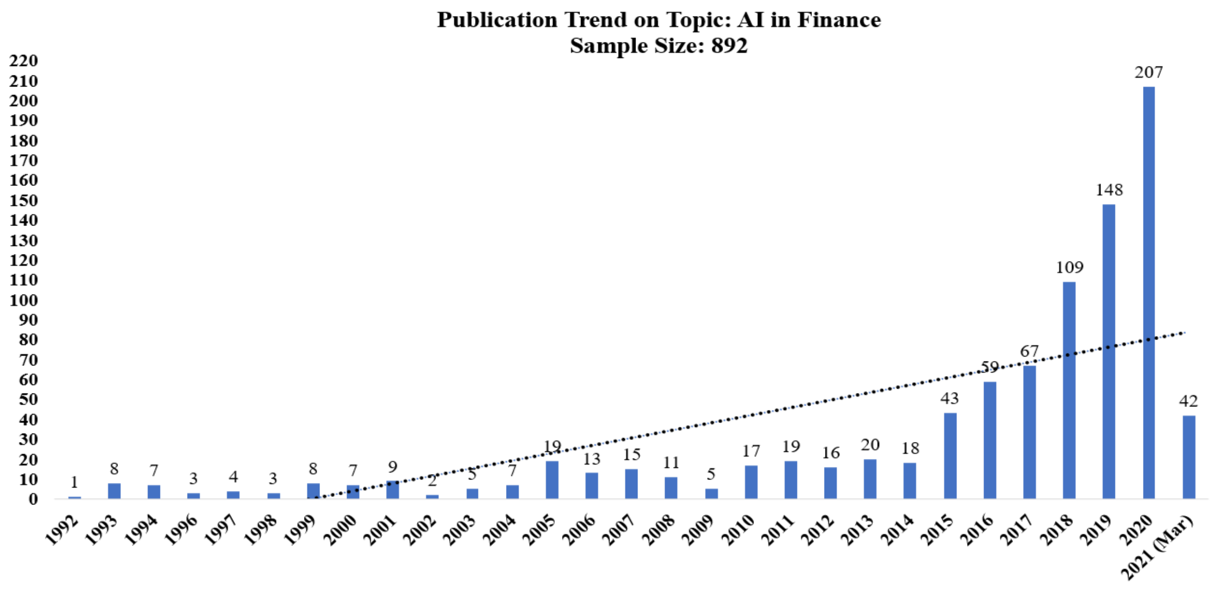

Figure 2. Publication Trend

first paper on the topic is published in 1993. Given the rising importance of the subject, there is an upward publication trend. Publications have significantly intensified in the last 5 years: from 43 articles in 2015 to 207 publications in 2020. This confirms the idea that AI is embedded in every aspect of the modern economy and the financial world. For this reason, research is conducted to analyse the potential implications and future directions of this phenomenon.

3.1.2. Top Journals Published on Topic

We identified two categories of top 10 journals published on the topic based on:

- total global citation (TGC): the number of times an article is cited by any other articles that are available on the WoS database on the same topic.
- total number of articles published by journal.

Table 2 presents the list of top 10 journals having an ABS ranking (4*, 4, 3, 2, 1)

Table 2. Top 10 journals published on the topic.

Ranking	**Journal**	**No of articles**	**TGC**	**Journal**	**No of articles**	**TGC**
1	Journal of Finance	9	1283	Quantitative Finance	68	368
2	Journal of Banking and Finance	28	1256	Intelligent Systems in Accounting, Finance and Management	43	273
3	International Journal of Forecasting	20	521	Journal of Banking and Finance	28	1256

4	Journal of Economic Dynamics and Control	4	377	International Journal of Finance and Economics	21	66
5	Quantitative Finance	68	368	International Journal of Forecasting	20	521
6	Journal of Forecasting	17	275	Computational Economics	17	87
7	Intelligent Systems in Accounting, Finance and Management	43	273	Journal of Forecasting	17	275
8	Accounting Organizations and Society	1	210	European Journal of Finance	16	73
9	Mathematical Finance	11	188	Technological Forecasting and Social Change	15	63
10	Journal Of Business Research	5	182	Pacific-Basin Finance Journal	14	53

Note: The table shows the list of journals.

3.1.3. Countries Studied in Prior Literature

Further, we summarized the list of countries and exemplary studies which are already examined in the prior literature. The identification will help the readers and researchers to understand which countries are analysed, and conclusions are drawn about specific economy.

Table 3 displays the list of countries studied in prior literature.

As evidenced, the papers focus on 74 countries across all continents. Most articles studied concentrate on three major economic areas: Europe, U.S.A., and China. These results corroborate the fact that the above regions are the leaders of the AI-driven finance industry, as suggested by Pwc, (2017) study. The United States, in particular, are considered the “early adopters” of AI and will benefit the most from this competitive advantage. Lately, emerging countries in Asia and the Middle East are receiving growing interest. A minor number of papers addresses underdeveloped regions in Africa and controversial economies in South America such as Argentina.

Table 3. List of countries

Sr. No.	Country where study is conducted	Author(s) / Year
EUROPE		
1.	Denmark	Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
2.	Iceland	Calomiris & Mamaysky, 2019; Jain, 2005;
3.	Austria	Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
4.	Italy	Altman, Marco, & Varetto, 1994; Varetto, 1998; Guotai, Abedin & E–Moula, 2017; Chen et al., 2013; Deku, Kara & Semeyutin, 2020; Corazza, De March, & Di Tollo, 2021; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
5.	Ireland	Deku, Kara & Semeyutin, 2020; Rasekhschaffe & Jones, 2019; Jain, 2005;
6.	France	Chen et al., 2013; Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Mselmi, Lahiani & Hamza, 2017; Holopainen & Sarlin, 2017; Jain, 2005;
7.	Netherlands	Chen et al., 2013; Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
8.	Norway	Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Jain, 2005;
9.	Finland	Caglayan et al., 2020; Calomiris & Mamaysky, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
10.	Sweden	Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017;
11.	Belgium	(Pompe, & Bilderbeek, 2005) Chen et al., 2013; Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; D’Hondt et al., 2020; Holopainen & Sarlin, 2017; Jain, 2005;
12.	Luxembourg	Calomiris & Mamaysky, 2019; Holopainen & Sarlin, 2017; Jain, 2005;

13.	Greece	Lahmiri, 2016; Guotai, Abedin & E–Moula, 2017; Frino et al., 2017; Rodrigues & Stevenson, 2013; Chen et al., 2013; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Loukeris & Eleftheriadis, 2015; Jain, 2005;
14.	Switzerland	Deku, Kara & Semeyutin, 2020; Rasekhschaffe & Jones, 2019; Jain, 2005;
15.	UK	Chen et al., 2013; Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Abdou et al., 2020; Kanas, 2001; Wanke et al., 2016; Holopainen & Sarlin, 2017; Kim & Kim, 2020; Jain, 2005; Sermpinis, Laws & Dunis, 2013;
16.	Germany	Lahmiri, 2016; Chen et al., 2013; Trinkle & Baldwin, 2016; Deku, Kara & Semeyutin, 2020; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Xu, Zhang, & Feng, 2019; Holopainen & Sarlin, 2017; Seriev & Germano, 2020; Jain, 2005; Creamer, 2012;
17.	Portugal	Deku, Kara & Semeyutin, 2020; Rasekhschaffe & Jones, 2019; Holopainen & Sarlin, 2017; Jain, 2005; Calomiris & Mamaysky, 2019; Jain, 2005;
18.	Spain	Cortés, Martínez & Rubio, 2008; Caglayan et al., 2020; Calomiris & Mamaysky, 2019; Holopainen & Sarlin, 2017; Jain, 2005;
19.	Czech Republic	Calomiris & Mamaysky, 2019; Jain, 2005;
20.	Ukraine	Calomiris & Mamaysky, 2019; Jain, 2005;
21.	Romania	Sabău Popa et al., 2021; Jain, 2005;
22.	Slovenia	Jagric et al., 2011; Jain, 2005;
23.	Slovakia	Calomiris & Mamaysky, 2019; Jain, 2005;
24.	Poland	Calomiris & Mamaysky, 2019; Trinkle & Baldwin, 2016; Seriev & Germano, 2020; Jain, 2005;
25.	Estonia	Caglayan et al., 2020; Calomiris & Mamaysky, 2019; Jain, 2005;
26.	Hungary	Calomiris & Mamaysky, 2019; Jain, 2005;
27.	East Europe	Seriev & Germano, 2020; Jain, 2005;
28.	Europe (no specif country)	Bucci et al.,2020; Jones & Wang, 2019; Kumar et al., 2019; Jones & Wang, 2019; Booth, Gerding, & McGroarty, 2015; Creamer, 2012;
NORTH AMERICA		
29.	USA	Coats & Fant, 1993; Jones, Johnstone, & Wilson, 2015; Jones, Johnstone, & Wilson, 2017; Butaru et al., 2016; Gepp, Kumar, & Bhattacharya, 2010; Scholtus, Van Dijk, & Frijns, 2014; Qi & Maddala, 1999; Sirignano, 2018; Fernandes, Medeiros, & Scharth, 2014; Kelejian & Mukerji, 2016; Le & Viviani, 2018; Wei et al., 2019; Qi, 1999; Litzenberger, Castura & Gorelick, 2012; Chen et al., 2013; Kanas, 2001; Vortelinos, 2017; Renault, 2017; Huang & Kuan, 2021; Houlihan & Creamer, 2021; Tao et al., 2021; Jain, Jain, & Khanapure, 2021;Calomiris & Mamaysky, 2019; Bekiros & Georgoutsos, 2008;Heston & Sinha, 2017;Rasekhschaffe & Jones, 2019; Cao et al., 2020; Kercheval & Zhang, 2015; Papadimitriou, Goga, & Agrapetidou, 2020; Soleymani & Vasighi, 2020;Abedin et al., 2019; Bucci et al.,2020; Jones & Wang, 2019; Creamer & Freund, 2010; Booth, Gerding & McGroarty, 2015; Zhao et al., 2018; Jang & Lee, 2019; Kim & Kim, 2020; Jain, 2005;
30.	Canada	Jones, Johnstone, & Wilson, 2015; Moshiri, & Cameron, 2000; Chen et al., 2013; Calomiris & Mamaysky, 2019; Jain, 2005;

SOUTH AMERICA		
31.	Brazil	Sun & Vasarhelyi, 2018; Calomiris & Mamaysky, 2019; Jain, 2005;
32.	Latin America	Jones, Johnstone, & Wilson, 2015; Jain, 2005;
33.	Mexico	Calomiris & Mamaysky, 2019; Jain, 2005;
34.	Peru	Calomiris & Mamaysky, 2019; Jain, 2005;
35.	Argentina	Calomiris & Mamaysky, 2019; Jain, 2005;
36.	Colombia	Calomiris & Mamaysky, 2019; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Jain, 2005;
37.	Bolivia	Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Jain, 2005;
38.	Chile	Calomiris & Mamaysky, 2019; Jain, 2005;
39.	Latin America	Jones, Johnstone, & Wilson, 2015; Jain, 2005;
40.	Mexico	Calomiris & Mamaysky, 2019; Jain, 2005;
ASIA		
41.	India	Calomiris & Mamaysky, 2019; Jain, 2005;
42.	Japan	Lahmiri, 2016;
43.	Thailand	Calomiris & Mamaysky, 2019; Jain, 2005;
44.	Indonesia	Calomiris & Mamaysky, 2019; Wanke et al., 2016;; Jain, 2005;
45.	Philippines	Calomiris & Mamaysky, 2019; Jain, 2005;
46.	Malaysia	Wanke, Azad & Barros, 2016; Calomiris & Mamaysky, 2019; Wanke et al., 2016; Jain, 2005;
47.	Mauritius	Amelot, Subadar Agathee, & Sunecher, 2021; Jain, 2005;
48.	Singapore	Chen et al., 2013; Jain, 2005; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019;
49.	Pakistan	Wanke et al., 2016; Jain, 2005;
50.	Hong Kong	Chen et al., 2013; Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Jain, 2005; Kim & Kim, 2020;
51.	Asia Pacific	Jones, Johnstone, & Wilson, 2015; Booth, Gerding & McGroarty, 2015;
52.	China	Guotai, Abedin & E–Moula, 2017; Lu, Shen & Wei, 2013; Jiang & Jones, 2018; Zhang, Chu, & Shen 2021; Calomiris & Mamaysky, 2019; Xu & Zhao, 2020; Uddin et al., 2020; Yin, Wu, & Kong, 2020; Abedin et al., 2019; Gao, Liu, & Wu, 2016; Li et al., 2020; Jain, 2005;
53.	Bangladesh	Wanke et al., 2016; Jain, 2005;
54.	South Korea	Calomiris & Mamaysky, 2019; Jain, 2005;
55.	Russia	Calomiris & Mamaysky, 2019; Jain, 2005;
56.	Taiwan	Lu, Shen & Wei, 2013; Jain, 2005; Abedin et al., 2019;
OCEANIA		
57.	New Zealand	Calomiris & Mamaysky, 2019; Rasekhschaffe & Jones, 2019; Jain, 2005;

58.	Australia	Lahmiri, 2016; Guotai, Abedin & E–Moula, 2017; Chen et al., 2013; Calomiris & Mamaysky, 2019; Xu, Zhang, & Feng, 2019; Frino, Garcia & Zhou, 2020; Jain, 2005;
MIDDLE EAST		
59.	Iran	Zhang & Feng, 2019; Wanke et al., 2016;; Jain, 2005;
60.	Qatar	Wanke et al., 2016;
61.	Bahrain	
62.	UAE	Wanke et al., 2016; Jain, 2005;
63.	Kuwait	Wanke et al., 2016; Jain, 2005;
64.	Turkey	Calomiris & Mamaysky, 2019; Wanke et al., 2016; Jain, 2005;
65.	Israeli	Dunis, Laws, & Karathanasopoulos, 2013; Deku, Kara & Semeyutin, 2020; Feldman & Gross, 2005; Calomiris & Mamaysky, 2019; Jain, 2005;
66.	Saudi Arabia	Wanke et al., 2016; Jain, 2005;
67.	Sudan	Wanke et al., 2016;
68.	Tunis	Wanke et al., 2016; Jain, 2005;
69.	Egypt	Abdou et al., 2020; Wanke et al., 2016; Jain, 2005;
AFRICA		
70.	South Africa	Calomiris & Mamaysky, 2019; Jain, 2005;
71.	Nigeria	Calomiris & Mamaysky, 2019; Jain, 2005;
72.	Kenya	Calomiris & Mamaysky, 2019; Jain, 2005;
73.	Ghana	Calomiris & Mamaysky, 2019; Jain, 2005;
74.	Gambia	Wanke et al., 2016; Jain, 2005;

Note: Table summarizes list of countries.

3.1.4. Industries Studied in Prior Literature

The key industries examined in the prior literature are summarized in Table 4.

The papers analyse a vast category of financial assets across various industries. Research converges primarily on banking and financial services. The massive variety of industries studied in the literature confirms that AI has an infinite range of application, meaning that any industry may benefit from its insights.

Table 4. List of Industries studied in prior literature.

Name of Industry	Author(s) / Year
Aerospace, airline, aircraft	Kelejian & Mukerji, 2016; Zhang, Chu, & Shen 2021; Reber, 2014; Kanas, 2001;
Agriculture, Hunting and forestry fishing	Cortés, Martínez & Rubio, 2008; Jones & Wang, 2019;
Agriculture Machinery	Kelejian & Mukerji, 2016;
Automotive industry, Vehicle Manufacturing, Repair of vehicles	Kelejian & Mukerji, 2016; Cortés, Martínez & Rubio, 2008; Zhang, Chu, & Shen 2021;
Banking /financial services	Khandani, Kim, & Lo, 2010; Butaru et al., 2016; Lahmiri, 2016; Kim & Kim, 2014; Sun & Vasarhelyi, 2018; Dunis, Laws, & Karathanasopoulos, 2013; Sirignano, 2018; Feldman & Gross, 2005; Fernandes, Medeiros, & Scharth, 2014; Wanke, Azad & Barros, 2016; Guotai, Abedin & E–Moula, 2017; Frino et al., 2017; Le & Viviani, 2018; Wei et al., 2019; Cortés, Martínez & Rubio, 2008; Jagric, Jagric, & Kracun, 2011; Trinkle & Baldwin, 2016; Culkin & Das, 2017; Law & Shawe-Taylor, 2017; Vortelinos, 2017; Renault, 2017; Jiang & Jones, 2018; Zhang, Chu, & Shen 2021; Deku, Kara & Semeyutin, 2020; Caglayan et al., 2020; Calomiris & Mamaysky, 2019; Reber, 2014; Kumar, Muckley, Pham, et al., 2019; Cao, Liu, Zhai, et al., 2020; Xu & Zhao, 2020; Papadimitriou, Goga, & Agrapetidou, 2020; Tao et al., 2021; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Kanas, 2001; Loukeris & Eleftheriadis, 2015; Abedin et al., 2019; Xu, Zhang, & Feng, 2019; Wanke et al., 2016; Jones & Wang, 2019; Episcopos, Pericli & Hu, 1998; Funahashi, 2020; Lu & Ohta, 2003; Holopainen & Sarlin, 2017; Zhao et al., 2018;
Business services	Uddin et al., 2020;
Raw Materials	Kim & Kim, 2014;
Commercial and service industry and/or general machinery	Varetto, 1998; Kelejian & Mukerji, 2016;
Construction	Altman, Marco, & Varetto, 1994; Varetto, 1998; Cortés, Martínez, & Rubio, 2008;Sabau, Popa et al., 2021; Reber, 2014; Uddin et al., 2020; Kanas, 2001; Jones & Wang, 2019;
Consumer goods	Kim & Kim, 2014; Kelejian & Mukerji, 2016; Kanas, 2001;
Commodities	Yang, Platt, & Platt, 1999; Fernandes, Medeiros, & Scharth, 2014; Kelejian & Mukerji, 2016; Trinkle & Baldwin, 2016; Zhang, Chu, & Shen 2021; Li et al., 2020;
Computer and peripheral equipment	Kelejian & Mukerji, 2016;
Communication	Kelejian & Mukerji, 2016; Cortés, Martínez & Rubio, 2008; Jones & Wang, 2019;
Cryptocurrency	Pichl & Kaizoji, 2017; Burggraf, 2021; Petukhina, Reule, & Härdle, 2021;
Education	Cortés, Martínez, & Rubio, 2008;
Electronics Equipment and Manufacturing industry	Reber, 2014; Kelejian & Mukerji, 2016;
Electronics	Kelejian & Mukerji, 2016;
Energy & utilities	Jones, Johnstone, & Wilson, 2017; Kim & Kim, 2014; Jiang & Jones, 2018; Sabau, Popa et al., 2021; Zhang, Chu, & Shen 2021; Cortés, Martínez & Rubio, 2008; Jones, Johnstone, & Wilson, 2017; Reber, 2014; Kelejian & Mukerji, 2016; Li et al., 2020;
Extractive industry	Sabău Popa et al., 2021;
FinTech	Jones, Johnstone, & Wilson, 2017; Kelejian & Mukerji, 2016; Cortés, Martínez, & Rubio, 2008; Tao et al., 2021;
Food, Tobacco, Beverages	Jones, Johnstone, & Wilson, 2017; Zhang, Chu, & Shen 2021; Cortés, Martínez, & Rubio, 2008; Kanas, 2001; Reber, 2014;
Footwear	Kanas, 2001;
Health Care	Kelejian & Mukerji, 2016; Kim & Kim, 2014; Cortés, Martínez, & Rubio, 2008; Jones, Johnstone, & Wilson, 2017; Reber, 2014; Kanas, 2001;
Gold	Law & Shawe-Taylor, 2017

Name of Industry	Author(s) / Year
Heating Industry	Kelejian & Mukerji, 2016; Pompe, & Bilderbeek, 2005;
Household goods	Jones, Johnstone, & Wilson, 2017;
Information services	Uddin et al., 2020;
IT industry	Jones, Johnstone, & Wilson, 2017; Uddin et al., 2020; Kanas, 2001; Varetto, 1998; D'Hondt et al., 2020; Creamer, 2012; Creamer & Freund, 2010;
Manufacturing (of woods, textile, leather products)	Sabau, Popa et al., 2021; Cortés, Martínez & Rubio, 2008; Reber, 2014; Jones & Wang, 2019;
Manufacture of Chemical, Plastics, Rubber	Coats & Fant, 1993; Gepp, Kumar, & Bhattacharya, 2010; Cortés, Martínez, & Rubio, 2008; Reber, 2014; Kanas, 2001;
Manufacture of electrical and optical equipment	Cortés, Martínez, & Rubio, 2008;
Medical equipment and supplies	Kelejian & Mukerji, 2016; Cortés, Martínez, & Rubio, 2008;
Metal	Li et al., 2020;
Mining industry	Kelejian & Mukerji, 2016; Rodrigues & Stevenson, 2013; Zhang, Chu, & Shen 2021; Jones & Wang, 2019;
Paper, paper products, publishing, printing	Cortés, Martínez, & Rubio, 2008;
Pharmaceutical and medicine	Kelejian & Mukerji, 2016; Cortés, Martínez & Rubio, 2008; Zhang, Chu, & Shen 2021; Reber, 2014; Kanas, 2001;
Power & automation Technology	Kelejian & Mukerji, 2016;
Petroleum, Nuclear fuel	Law & Shawe-Taylor, 2017; Kanas, 2001;
Restaurants. Hotel, tourism and personal services	Cortés, Martínez & Rubio, 2008;Sabau, Popa et al., 2021; Reber, 2014; Uddin et al., 2020;
Wholesale and Retail	Jones, Johnstone, & Wilson, 2017; Cortés, Martínez & Rubio, 2008; Jiang & Jones, 2018; Sabau, Popa et al., 2021; Reber, 2014; Uddin et al., 2020; Kanas, 2001; Jones & Wang, 2019;
Public administration and defence	Altman, Marco, & Varetto, 1994; Jones, Johnstone, & Wilson, 2015; Jones, Johnstone, & Wilson, 2017; Gepp, Kumar, & Bhattacharya, 2010; Cortés, Martínez & Rubio, 2008; Reber, 2014; Jones & Wang, 2019;
Real estate, renting and business activities	Cortés, Martínez & Rubio, 2008; Chen et al., 2013; Zhang, Chu, & Shen 2021; Uddin et al., 2020; Jones & Wang, 2019;
Robotics /automation industry	Cortés, Martínez & Rubio, 2008;
Hygiene products	Jones, Johnstone, & Wilson, 2017;
Social media platforms Software Engeerning	Houlihan & Creamer, 2021; Xu & Zhao, 2020;
Soap, cleaning compound &toilet preparation	Kelejian & Mukerji, 2016;
Technology company Trading	Cortés, Martínez & Rubio, 2008; Kim & Kim, 2014;
Telecommunication (service and manufacturing, companies)	Kim & Kim, 2014; Jones, Johnstone, & Wilson, 2017; Zhang, Chu, & Shen 2021; Reber, 2014; Heston & Sinha, 2017; Kanas, 2001;
Transportation and storage	Dunis, Laws, & Karathanasopoulos, 2013; Scholtus, Van Dijk, & Frijns, 2014; Reboredo, Matías, & Garcia-Rubio, 2012; Sabau, Popa et al., 2021; Cortés, Martínez, & Rubio, 2008; Reber, 2014; Uddin et al., 2020; Jones & Wang, 2019;
Vehicle manufacturing	Jones, Johnstone, & Wilson, 2017;
Professional Scientific and technical activities	Sabău Popa et al., 2021;
Warehousing	Uddin et al., 2020;

Note: List of industries examined in prior literature.

3.1.5. Theories and framework studied in prior literature.

Through our in-depth analysis, we also identify the key theories and frameworks applied by researchers in the prior literature. Table 5 shows the details.

Out of 110 papers, only 73 papers mention theoretical frameworks. The remaining articles do not mention the theories used by the authors. Of the 73 papers, 10 (14%) used computational learning theory, an extension of statistical learning. This is one of the most important and most used theories in the. It provides a theoretical guide for researchers to find the learning model best suited for the problem.

Specific theories regarding types of neural networks and learning methods are fuzzy set theory mentioned in 8% of total papers only, and to a lesser extent, Naives Bayes' theorem, theory of neural networks, theory of genetic programming, and TOPSIS analytical framework.

Finance theories (e.g., Arbitrage Pricing Theory, Black&Scholes) are used simultaneously with portfolio management theories (e.g., modern portfolio theory). They count together for 21% (15) of total papers.

Bankruptcy theories support business failure forecasts. Other theoretical underpinnings refer to mathematical and probability concepts.

Table 5. Theories and Frameworks studied in prior literature.

Theories/Frameworks	No of Articles	Author(s) / Year
Statistical Learning Theory/ Computational Learning Theory	10	Qi, 1999; Rodrigues & Stevenson, 2013; Law & Shawe-Taylor, 2017; Xu, Zhang, & Feng, 2019; Episcopos, Pericli, & Hu., 1998; Chabou et al., 2014; Jones, Johnstone & Wilson, 2017; Lahmiri, 2016; Reboredo, Matías, & Garcia-Rubio, 2012; Le & Viviani, 2018;
Finance theories (Arbitrage Pricing Theory, Efficient Market Theory, Black and Scholes theory)	10	Qi & Maddala, 1999; Lu, Shen, & Wei, 2013; Caglayan et al., 2020; Moshiri & Cameron, 2000; Kim & Kim, 2020; Litzenberger, Castura, & Gorelick, 2012; Fernandes, Medeiros, & Scharth, 2014; Culkin & Das, 2017; Chen & Wan, 2021; Lu & Ohta, 2003;
Fuzzy set theory	6	Trinkle & Baldwin, 2016; Huang & Guo, 2021; Xu, Zhang, & Feng, 2019; Jiang & Jones, 2018; Lahmiri & Bekiros, 2019; Uddin et al., 2020;
Modern Portfolio Theory	5	Loukeris & Eleftheriadis, 2015; Soleymani & Vasighi, 2020; Zhao et al., 2018; Petukhina, Reule & Härdle, 2021;
Naives Bayes' theorem (Information Criterion, decision-making)	5	Lahmiri, 2016; Law & Shawe-Taylor, 2017; Jones, Johnstone & Wilson, 2017; Moshiri & Cameron, 2000; Jagric, Jagric, & Kracun, 2011; Yang, Platt, & Platt, 1999; Gepp, Kumar, & Bhattacharya, 2010;
Econometric Theory	4	Reboredo, Matías, & Garcia-Rubio, 2012; Parot, Michell, & Kristjanpoller, 2019; Bucci, 2020;
Theory of Neural networks	4	Altman, Marco, & Varetto, 1994; Wanke, Azad & Barros, 2016; Qi, 1999; Sariev & Germano, 2020;
Framework of Hasbrouck	3	Hendershott, Jones, & Menkveld, 2011; Frino et al., 2017;
Probability theories (Dempster–Shafer (D–S) evidence theory)	3	Gepp, Kumar, & Bhattacharya, 2010; Coats & Fant, 1993; Jiang & Jones, 2018;
Bankruptcy theory / Business failure theory	2	Varetto, 1998; Cortés, Martínez, & Rubio, 2008;
Random matrix theory	2	Soleymani & Vasighi, 2020; D'Hondt et al., 2020;
Signal detection theory	2	Varetto, 1998; Mselmi, Lahiani, & Hamza, 2017;
Theory of intraday patterns	2	Fernandes, Medeiros, & Scharth, 2014; Litzenberger, Castura, & Gorelick, 2012;
Entropy theory	2	Lu, Shen, & Wei, 2013; Heston & Sinha, 2017;
Markov decision-making process	1	Dunis, Laws & Karathanasopoulos, 2013;
Agency theory	1	Cao et al., 2020;
Behavioral consistency theory	1	Kamiya, Kim, & Park, 2018;
Theory of power-law distribution (financial markets)	1	Booth, Gerding, & McGroarty, 2015;
Conventional valuation theory	1	Jiang & Jones, 2018;
Cox–Ross–Rubinstein framework	1	Reber, 2014;
Decision theory	1	Law & Shawe-Taylor, 2017;
Economic theory	1	Bucci, 2020; Wei et al., 2019;
Economic theories of 'Matching and managerial talent'	1	Jiang & Jones, 2018;
Elder financial abuse: conceptual framework	1	Kumar et al., 2019;
Forecast combinations framework	1	Rasekhschaffe & Jones, 2019;
Gradient Theory	1	Culkin & Das, 2017;
Graph theory	1	Burggraf, 2021;
Individual theory	1	Cao et al., 2020;
KPCA theory (Kernel principal component analysis)	1	Amelot, Subadar Agathee, & Sunecher, 2021;

Limit order book Dynamics (theoretical model)	1	Sirignano, 2018;
Managerial signalling theory	1	Cao et al., 2020;
Preference theory	1	Guotai, Abedin & E–Moula, 2017;
Risk parity approach	1	Burggraf, 2021;
Sentiment theory	1	Heston & Sinha, 2017; Yin, Wu, & Kong, 2020;
Stochastic optimal theory	1	Chen & Ge, 2021;
Theory of Genetic programming	1	Dunis, Laws & Karathanasopoulos, 2013;
Time-varying risk premium theory	1	Bekiros & Georgoutsos, 2008;
TOPSIS Analytical framework	1	Wanke, Azad & Barros, 2016;
Grey system Theory	1	Chen et al., 2013;
Generalizability Theory	1	Varetto, 1998; Feldman & Gross, 2005;
Transactions on Information Theory	1	Reboredo, Matías & Garcia-Rubio, 2012;
Transaction Cost Theory	1	Feldman & Gross, 2005;

Note: The table shows the list of theories and frameworks.

3.1.6. Companies and firms studied in prior literature.

We enlist the types of companies and firms analysed in the prior literature on the topic, AI in artificial intelligence. Table 6 summarizes the details.

Out of 110, 30 articles focus on large companies listed on stock exchanges, while small and medium enterprises are studied only by 16 research papers. Similarly, trading and digital platforms are analysed by 16 papers that deal with derivatives and cryptocurrences.

Table 6. Types of firms studied in prior literature.

Type/Nature of Company/Firm	No of Articles	Author (s) / Year
Based on Size		
Large Companies (listed)	30	Khandani, Kim, & Lo, 2010; Hendershott, Jones, & Menkveld, 2011; Kim & Kim, 2014; Sirignano, 2018; Feldman & Gross, 2005; Jones, Johnstone, & Wilson, 2015 ,Qi & Maddala, 1999; Fernandes, Medeiros, & Scharth, 2014; Kelejian & Mukerji, 2016; Qi & Maddala, 1999; Qi, 1999; Cortés, Martínez & Rubio, 2008; Litzenberger, Castura & Gorelick, 2012; Lu, Shen & Wei, 2013; Rodrigues & Stevenson, 2013;Vortelinos, 2017; Renault, 2017; Sabau, Popa et al., 2021; Zhang, Chu, & Shen 2021; Jain, Jain, & Khanapure, 2021; Kamiya, Kim, & Park, 2018; Bekiros & Georgoutsos, 2008; Heston & Sinha, 2017; Rasekhschaffe & Jones, 2019; Cao et al., 2020; Abdou et al., 2020; Soleymani & Vasighi, 2020; Kanas, 2001; Seriev & Germano, 2020; Butaru et al., 2016;
Small Medium Enterprises (small cap) (SMEs)	16	Altman, Marco, & Varetto, 1994; Pompe & Bilderbeek, 2005; Cortés, Martínez, & Rubio, 2008; Litzenberger, Castura & Gorelick, 2012; Rodrigues & Stevenson, 2013; Chen et al., 2013; Tao et al., 2021; Corazza, De March, & Di Tollo, 2021; Jain, Jain, & Khanapure, 2021; Kamiya, Kim, & Park, 2018; Heston & Sinha, 2017; Rasekhschaffe & Jones, 2019; Mselmi, Lahiani, & Hamza, 2017; Jones & Wang, 2019; Jones & Wang, 2019; Seriev & Germano, 2020
Trading/ Digital platforms/ Lending online platform (Stocks, crypto, derivatives, loans)	16	Kelejian & Mukerji, 2016; Cortés, Martínez & Rubio, 2008; Litzenberger, Castura & Gorelick, 2012; Trinkle & Baldwin, 2016; Tao et al., 2021; Amelot, Subadar Agathee, & Sunecher, 2021; Jain, Jain, & Khanapure, 2021; D'Hondt et al., 2020; Gao, Liu & Wu, 2016; Frino, Garcia & Zhou, 2020; Funahashi, 2020; Lu, & Ohta, 2003; Creamer & Freund, 2010; Creamer, 2012; Tashiro, Matsushima et al., 2019; Caglayan et al., 2020;
Banks / Financial Institution (Large and small)	9	Sun & Vasarhelyi, 2018; Sirignano, 2018; Feldman & Gross, 2005; Frino et al., 2017; Wei et al., 2019; Kumar et al., 2019; Xu & Zhao, 2020; Wanke, Azad, & Barros, 2016; Papadimitriou, Goga & Agrapetidou, 2020;
Micro enterprises	3	Gepp, Kumar, & Bhattacharya, 2010; Uddin et al., 2020; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021;
National Banks	1	Wei et al., 2019;
Venture capitals	1	Reber, 2014;

Note: Types of firms analysed. Only 76 articles out of 110 define firms' size. 34 articles do not provide information on companies' size for privacy reasons.

3.1.7. Key methods applied in prior literature.

In Table 7, we summarize the key methods applied in the literature and divide them by category. As indicated in the table, machine learning and artificial neural networks are the most employed research methods. Out of 110 articles, 41 apply machine learning and 51 use neural networks. Most papers use different methods to compare the results with those obtained by autoregressive and regression models or conventional statistics, considered as the benchmark. Therefore, numbers may overlap. Nevertheless, we notice that support vector machine and random forest are the most widespread machine learning methods.

On the other hand, the use of ANNs is highly fragmented, as evidenced in the table. Backpropagation, Recurrent, and Feed-Forward NNs are considered basic neural nets, therefore commonly employed. Advanced NNs, such as Higher Order Neural network (HONN) and Long Short-Term Memory Networks (LSTM) are more performing than their standard version but also much more complicated to apply. The above methods are usually compared to autoregressive models and regression, as ARMA, ARIMA, GARCH.

The majority of the papers in the prior literature is quantitative. Only three qualitative papers and four literature reviews.

Table 7. Key method applied.

Method	n. of articles	Author (s) / Years
MACHINE LEARNING	41	Khandani et al., 2010; Varetto, 1998; Jones et al., 2017; Galeshchuk & Mukherjee, 2017; Butaru et al., 2016; Lahmiri, 2016; Kercheval & Zhang, 2015; Kim, & Kim, 2014; Sun & Vasarhelyi, 2018; Gepp, Kumar, & Bhattacharya, 2010; Dunis, Laws, & Karathanasopoulos, 2013; Feldman and Gross, 2005; Reboredo, Matías, & Garcia-Rubio, 2012; Le and Viviani, 2018; Cortés, Martínez, & Rubio, 2008; Butaru et al., 2016; Law & Shawe-Taylor, 2017; Renault, 2017; Jiang & Jones, 2018; Lahmiri & Bekiros, 2019; Burggraf, 2021; Huang and Guo, 2021; Deku, Kara & Semeyutin, 2020; Houlihan & Creamer, 2021; Amelot et al., 2021; Caglayan et al., 2020; Kumar et al., 2019; Rasekhschaffe & Jones, 2019; Cao et al., 2020; Papadimitriou, Goga & Agrapetidou, 2020); Soleymani & Vasighi, 2020; Uddin et al., 2020; Abedin et al., 2019; Mselmi, Lahiani & Hamza, 2017; D'Hondt, De Winne, Ghysels et al., 2020; Jones & Wang, 2019; Creamer & Freund, 2010; Creamer, 2012; Booth, Gerding & McGroarty, 2015; Holopainen & Sarlin, 2017; Jang & Lee, 2019; Xu & Zhao, 2020;
Support Vector Machine (SVM)	19	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017; Galeshchuk & Mukherjee, 2017; Lahmiri, 2016; Kercheval & Zhang, 2015; Reboredo, Matías, & Garcia-Rubio, 2012; Le and Viviani, 2018; Law & Shawe-Taylor, 2017; Huang & Guo, 2021; Houlihan & Creamer, 2021; Kumar et al., 2019; Rasekhschaffe & Jones, 2019; Cao et al., 2020; Papadimitriou, Goga & Agrapetidou, 2020; Abedin et al., 2019; Mselmi, Lahiani & Hamza, 2017; Booth, Gerding & McGroarty, 2015; Holopainen & Sarlin, 2017; Jang & Lee, 2019; Hamdi & Aloui, 2015;
Random forest	8	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017; Butaru et al., 2016; Deku, Kara & Semeyutin, 2020; Kumar et al., 2019; Uddin et al., 2020; D'Hondt et al., 2020; Booth, Gerding & McGroarty, 2015;
Naïve Bayes	5	Lahmiri, 2016; Kim & Kim, 2014; Sun & Vasarhelyi, 2018; Deku, Kara & Semeyutin, 2020; Xu & Zhao, 2020;
Adaboost	5	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017; Cortés, Martínez, & Rubio, 2008; Rasekhschaffe & Jones, 2019; Creamer, 2012;
Least absolute shrinkage and selection operator (LASSO)	3	Caglayan et al., 2020; Cao et al., 2020; Holopainen & Sarlin, 2017;
CART	3	Khandani et al., 2010; Gepp, Kumar, & Bhattacharya, 2010;
Decision trees	3	Butaru et al., 2016; Sun & Vasarhelyi, 2018; Gepp, Kumar, & Bhattacharya, 2010;
Generalized Boosting	2	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017;
Genetic programming	2	Dunis, Laws, & Karathanasopoulos, 2013; Feldman & Gross, 2005;
Logiboost	1	Creamer & Freund, 2010;
TreeNet	1	Jones & Wang, 2019;
Genetic algorithm	1	Varetto, 1998;
Gradient boosted regression tree	1	Rasekhschaffe & Jones, 2019;
ARTIFICIAL NEUTRAL NETWORK (ANN)	51	Altman, Marco, & Varetto, 1994; Jones, Johnstone, & Wilson, 2015; Trippi & DeSieno, 1992; Yang, Platt, & Platt, 1999; Lahmiri, 2016; Dunis, Laws, & Karathanasopoulos, 2013; Wanke, Azad & Barros, 2016; Guotai, Abedin, & E–Moula, 2017; Qi, 1999; Nag & Mitra, 2002; Pompe & Bilderbeek, 2005; Rodrigues & Stevenson, 2013; Galeshchuk & Mukherjee, 2017; Sun & Vasarhelyi, 2018; Qi & Maddala, 1999; Reboredo, Matías, & Garcia-Rubio, 2012; Le & Viviani, 2018; Parot, Michell, & Kristjanpoller, 2019; Chen et al., 2013; Pichl & Kaizoji, 2017; Vortelinos, 2017; Lahmiri

		& Bekiros, 2019; Sabau, Popa et al., 2021; Zhang, Chu, & Shen, 2021; Chen & Wan, 2021; Corazza, De March, & Di Tollo, 2021; Amelot, Subadar Agathee, & Sunecher, 2021; Bekiros & Georgoutsos, 2008; Dunis, Laws, & Karathanasopoulos, 2013; Dunis, Laws, & Sermpinis, 2010; Sermpinis, Laws, and Dunis, 2013; Reber, 2014; Heston & Sinha, 2017; Rasekhschaffe & Jones, 2019; Abdou et al., 2020; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Kanas, 2001; Loukeris & Eleftheriadis, 2015; Abedin et al., 2019; Mselmi, Lahiani & Hamza, 2017; D'Hondt et al., 2020; Bucci, 2020; Funahashi, 2020; Lu & Ohta, 2003; Booth, Gerding & McGroarty, 2015; Holopainen & Sarlin, 2017; Zhao et al., 2018; Jang & Lee, 2019; Sariev & Germano, 2020; Jagric, Jagric, & Kracun, 2011; Hamdi & Aloui, 2015;
Multilayer perceptron (MLP)	9	Dunis, Laws, & Karathanasopoulos, 2013; Dunis, Laws, & Sermpinis, 2010; Sermpinis, Laws, and Dunis, 2013; Reber, 2014; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Kanas, 2001; Loukeris & Eleftheriadis, 2015; Abedin et al., 2019; Zhao et al., 2018;
Backpropagation Neural Network (BPNN)	8	Qi & Maddala, 1999; Lahmiri & Bekiros, 2019; Moshiri & Cameron, 2000; Pichl & Kaizoji, 2017; Yang, Platt, & Platt, 1999; Sermpinis, Laws, & Dunis, 2013; Hamdi & Aloui, 2015; Amelot, Subadar Agathee, & Sunecher, 2021;
Recurrent Neural Network (RNN)	5	Dunis, Laws, & Karathanasopoulos, 2013; Dunis, Laws, & Sermpinis, 2010; Sermpinis, Laws, & Dunis, 2013; Zhao et al., 2018;
Cascade-correlation Neural network (CASCOR)	3	Altman, Marco, & Varetto, 1994; Coats & Fant, 1993; Reber, 2014;
Higher order Neural network (HONN)	3	Dunis, Laws, & Karathanasopoulos, 2013; Dunis, Laws, & Sermpinis, 2010; Sermpinis, Laws, & Dunis, 2013;
Long Short-Term Memory Networks (LSTM)	2	Zhang, Chu, & Shen, 2021; Bucci, 2020;
Radial basis function Network (RBFN)	2	Lahmiri & Bekiros, 2019; Episcopos, Pericli, & Hu, 1998;
Principal component combining/ analysis	2	Vortelinos, 2017; Amelot, Subadar Agathee, & Sunecher, 2021;
Feed-forward neural network	1	Hamdi & Aloui, 2015;
Generative Bayesian Neural network (GBNN)	1	Jang & Lee, 2019;
NARX-Neural Network	1	Xu & Zhao, 2020; Amelot, Subadar Agathee, & Sunecher, 2021;
Fixed geometry neural networks (FGNN)	1	Nag & Mitra, 2002;
Genetic algorithm neural networks (GANN)	1	Nag & Mitra, 2002;
Psi sigma Neural Network	1	Dunis, Laws, & Sermpinis, 2010;
Probabilistic Neural Network	1	Yang, Platt, & Platt, 1999;
Leaning vector quantization Neural network (LVQ)	1	Jagric, Jagric, & Kracun, 2011;
DEEP LEARNING (Deep neural networks / deep convolution neural network CNN)	12	Galeshchuk & Mukherjee, 2017; Tashiro et al., 2019; Sun & Vasarhelyi, 2018; Sirignano, 2018; Dixon, Klabjan, & Bang, 2017; Culkin & Das, 2017; Cao et al., 2020; Kim & Kim, 2020; Chen & Ge, 2021; Lahmiri & Bekiros, 2019; Abdou et al., 2020; Lahmiri & Bekiros, 2019;
HYBRID METHODS	3	Mselmi, Lahiani & Hamza, 2017; Wanke, Azad, & Barros, 2016; Wanke et al., 2016;

Multi criteria decision making (TOPSIS) combined with Neural Network	2	Wanke, Azad & Barros, 2016; Wanke et al., 2016;
Partial least squares regression (PLS+ Support Vector Machine)	1	Mselmi, Lahiani, & Hamza, 2017
REGRESSION (Panel regression, linear regression, multivariate regression, cross-sectional, OLS, multivariate adaptive regression splines MARS)	9	Qi, 1999; Reber, 2014; Scholtus, van Dijk, & Frijns, 2014; Qi & Maddala, 1999; Calomiris & Mamaysky, 2019; Jain, Jain, & Khanapure, 2021; Kim & Kim, 2014; Hendershott, Jones, & Menkveld, 2011; Kamiya, Kim, & Park, 2018; D'Hondt et al., 2020; Jain, Jain, & Khanapure, 2021; Kim & Kim, 2014; Hendershott, Jones, & Menkveld, 2011;
Logit	17	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017; Jagric, Jagric, & Kracun, 2011; Butaru et al., 2016; Sun & Vasarhelyi, 2018; Le & Viviani, 2018; Lu, Shen, & Wei, 2013; Rodrigues & Stevenson, 2013; Deku, Kara & Semeyutin, 2020; Kamiya, Kim, & Park, 2018; Kumar et al., 2019; Cao et al., 2020; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Mselmi, Lahiani & Hamza, 2017; Episcopos, Pericli, & Hu, 1998; Creamer, 2012; Holopainen & Sarlin, 2017;
AUTOREGRESSIVE MODELS (Arma, Arima, Garch, Har, Var)1[2]	14	Zhao et al., 2018; Galeshchuk & Mukherjee, 2017; Moshiri & Cameron, 2000; Amelot, Subadar Agathee, & Sunecher, 2021; Herdershott, Jones, & Menkveld, 2011; Chabou et al., 2014; Frino et al., 2017; Parot, Michell, & Kristjanpoller, 2019; Calomiris & Mamaysky, 2019; Reboredo, Matías, & Garcia-Rubio, 2012; Vortelinos, 2017; Fernandes, Medeiros, & Scharth, 2014; Bucci, 2020; Jones, Johnstone, & Wilson, 2015;
Linear Discriminant Analysis (LDA)	7	Altman, Marco, & Varetto, 1994; Jones et al., 2017; Varetto, 1998; Lahmiri, 2016; Le & Viviani, 2018; Cortés, Martínez, & Rubio, 2008; Holopainen & Sarlin, 2017;
Probit	3	Jones, Johnstone, & Wilson, 2015; Jones et al., 2017; Lahmiri, 2016;
Nonlinear autoregressive exogenous model (NARX)	2	Amelot, Subadar Agathee, & Sunecher, 2021; Bucci, 2020;
Multiple discriminant analysis (MDA)	2	Coats & Fant, 1993; Pompe & Bilderbeek, 2005;
Exponential smoothing (ETS)	1	Galeshchuk & Mukherjee, 2017;
Generalized additive-model (GAM)	2	Jones, Johnstone, & Wilson, 2015; Petukhina, Reule, & Härdle, 2021;
OTHER		
Spatial model	2	Litzenberger, Castura, & Gorelick, 2012; Kelejian & Mukerji, 2016;
Data mining/Text mining/Text analysis	6	Wei et al., 2019; Lu, Shen, & Wei, 2013; Huang & Kuan, 2021; Li et al., 2020; Trinkle & Baldwin, 2016; Gepp, 2018; Yin, Wu & Kong, 2020;
Sentiment analysis	2	Huang & Kuan, 2021; Houlihan & Creamer, 2021;
Natural Language Processing	1	Calomiris & Mamaysky, 2019;
Asset pricing models	1	Tao et al., 2021;
Image processing	1	Kamiya, 2018;

1 ARMA: Autoregressive–moving-average model, ARIMA: Autoregressive integrated moving average, HAR: Heterogeneous autoregressive approach, VAR: vector autoregressive approach.

Grey relational analysis	1	Chen et al., 2013;
Random walk	2	Qi & Maddala, 1999; Reboredo, Matías, & Garcia-Rubio, 2012;
Type of Method/Paper		
Qualitative Paper	3	Huang & Kuan, 2021; Wei et al., 2019; Xu, Zhang, & Feng, 2019;
Quantitative Paper	103	Hendershott, Jones, & Menkveld, 2011; Calomiris & Mamaysky, 2019; Altman, Marco, & Varetto, 1994; Chabou et al., 2014; Khandani, Kim, & Lo, 2010; Coats & Fant, 1993; Jones, Johnstone, & Wilson, 2015; Jones, Johnstone, & Wilson, 2017; Galeshchuk & Mukherjee, 2017; Butaru et al., 2016; Varetto, 1998; Trippi & DeSieno, 1992; Jain, 2005; Lahmiri, 2016; Kim & Kim, 2014; Kercheval & Zhang, 2015; Sun & Vasarhelyi, 2018; Gepp, Kumar, & Bhattacharya, 2010; Dunis, Laws, & Karathana-sopoulos, 2013; Dunis, Laws, & Sermpinis, 2010; Yang, Platt, & Platt, 1999; Serm-pinis, Laws, and Dunis, 2013; Mirmirani & Li, 2004; Scholtus, van Dijk, & Frijns, 2014; Sirignano, 2018; Qi & Maddala, 1999; Feldman & Gross, 2005; Reboredo, Matías, & Garcia-Rubio, 2012; Fernandes, Medeiros, & Scharth, 2014; Wanke, Azad & Barros, 2016; Kelejian & Mukerji, 2016; Guotai, Abedin, & E–Moula, 2017; Frino et al., 2017; Le & Viviani, 2018; Parot, Michell, & Kristjanpoller, 2019; LeBaron, Ar-thur, & Palmer, 1999; Qi, 1999; Moshiri & Cameron, 2000; Nag & Mitra, 2002; Pompe & Bilderbeek, 2005; Cortés, Martínez, & Rubio, 2008; Jagric, Jagric, & Kra-cun, 2011; Lu, Shen & Wei, 2013; Rodrigues & Stevenson, 2013; Chen et al., 2013; Dixon, Klabjan, & Bang, 2017; Culkin & Das, 2017; Law & Shawe-Taylor, 2017; Pichl & Kaizoji, 2017; Vortelinos, 2017; Renault, 2017; Dubey, Chauhan, & Syamala, 2017; Jiang & Jones, 2018; Sabau, Popa et al., 2021; Zhang, Chu, & Shen, 2021; Chen and Ge, 2021; Deku, Kara & Semeyutin, 2020; Burggraf, 2021; Huang & Guo, 2021; Chen & Wan, 2020; Petukhina, Reule, & Härdle, 2021; Houlihan & Creamer, 2019; Tao et al., 2021; Corazza, De March, and Di Tollo, 2021; Amelot, Subadar Agathee, & Sunecher, 2021; Jain, Jain, & Khanapure, 2021; Caglayan et al., 2020; Calomiris & Mamaysky, 2019; Kamiya, Kim, & Park, 2018; Bekiros & Georgoutsos, 2008; Reber, 2014; Kumar et al., 2019; Heston & Sinha, 2017; Rasekhschaffe & Jones, 2019; Cao et al., 2020; Abdou et al., 2020; Xu & Zhao, 2020; Papadimitriou, Goga & Agrape-tidou, 2020; Soleymani and Vasighi, 2020; Uddin et al., 2020; Yin, Wu & Kong, 2020; Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, 2021; Kanas, 2001; Loukeris & Eleftheriadis, 2015; Abedin et al., 2019; Mselmi, Lahiani, and Hamza, 2017; D'Hondt et al., 2020; Bucci, 2020; Gao, Liu & Wu, 2016; Frino, Garcia & Zhou, 2020; Wanke et al., 2016; Jones & Wang, 2019; Episcopos, Pericli, & Hu, 1998; Funahashi, 2020; Lu & Ohta, 2003; Creamer & Freund, 2010; Creamer, 2012; Booth, Gerding, & McGroarty, 2015; Holopainen & Sarlin, 2017; Zhao et al., 2018; Jang & Lee, 2019; Tashiro et al., 2019; Sariev & Germano, 2020; Kim & Kim, 2020; Li et al., 2020;
Literature Review	4	Litzenberger, Castura, & Gorelick, 2012; Trinkle & Baldwin, 2016; Lahmiri & Be-kiros, 2019; Hamdi & Aloui, 2015;

Note: The table enlists the type of method applied. All papers utilize more than one method.

3.1.8 Top cited and trending articles.

We also summarize the top-cited articles in the literature by using HistCite software. Table 8 shows the lists.

Table 8. Top cited articles

Top Cited Articles Based on Total Local Citations				Top Cited Articles Based on Total Global Citations			
Authors/ Year	**TLC**	**TLC/T**	**ABS**	Authors/ Year	**TGS**	**TGS/T**	**ABS**
Mclean & Pontiff, (2016)	8	1,33	4*	Mclean & Pontiff, (2016)	243	40,5	4*
Hendershott, Jones, & Menkveld, (2011)	46	4,18	4*	Ferson, Sarkissian, & Simin, (2003)	210	11,05	4*
Chaboud et al., (2014)	18	2,25	4*	Baines & Langfield-Smith, (2003)	210	11,05	4*
Jain, (2005)	6	0,35	4*	Chaboud et al., (2014)	143	17,88	4*
Szakmary, Shen, & Sharma, (2010)	5	0,42	3	Pompe & Bilderbeek, (2005)	78	4,59	4
Altman, Marco & Varetto, (1994)	25	0,89	3	Hendershott, Jones, & Menkveld (2011)	476	43,27	4*
Jones, Johnstone, & Wilson, (2017)	10	2	3	Lebaron, Arthur, & Palmer, (1999)	347	15,09	4*
Leung, Daouk, & Chen, (2000)	8	0,36	3	Jain, (2005)	83	4,88	4*
Cartea & Jaimungal, (2015)	8	1,14	3	Altman, Marco & Varetto, (1994)	380	13,57	3
Butaru et al., (2016)	8	1,33	3	Coats & Fant, (1993)	162	5,59	3
Yang, Platt, & Platt, (1999)	6	0,26	3	Yang, Platt, & Platt, 1999)	132	5,74	3
Buehler et al., (2019)	6	2	3	Rapach, Wohar, & Rangvid, (2005)	132	7,76	3
Varetto, (1998)	7	0,29	3	Khandani, Kim, & Lo, (2010)	126	10,5	3
Khandani, Kim, & Lo (2010)	16	1,33	3	Szakmary, Shen, & Sharma, (2010)	86	7,17	3
Coats & Fant, (1993)	14	0,48	3	Fuertes, Miffre, & Rallis, (2010)	79	6,58	3
Jones, Johnstone, & Wilson, (2015)	11	1,57	3	Kim & Laskowski, (2018)	119	29,75	1
Trippi & Desieno, (1992)	6	0,2	2	Varetto, (1998)	126	5,25	3
Fisher, Garnsey, & Hughes, (2016)	10	1,67	1	Helmbold et al., (1998)	118	4,92	3
Lahmiri, (2016)	6	1	1	Leung, Daouk, & Chen, (2000)	166	7,55	3
Galeshchuk & Mukherjee, (2017)	9	1,8	1	Lebaron, (2001)	81	3,86	2

Note: Table summarises top-cited articles.

3.1.9. Keyword Analysis

By using the VOSviewer software, we conducted a cartography analysis and identified a network among keywords in Figure 3.

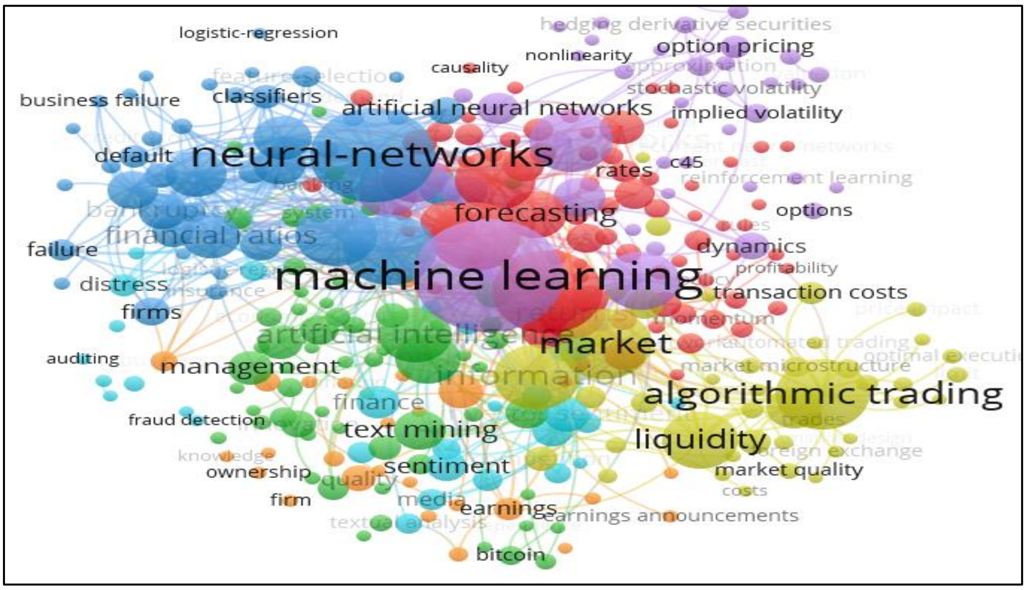

Figure 3. Keyword Analysis

3.2 IDENTIFICATION OF RESEARCH STREAMS

Through CiteSpace software, we identified ten research streams in the literature. Figure 4 shows citation mapping, a visual representation of citation relationships among papers.

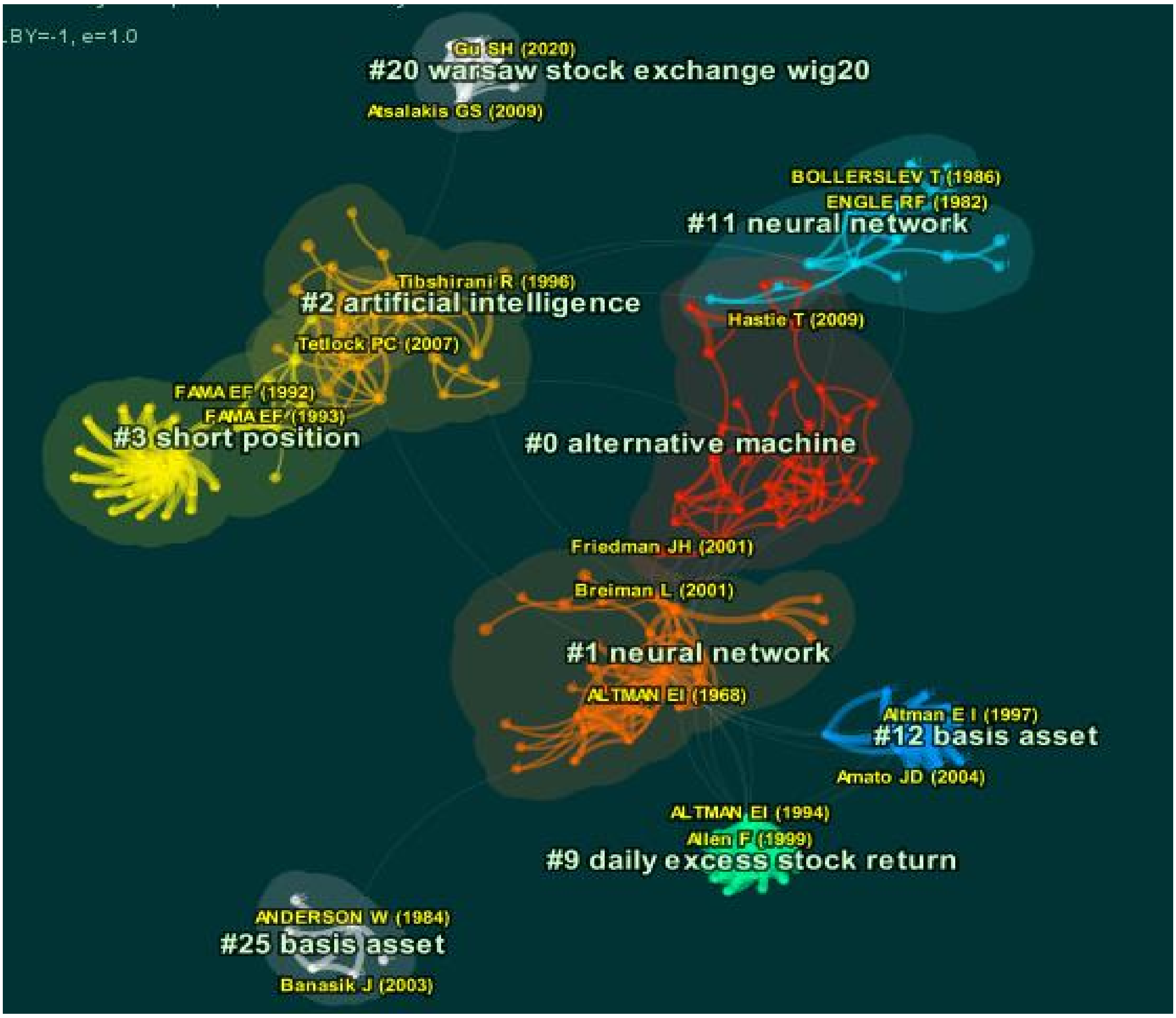

Figure 4. Citation Mapping: Identification of Research Streams

This technique maps top-cited articles in relation to the papers that cite them to allow for further interpretation (Bahoo, Alon, & Paltrinieri, 2020). As shown in the figure above, literature on AI in finance is extensive.

We identified ten research streams : (1) AI and the stock market, (2) AI and Trading Models, (3) AI and Volatility Forecasting, (4) AI and Portfolio Management, (5) AI and Performance, Risk, & Default Valuation, (6) AI and Bitcoin, Cryptocurrencies, (7) AI and Derivatives, (8) AI and Credit Risk in Banks, (9) AI and Investor Sentiments Analysis, (10) AI and Foreign Exchange Management. Some research streams are further divided into sub-streams as they deal with various aspects of the same main topic. We now discuss the ten research streams and summarize the key papers in Table 9.

3.2.1. Stream 01: AI and Stock Market

This stream comprises two sub-streams: (1.1) Algorithmic trading and stock market, and (1.2) AI and stock price prediction.

The first sub-stream deals with the impact of algorithmic trading (AT) on financial markets: Herdershott, Jones, & Menkveld, (2011) argue that AT increases market liquidity by reducing spreads, adverse selection, and trade-related price discovery. This results in a lowered cost of equity for listed firms in the medium-long term, especially in emerging markets (Litzenberger, Castura, & Gorelick, 2012). As opposed to human traders, algorithmic trading adjusts faster to information and generates higher profits around news announcements thanks to better market timing ability and rapid executions (Frino et al., 2017).

Even though high-frequency trading (i.e., a subset of AT) has sometimes increased volatility related to news or fundamentals, and transmitted it within and across industries, AT has overall reduced return volatility variance and improved market efficiency (Kelejian & Mukerji, 2016; Litzenberger, Castura, & Gorelick, 2012).

The second sub-stream investigates the use of neural networks and traditional methods to forecast stock price and assets performance. ANNs are preferred to linear models because they capture the non-linear relationships between stock returns and fundamentals and are more sensitive to changes in variables relationships (Kanas, 2001; Qi, 1999). Dixon, Klabjan, & Bang, (2017) argue that deep neural networks have strong predictive power with an accuracy rate equal to 68%, whereas Zhang, Chu, & Shen, (2021) propose a model that outperforms all classical ANNs in terms of prediction accuracy and rational time cost: the Long Short-Term Memory Networks (LSTM) empowered with online investor attention proxies.

3.2.2. Stream 02: AI and Trading Models

Neural networks and machine learning algorithms are used to build intelligent automated trading systems. Creamer & Freund, (2010) create a machine learning-based model that analyses stock price series and then selects the best performing assets by suggesting a short or long position. The model is also equipped with a risk management overlayer preventing transaction when the trading strategy is not profitable. Similarly, Creamer, (2012) uses the above-mentioned logic in high-frequency trading futures: the model selects the most profitable and less risky futures by sending a long or short recommendation. To build an efficient trading model, Trippi & DeSieno, (1992) combine several neural networks into a single decision rule system that outperforms the single neural networks; Kercheval & Zhang, (2015) use a supervised learning method (i.e., multi-class SVM) that automatically predicts mid-price movements in high-frequency limit order books by classifying them in low-stationary-up. These predictions are embedded in trading strategies and yield positive payoffs with controlled risk.

3.2.3. Stream 03: AI and Volatility Forecasting

The volatility index (VIX) from Chicago Board Options Exchange (CBOE) is a measure of market sentiment and expectations. Forecasting volatility is not a simple task because of its very persistent nature (Fernandes, Medeiros, & Scharth, 2014).

According to Fernandes, Medeiros, & Scharth, (2014), the VIX is negatively related to the S&P500 index return and positively related to its volume. The heterogeneous autoregressive (HAR) model yields the best predictive results as opposed to classical neural networks (Fernandes, Medeiros, & Scharth, 2014; Vortelinos, 2017). Modern neural networks such as LSTM and NARX (nonlinear autoregressive exogenous network), also qualify as valid alternatives (Bucci, 2020). Another promising class of neural networks is the higher-order neural network (HONN) used to forecast the 21-day-ahead realised volatility of FTSE100 futures. Thanks to its ability to capture higher-order correlations within the dataset, HONN shows remarkable performance in terms of statistical accuracy and trading efficiency over multilayer perceptron (MLP) and the recurrent neural network (RNN) (Sermpinis, Laws & Dunis, 2013).

3.2.4. Stream 04: AI and Portfolio Management

This research stream analyses AI in portfolio selection. Soleymani & Vasighi, (2020) consider a clustering approach paired with VaR analysis to improve asset allocation: they group the least risky and more profitable stocks and allocate them in the portfolio. More elaborate asset allocation designs incorporate a bankruptcy detection model and an advanced utility performance system: before adding the stock to the portfolio, the sophisticated neural network estimates the default probability of the company and asset's contribution to the optimal portfolio (Loukeris & Eleftheriadis, 2015). Index-tracking powered by deep learning technology minimizes tracking error and generates positive performance (Kim & Kim, 2020). The asymmetric copula method for returns dependence estimates, further promotes the portfolio optimization process (Zhao et al., 2018).

To sum up, all papers show that AI-based prediction models improve the portfolio selection process by accurately forecasting stock returns (Zhao et al., 2018).

3.2.5. Stream 05: AI and Performance, Risk, Default Valuation

This research stream comprehends three sub-streams: (1) AI and Corporate Performance, Risk, & Default Valuation; (2) AI and Real Estate Investment Performance, Risk, & Default Valuation; (3) AI and Banks Performance, Risk, & Default Valuation.

The first sub-stream examines corporate financial condition to predict financially distressed companies (Altman, Marco, & Varetto, 1994). Jones, Johnstone, & Wilson, (2017) and Gepp, Kumar, & Bhattacharya, (2010) determine the probability of corporate default. Sabău Popa et al., (2021) predict business performance based on a composite financial index. Results of the afore-mentioned papers confirm that AI-powered classifiers are extremely accurate and easy to interpret, hence, superior to classic linear models. A quite interesting paper surveys the relation between face masculinity traits in CEOs and firm riskiness through image processing (Kamiya, Kim, & Park, 2018). Results reveal that firms lead by masculine-faced CEO have higher risk and leverage ratio and are more frequent acquirers in M&A operations. The second research stream focuses on mortgage and loan default prediction (Feldman & Gross, 2005; Episcopos, Pericli, & Hu, 1998). Chen et al., (2013) evaluate real estate investments returns by forecasting the REIT index: results indicate that industrial production index, lending rate, dividend yield and stock index influence real estate investments. All forecasting techniques adopted (i.e., supervised machine learning and ANNs) outperform linear models in terms of efficiency and precision.

The third sub-stream deals with banks' performance. In contradiction with past research, a text-mining study argues that the most important risk factors in banking are non-financial, i.e., regulation, strategy, management operation. However, findings from text analysis are limited to the disclosed content in the papers (Wei et al., 2019). A highly performing NN-based study on the Malaysian and Islamic banking sector asserts negative cost structure, cultural aspects and regulatory barriers (i.e., low competition) lead to inefficient banks compared to the U.S.,' which, on the contrary, are more resilient, healthier and well regulated (Wanke, Azad, & Barros, 2016; Wanke et al., 2016; Papadimitriou, Goga, & Agrapetidou, 2020).

3.2.6. Stream 06: AI and Cryptocurrencies

Although algorithms and AI advisors are gaining ground, human traders still dominate the cryptocurrency market (Petukhina, Reule, & Härdle, 2021). For this reason, substantial arbitrage opportunities are available in the Bitcoin market, especially for USD-CNY and EUR-CNY currency pairs (Pichl & Kaizoji, 2017). Concerning daily realised volatility, the HAR model delivers good results. Likewise, the feed-forward neural network effectively approximates the daily logarithmic returns of BTCUSD and the shape of their distribution (Pichl & Kaizoji, 2017).

The Hierarchical Risk Parity (HRP) approach, an asset allocation method based on machine learning, represents a powerful risk management tool able to manage the high volatility characterizing Bitcoin prices, thereby helping cryptocurrency investors (Burggraf, 2021).

3.2.7. Stream 07: AI and Derivatives

ANNs and machine learning models are accurate predictors in pricing financial derivatives. Jang & Lee, (2019) propose a machine learning model that outperforms traditional American option pricing models: the generative Bayesian NN; Culkin & Das (2017) use a feed-forward deep NN to reproduce Black&Scholes option pricing formula with a high accuracy rate. Similarly, Chen & Wan, (2021) suggest a deep NN for American option and deltas pricing in high dimensions. Funahashi, (2020), on the contrary, rejects deep learning for option pricing due to the prices instability and introduces a new hybrid method that combines ANNs and asymptotic expansion (AE). This model does not directly predict the option price but measures instead, the difference between the target (i.e., derivative price) and its approximation C. As a result, the ANN becomes faster, more accurate and "lighter" in terms of layers and training data volume. This innovative method mimics a human learning process when one learns about a new object by recognizing its differences from a similar and familiar item (Funahashi, 2020).

3.2.8. Stream 08: AI and Credit Risk in Banks

Since credit risk in the banking industry is completely different from credit risk in firms, the two are treated separately.

This research stream includes: (1) AI and Bank Credit Risk, (2) AI and Consumer Credit Risk & Default, (3) AI and Financial Fraud detection/ Early Warning System, (4) AI and Credit Scoring Models.

The first sub-stream addresses bank failure prediction. Machine learning and ANNs significantly outperform statistical approaches, although they lack transparency (Le & Viviani, 2018). To overcome this limitation, Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, (2021) combine traditional methods (i.e., logistic regression) with

AI (i.e., MLP)[3] thus, gaining valuable insights on explanatory variables. With the scope of preventing further global financial crises, the banking industry relies on financial decision support systems (FDSSs), which are strongly improved by AI-based models (Abedin et al., 2019).

The second sub-stream confronts classic and advanced consumer credit risk models. Supervised learning tools as SVM, random forest and advanced decision trees architectures are powerful predictors of credit card delinquency: some of them can predict credit events up to 12 months in advance (Lahmiri, 2016; Khandani, Kim, & Lo, 2010; Butaru et al., 2016).

Jagric, Jagric, & Kracun, (2011) propose a learning vector quantization (LVQ) NN that better deals with categorical variables, achieving an excellent classification rate (i.e., default, non-default). Such methods overcome logit-based approaches and result in cost savings ranging from 6% up to 25% of total losses (Khadani, Kim, & Lo, 2010).

The third group discusses the role of AI in early warning systems. On a retail level, advanced random forests accurately detect credit card fraud based on customer financial behaviour and spending pattern, and then flag it for investigation (Kumar et al., 2019). Similarly, Coats & Fant, (1993) build a NN alert model for distressed firms that outperforms linear techniques.

[3] Multiple layer perceptron

On a macroeconomic level, systemic risk monitoring models enhanced by AI technologies, i.e., k-nearest neighbours and sophisticated NNs, support macroprudential strategies and send alerts in case of global unusual financial activities (Holopainen, & Sarlin, 2017; Huang & Guo, 2021). However, these methods are still a work-in-progress.

The last group studies intelligent credit scoring models. Once again, machine learning systems, Adaboost and random forest, in this case, deliver the best forecasts for credit rating changes. These models are robust to outliers, missing values, overfitting and require minimal data intervention (Jones, Johnstone, & Wilson, 2015). Combining data mining and machine learning, Xu, Zhang & Feng, (2019) build a highly sophisticated model that selects the most important predictors and eliminates noisy variables, before performing the task.

3.2.9. Stream 09: AI and Investor Sentiment Analysis

Investor sentiment has become increasingly important in stock prediction. For this purpose, sentiment analysis extracts investor sentiment from social media platforms (e.g., StockTwits, Yahoo-finance, eastmoney.com) through natural language processing and data mining techniques and classifies it into negative or positive (Yin, Wu, & Kong, 2020). We can use the resulting sentiment as (1) risk factors in asset pricing models; (2) input data to forecast asset price direction; (3) intraday stock index returns (Houlihan & Creamer, 2021; Renault, 2017). Based on Yin, Wu, & Kong, (2020) study, investor sentiment correlates positively with stock liquidity through order flow imbalance, especially in bear markets. Liquidity sensitivity is higher for firms with a higher book-to-market ratio, larger size, and lower risk, operating in less regulated markets (Yin, Wu, & Kong, 2020). Likewise, daily news predicts stock returns for only one to two days, but weekly news predicts stock returns for one quarter (Heston & Sinha, 2017). Positive news stories increase stock gains quickly, while negative stories receive a long-delayed reaction. Much of the delayed response to news occurs around the subsequent earnings announcement (Heston & Sinha, 2017).

3.2.10. Stream 10: AI and Foreign Exchange Management

Cost-effective trading or hedging activities in the forex market require accurate exchange rates forecasts (Galeshchuk & Mukherjee, 2017). The HONN model significantly outperforms traditional neural networks (i.e., multi-layer perceptron, recurrent NNs, Psi sigma-models) in forecasting and trading the EUR/USD currency pair using ECB daily fixing series as input data (Dunis, Laws, & Sermpinis, 2010). On the contrary, Galeshchuk & Mukherjee, (2017), consider these methods unable to predict the direction of change of forex rates and, therefore, ineffective at supporting profitable trading. For this reason, they apply a deep NN (Convolution NNs) to forecast three main exchange rates (i.e., EUR/USD, GBP/USD, JPY/USD). The model performs remarkably better than time series models (e.g., ARIMA: Auto-regressive integrated moving average) and machine learning classifiers. To summarize, AI-based models such as NARX and the above-mentioned techniques, achieve better prediction performance than statistical or time series models (Amelot, Subadar Agathee, & Sunecher, 2021).

Table 09. Summary of Key Papers

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Streams 1: AI and Stock Market						
Sub-Stream 1.1: Algorithmic Trading (AI) and Stock Market						
Herdershott, Jones, & Menkveld, (2011)	- How does Algorithmic Trading (AT) improve liquidity?	- AT	- NYSE - 2002-2003 - NYSE, CRSP[4], TAQ[5] databases - USA	- Liquidity and spread measures	- AT	- AT improves liquidity and informativeness of quotes. - For large stocks, it reduces spreads, adverse selection and trade-related price discovery
Jain, (2005)	- How does AT reduce the Cost of Equity?	- AT	- 120 stock exchanges - 1969-2001 - Bloomberg, Lexis Nexis, Handbook of World Stock, Derivative and Commodity exchanges - Europe, Asia, America	- Equity premium	- AT	- In the long run, AT reduces the cost of equity for listed firms, especially in emerging markets.
Frino et al., (2017)	- Impact of corporate earning news on algorithmic trading - Speed of price adjustments	- AT	- ASX 200 - 2008-2009 - Thompson Reuters - Australia	- Speed of price reaction - Trading profits	- AT	- Algorithmic traders react faster to information than non-algorithmic traders thanks to rapid execution (better market timing) - AT generate profits up to 90s after news release while non-AT generate losses during this time. - AT accelerates information incorporation process and improves market efficiency
Kelejian & Mukerji, (2016)	- How does high-frequency trading (HTF) impact asset prices volatility?	- AT	- S&P500 - 1985-2012 - CRSP, FRED[6], SEC[7] - USA	- Return volatility	- HFT - Industry measures (production, employment)	- In some cases, HFT increases volatility arising from news relating to fundamentals and is associated with its transmission within and across industries. - The advent of AT has increased both variance and covariance of return volatility in most industries: overall, AT has coincided with reduced return volatility variance

[4] Centre for Research in Security Prices
[5] Trades and Quotes
[6] Federal Reserve Economic Data
[7] Securities and Exchange Commission

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Litzenberger, Castura, & Gorelick, (2012)	- How does AT improve equity market quality?	- AT	- NYSE, NASDAQ stocks - 1994-2009 - TAQ, CRSP, CBOE - USA	- Market efficiency	- HFT	- HTF has improved overall market efficiency by narrowing bid-ask spreads, increasing liquidity, reducing transitory pricing errors and intraday volatility (short term variance)
Sub-Stream 1.2: AI and Stock Price Prediction & Performance						
Qi, (1999)	- Linear regression (LR) *vs* nonlinear NN models: who has the best predictive performance and profitability?	- Predictive/ forecasting systems	- S&P500 - 1954-1992 - NYSE	- excess returns	- dividend yield - earning price ratio - 1-month treasury bill - inflation rate - rate of change in industrial output - grow rate of money stock	- The NN model performs better stock returns forecasts than LR models. - A recursive approach makes NN more sensitive to changes in variables relationships, thus more accurate and performing.
Dixon, Klabjan, & Bang, (2017)	- Application of deep neural network in financial market forecasting	- Predictive/ forecasting systems	- Commodities, FX futures - 1991-2014 - CME[8] - USA	- Price direction	- Historical price movements and co-movements between symbols	- Deep neural networks are strong and accurate stock predictive methods (up to 68% accuracy).
Kanas, (2001)	- Best stock performance forecaster: linear method vs ANN[9]	- Predictive/ forecasting systems	- Dow Jones, FT - 1980-1990 - Datastream - UK, USA	- Stock returns	- Trading volume - Dividends	- ANN and linear regression perform badly in terms of predicting the directional change of the two indices; - ANN is preferable to linear forecast because they capture the non-linear relationship between stock returns and fundamentals.
Zhang, Chu, & Shen, (2021)	- Prediction of stock prices replicating investor attention	- Predictive/ forecasting systems	- SSE50 index, Baidu Index - 2016-2019 - CSMAR database - Shanghai (China)	- Stock Price	- Investor attention proxies - Market variable (price, volume, turnovers attention variables: media coverage index, ASVI abnormal Baidu search volume)	- Compared with other ANNs, Long Short-Term Memory Networks (LSTM) is more suitable to process the non-linear, non-stationary, and complicated financial time series. - LSTM employing online investor attention proxies outperforms other models (ANN) with the best prediction accuracy and rational time cost.

[8] Chicago Mercantile Exchange
[9] Artificial Neural Network

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Stream 2: AI and Trading Models						
Kercheval & Zhang, (2015)	- Automation of stock price forecast in high-frequency limit order books	Machine learning	- MSFT, INTC, AMZN, AAPL, GOOG order books - NASDAQ database - USA	- Spread crossing. - Mid-Price movements (upward, downward, stationary)	Price and volumes of bid and ask side	- They design a framework to automate price prediction for limit order book dynamics in real-time. The Multiclass-SVM model predicts various metrics with high accuracy and delivers efficient predictions that can be embedded in trading strategies and yield profits with low risk.
Trippi & DeSieno, (1992)	- Automated Trading with NN	Robo-advisory	- S&P500 index futures - 1986 – 1990 - USA	- Long-short recommendation	- Open, high, low and close price information, recent volatility, statistics from past data	- By incorporating several trained neural networks into a single composite Boolean decision rule system, this system outperforms each of its individual networks and the index.
Creamer & Freund, (2010)	- Smart automated trading system and risk management layer	- AT	- S&P 500 index - 2003-2005 - CRSP - USA	- Long-short position	- Price series (close, open, high and low prices, volume), beta excess return - Investments signals	- Combining the experts and a risk management layer, this model selects only the stocks with the strongest predictions and avoids trading when there is a history of negative performance. - The boosting approach improves the predictive capacity when indicators are aggregated as a single predictor and reduces the use of computational resources.
Creamer, (2012)	- Trading model that selects most profitable and less risky futures (High-frequency trading futures)	- AT/Machine learning	- FDAX, FESX[10] - March 2009 (22 trading days) - Eurex - Europe	- return of the futures contract (negative: sell - positive: buy)	- Price and volume indicators, transaction costs - Momentum and oscillation indicators - Volatility, liquidity and return indicators	- The models are made up of a learning layer that sends a buy-sell limit order based on futures return forecast. - The risk management layer minimizes risky trades and trading strategy makes a profit from bid-ask spreads.
Stream 3: AI and Volatility Forecasting						
Fernandes, Medeiros, & Scharth, (2014)	- Forecasting and modelling the volatility index using NN	- Predictive/ forecasting systems - Neural networks	- S&P500 - 1990-2013 - CBOE - USA	- VIX	- S&P 500 index k-day return, oil futures return, USD change, Credit spread, Term spread, Federal Fund rates (deviation)	- Vix is independent of Fed rates deviation and credit spreads. - It holds a negative relationship with the S&P 500 index return as well as a positive link with the volume of the S&P 500 index. NN do not perform good forecast of the VIX because of its persistent nature.

[10] Dow Jones EURO STOXX 50 Index Future

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Bucci, (2020)	- Can ANN outperform econometric models?	- Predictive/ forecasting systems	- S&P500 - 1950-2017 - Robert Shiller's and Kenneth website, Datastream - USA	- Log realized volatility	- dividend price ratio, earnings price ratio, Tbill, term spread, default yield spread, inflation, equity market return, value factor[11], Size Premium Factor, Short Term Reversal Factor	- LSTM and NARX neural networks outperform econometric models and improve forecasting accuracy also in a highly volatile framework.
Vortelinos, (2017)	- HAR vs NN combined models: which is more accurate at forecasting volatility?	- Predictive/ forecasting systems	- DJ Industrial average, EUR/USD, PowerShares QQQ, E-mini-Dow futures YM, 30-y US Treasury bonds futures (TXY), energy futures (QQ), gold index options (GOX) - 2002-2011 - USA	- Realized volatility	- realized volatility time series	- Ranking of forecasting models by order of highest performance and accuracy: HAR, PCC, NN, GARCH. - HAR outperforms all other methods.
Sermpinis, Laws & Dunis, (2013)	- Best forecasting model: HONNS *vs* MLP, RNN[12]	- Predictive/ forecasting systems	- FTSE100 - 2007-2008 - UK	- Realized volatility of last 21 trading days	- realised daily return	- Volatility increases as FTSE100 maturity month approaches. - HONNs outperforms RNN and MLP in terms of statistical accuracy and trading efficiency thanks to their ability to capture higher-order correlations within a data set.
Stream 4: AI and Portfolio Management						
Soleymani & Vasighi, (2020)	- Build a model that analyses the efficiency of large portfolios	- Machine learning	- NYSE stocks - March 2020 - USA	- Profitability cluster - Riskiness Cluster	- Open-High-Low-Close (OHLC) prices of the latest trades - VaR and CVaR	- K-means++ clustering technique is an unsupervised learning model: it selects the least risky and more profitable stocks leaving out the riskiest stock from the portfolio.
Zhao et al., (2018)	- Can NN forecasts improve portfolio management decision? - Portfolio optimization process: Neural network Copula (NNC)	- Neural Networks	- ETFs: SPY, DIA, QQQ[13] - 2011-2015 - USA	- ETFs daily returns - Portfolio optimization	- Weight factors - ETFs returns, covariance matrix	- Psi Sigma Network (PSN) outperforms all models in statistical and trading terms. - NNC model leads to significant improvements in the portfolio optimization process.

[11] Value factor, Size premium factor and Short-Term Reversal Factor are all related to Fama-French's models)
[12] HONNs (Higher order neural networks), MLP (multi-layer perceptron), RNN (recurrent neural network)
[13] SPDR S&P 500 ETF Trust (SPY), SPDR Dow Jones Industrial Average ETF Trust (DIA) and Power- Shares QQQ Trust (QQQ)

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Kim & Kim, (2020)	- Build a portfolio that replicates a market index with zero tracking error	- Deep learning	- S&P500, FTSE100, HSI - 2017-2018 - Yahoo! Finance, Investing.com - USA, UK, Hong Kong	- Assets to include in tracking portfolio	- Deep latent representation of asset returns	- The method generates the best index-tracking performance.
Loukeris & Eleftheriadis, (2015)	- Build a model that identifies: (1) if a company will default (2) if the company contributes to optimal portfolio before adding its stock to the portfolio	- Neural Networks, Classification system	- Commercial bank credit portfolio - 1994-1997 - Greece	- Healthy-distressed - Optimal firms to include in portfolio	- Fundamentals, accounting data, market prices	- The most efficient method is a hybrid MLP neural network with genetic optimization: higher classification results and fitness of the data to the model (low error). - The asset allocation model incorporates a bankruptcy detection model and an advanced utility performance system: the hybrid MLP neural network with genetic optimization best predicts company default and the stock contribution to optimal portfolio before adding it
Stream 5: AI and Performance, Risk, & Default Valuation						
Sub-Stream 5.1: AI and Corporate Performance, Risk, & Default Valuation						
Altman, Marco, & Varetto, (1994)	- Financial distress classification and prediction: linear vs NN models	- Predictive/ forecasting systems	- SMEs - 1985-1992 - CB database - Italy	- Sound/unsound	- Financial ratios	- NN is more accurate than Linear discriminant analysis (LDA) - NN limitations: overfitting, black box.
Kamiya, Kim, & Park, (2018)	- Predict firm riskiness based on CEO's facial masculinity with AI.	- Big data analytics (image processing)	- Ceo faces. - 1993-2009 - Google search	- Corporate risk, leverage, acquisition	- CEO masculinity proxy, age, Company size, Roa, Cash Flow, dividend yield	- Masculine-faced CEOs are associated with more riskiness in the firms, keep the leverage ratio higher, and are frequent acquirers.
Jones, Johnstone, & Wilson, (2017)	- Can complex classifiers predict corporate bankruptcies better, compared to simpler more classifiers? - What about interpretability and feasibility?	- Predictive/ forecasting systems - Classification	- Bankrupt firms - 1987–2013 - Standard and Poor's Capital IQ - US	- bankruptcy: 0, healthy: 1	- financial ratios - corporate failure indicators - age, firm size	- Modern classifiers outperform other classifiers. - They are accurate, easy to implement and interpret, require minimal data intervention (predictive performance is immune to shape and structure of data)
Gepp, Kumar, & Bhattacharya, (2010)	- Business failure[14] forecasting	- Predictive/ forecasting systems	- Firms - 1971-1981 - Compustat - USA	- Financial ratios	- Failed/ non failed	- Decision trees are better predictors of business failure than discriminant models.

[14] Failure definition: legally filed for bankruptcy.

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Sabău Popa et al., 2021	- Design a composite financial index to determine the financial performance of listed companies	- Predictive/ forecasting systems	- Listed firms. - 2011-2018 - Bucharest Stock Exchange - Romania	Composite financial performance index (1-100)	- Value, accounting and cash-based indicators	- The index built with the NN approach has good predictive behaviour, but it needs real data and more than one year of data observations.
***Sub-Stream 5.2**: AI and Real Estate Investment Performance, Risk, & Default Valuation*						
Feldman & Gross (2005)	- Classification of mortgage borrowers	Classification /detection /early warning systems	- Residential mortgage contracts - 1993-1997 - Bank of Israeli - Israel	- GOOD: non-defaulters BAD: defaulters	- Mortgage contract features - Borrower's features	- Borrowers' features, rather than mortgage contract features are the strongest predictors of default if accepting bad borrowers is more costly than rejecting good ones. If the costs are equal, mortgage features are used as well.
Chen et al., (2013)	- What impacts the forecasting performance of real estate investment trust (REIT) returns?	- Predictive/ forecasting systems	- REIT index - 2001-2005 - EPRA website - North America, Europe, Asia	- REIT returns index	- interest rate; inflation rate; economic growth rate; industrial production index; money supply growth rate; stock index; dividend yield; lagged REIT price; foreign direct and foreign equity investment.	- REIT index is influenced by real estate characteristics (i.e., industrial production index and interest rates) stock properties of REIT and lagged REIT price. - It is not affected by inflation nor business cycle; money supply, growth rate and foreign equity investment may have spillover effects on the REIT market.
Episcopos, Pericli, & Hu, (1998)	- Can NN predict mortgage default?	- Predictive/ forecasting systems	- Mortgage loans - 1962-1989 - Insurance company database	- Default/ Non default	- Borrower features, location by region, Mortgage features	- ANN outperforms linear models in mortgage default forecasting.
***Sub-Stream 5.3:* AI and Banks Performance, Risk, & Default Valuation**						
Wanke, Azad, & Barros, (2016)	- Analysis of bank efficiency	- Data mining, Predictive/ forecasting systems	- Banks - 2009-2013 - Bank Negara Malaysia - Malaysia	- efficiency score	- personnel expenses, total operating expenses, efficiency levels, total earning asset, total deposits, net interest income operating profit, net income	- Bank performance is mostly impacted by cost structure, cultural factors and regulatory barriers
Papadimitriou, Goga, & Agrapetidou, (2020)	- Analysis of banking system resilience	- Predictive/ forecasting systems	- Financial institutions - 2000-2018 - Federal Deposit Insurance Corporation - USA	- Solvent/non-solvent - Resilience	- Capital adequacy, operational efficiency. - Safety margin, distance from default	- Highly accurate SVM (99.22%): - Lower competition and new regulations have widened the safety margin of the banking system, resulting in a healthier financial sector as banks act more prudently and their number reduces.

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Wei et al., (2019)	- Analysis of bank risk factors	- Text/Data mining	- Financial statements - 2010-2016 - SECS website - USA	- Bank risk factors	- Textual risk disclosures	- The 3 most important bank risk factors are non-financial: regulation, strategy and management operation and politics. - Strategy and reputation-related factors are becoming increasingly important. - Text analysis is limited to the disclosed content
Wanke et al., (2016)	- Model for banking performance analysis	- Predictive/ forecasting systems	- Islamic banks - 2010-2014 - BankScope database - Middle East	- Efficiency score	- Topsis criteria - Contextual and business-related characteristics	- The combined Topsis and NN model suggests country origin and cost structure have a prominent impact on efficiency. - Islamic banking market would benefit from a higher level of competition between institutions.
Stream 6: AI and Bitcoin, Cryptocurrencies						
Pichl & Kaizoji, (2017)	- Prediction of market performance - Are there Bitcoin arbitrage opportunities? - Prediction of Price volatility	- Predictive/ forecasting systems	- Crypto-currency pairs - 2013-2017 - Bloomberg, data.bitcoinity.org server	- log return of Bitcoin - arbitrage spread. - Realized volatility	- Currency pairs: BTCEUR-BTCUSD BTCUSD-BTCCN - Price of Bitcoin - log-returns of Bitcoin	- Time series of Bitcoin prices are more volatile than other exchange rates. - The bitcoin market has space for arbitrage opportunities, especially for USD-CNY and EUR-CNY currency pairs. - NN model approximates daily log returns (for the next day) and their distribution of BTC/USD quite effectively. For better accuracy, more sophisticated techniques are required
Burggraf, (2021)	- Asset allocation strategy on cryptocurrency: Hierarchical risk parity (HRP)	- Machine learning	- Cryptocurrencies - 2015-2019 - Coinmarketcap website	- Return and volatility of HRP	- Covariance matrix of similar and dissimilar cryptos	- HRP better navigates volatility and tail risk compared to traditional risk-based strategies. - It can be an important risk management tool for cryptocurrency investors.
Petukhina, Reule, & Härdle, (2021)	- Is crypto market governed by human or AI advisors?	- AT	- Cryptocurrency index - July 2018 - 31 August 2018 - Europe databases	- Algorithmic or Human-driven market	- trade volume	- Although AI advisors are gaining ground, the market of cryptocurrencies is still dominated by human traders.
Stream 7: AI and Derivatives						
Culkin & Das (2017)	- Option pricing model	- Deep Learning	Simulated data	- call option price	- stock price, strike price, maturity dividend rate, risk-free rate volatility	- DL model is trained to reproduce the Black&Scholes formula and can be used to price options with exceptionally low error.
Jang & Lee, (2019)	- American traditional option pricing models *vs* NN models: which model has the best predictability and good fit?	- Neural networks	- S&P 100 index options - 2003-2012 - Standard & Poor's - USA	- Option price	- Past volatilities - Options market factors	- Machine learning models demonstrate better prediction performance than the classical financial option models: the generative Bayesian NN model demonstrates the best overall prediction performance.

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Funahashi, (2020)	- Option pricing model by combining ANN and asymptotic expansion (AE)	- Neural networks, Modelling	- Options	- residual terms of AE)	- interest rate, strike spot asset price, maturities	- The model does not directly apply ANN to predict the derivative price but uses the technique to train the residual term D, between the derivative price, C, and its asymptotic approximation, Ç. - The new model is lighter in terms of data, layers: this enhances predictions accuracy and speeds up calculations.
Chen & Wan, (2021)	- Model for Pricing and hedging American options	- Deep Learning, Modelling	- Options	- Option price - Delta	- price of underlying asset, payoff function, price function	- The model yields prices and deltas for the entire spacetime and outperforms state-of-the-art approaches in high dimensions.
Stream 8: AI and Credit Risk in Banks						
***Sub-Stream 8.1*: AI and Bank Credit Risk**						
Le & Viviani, (2018)	- Traditional techniques vs machine learning: which is the best at predicting bank failure?	- Classification/detection /early warning systems	- Active - inactive banks - 5y prior inactivity - BankScope database - USA	- Bankrupt/ non-Bankrupt	- Financial ratios: loan quality, capital quality, operation efficiency, profitability, liquidity	- ANN and k-nearest neighbour methods are the most accurate in predicting bank default. They are based on ratios analysis, but the role of each ratio cannot be defined in machine learning techniques.
Durango-Gutiérrez, Lara-Rubio, & Navarro-Galera, (2021)	What are the main explanatory variables of the probability of default on loans granted by MFIs?	- Classification/detection /early warning systems	- Microfinance loans - 2012-2013 - Bolivian Development Finance Institution, Encumbra - Bolivia, Columbia	- default - non default[15]	- Idiosyncratic variables, Loan variables, Systemic variables, financial variables	- Two-step model combining logistic regression and ANNs to overcome the theoretical problems of both methods and achieve better results. - The main explanatory variables for loan default are amount of the loan, number of payments in arrears, the guarantees provided, the assessment of the credit analyst, male gender of the borrower and the level and trend of the general stock exchange.
Abedin et al., (2019)	- Can Machine learning improve the performance and classification accuracy of financial decision support systems (FDSS)?	- Classification/detection /early warning systems	- Credit and bankruptcy databases - China, Taiwan, USA, Japan, UCSD	- default - non default	- client features	- SVM trained with the linear kernel function achieves better prediction results. - Random forest brings significant improvements in financial decisions. - FDSSs are correlated with the nature of databases and the performance criteria of the trained algorithms

[15] Definition of default according to national regulation authorities

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
***Sub-Stream 8.2*: AI and Consumer Credit Risk & Default**						
Lahmiri, (2016)	- Which is the best bankruptcy/credit risk predictive system?	- Classification/detection /early warning systems	- Credit approval datasets - UCI Irvine Machine Learning Database Repository - Germany, Australia, Japan	- Risky / not risky accounts	- Customer banking/account features (present and past data) - Customer credit behaviour - Customer personal information - Property, housing	- Support vector machine provides the best bankruptcy predictor in terms of accuracy, specificity, and sensitivity
Khandani, Kim, & Lo (2010).	- Forecasting model for consumer credit risk	- Classification/detection /early warning systems	- Credit accounts - 2005-2009 - US bank database - USA	- Probability of delinquency	- Customer transaction data, credit scores, account-balance data	- Machine learning method has strong predictive power in forecasting credit events 3 to 12 months in advance. - These forecasts yield cost savings ranging from 6% to 23% of total losses.
Butaru et al., (2016)	- Delinquency[16] prediction model - Assessment of risk management	- Classification/detection /early warning systems	- Customer Accounts - 2009-2013 - USA	Bad accounts (delinquent) Good accounts (otherwise)	- Account credit features, credit bureau features, macroeconomic features	- Decision trees and random forests outperform logistic regression in delinquency forecasting. - The results evidence heterogeneity among risk management practices which makes the banking system sensitive to macroeconomic shocks.
Jagric, Jagric, & Kracun, (2011)	- Method for retail credit risk modelling: learning vector quantization (LVQ)	- Classification/detection /early warning systems	- Loans - 2006-2007 - Slovenian bank database - Slovenia	Good (not defaulted over the next 12m) Bad (defaulted borrowers)	- loan characteristics - applicants' financial data and credit history	- LVQ model is better at capturing non-linear relationships among variables. It can manage the properties of categorical variables better than linear techniques (i.e., logistic regression).
***Sub-Stream 8.3*: AI and Financial Fraud detection/ Early Warning System**						
Huang & Guo, (2021)	- Early warning system to predict extreme financial risks	- early warning systems	- SSEC (Shangai composite index) - 2000-2013 - Shanghai Stock Exchange, National Bureau of Statistics of the People's Republic of China, Yahoo Finance - China	- Positive/negative class instance	- Price indicators, macroeconomic indicators, overseas return rate indicators	- The model used is kernel fuzzy twin support vector machine (KFT-SVM): it is accurate and effectively overcomes class imbalance problems.
Coats & Fant, (1993)	- How successfully can NN send warning signals of distressful conditions in currently viable firms?	- early warning systems	- Distressed and non Firms - 1970-1989 - Standard & Poor's, COMPUSTAT - USA	- viable or distressed	- financial ratios	- NN approach is more effective for the early detection of financial distress compared to linear models

[16] Delinquency status is defined as credit card account greater than or equal to 90 days past due.

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Kumar et al., 2019	- Alert model for the protection of elderly clients from financial fraud	- early warning systems	- Accounts level transactions and alert data - 2015-2016 -	- Issue cases/ non-issue/ second review cases	- Clients features. - Accounts features	- Random forest type modelling technique provides the best out-of-sample predictive accuracy: it detects 90% of suspicious activity and 57% of false alerts.
Holopainen, & Sarlin, (2017)	- Early warning model for systemic risk measurement combining different methods. - Performance evaluation	- early warning systems	- Banking sector - 1976-2014 - ESCB - Europe	- Contingency matrix based on matric based on: - pre-crisis period 1, tranquil periods 0	- Crisis events - Early warning indicators: house prices to income, house price growth, Current account to GDP, Government debt to GDP, Debt to service ratio, Loans to income, credit to GDP, credit to GDP growth, Bond yield, GDP growth, credit growth, inflation	- Advanced machine learning methods (k-nearest neighbors and neural network) and aggregated approaches through ensemble learning outperform statistical models in terms of robustness and performance
Sub-Stream 8.4: AI and Credit Scoring Models						
Jones, Johnstone, & Wilson, (2015)	- Predicting credit rating changes: comparison of binary classifiers performance in	- Predictive/ forecasting systems	- Credit ratings of public companies - 1983-2013 - Standard & Poor's Ratings Direct - USA, EU, Africa, Asia, Middle East	- Rating upgrade 1 - Downgrade 0	- financial indicators - market variables - corporate governance proxy, - analyst forecasts - macro-economic variables (real GDP, interest rates, public debt/ GDP, inflation rates)	- Downgrades in credit ratings tend to be slightly higher than upgrades. - Newer classifiers (Adaboost and random forests) outperform linear classifiers, as their predictive performance is immune to the shape and structure of input variables
Xu, Zhang & Feng, (2019).	- Hybrid Credit scoring model	- Data mining, Classification system, Machine learning	- Historical Credit data - Public/private credit scoring database - Germany, Australia, Japan, Iran	- Good/bad	- Clients' financial data	- The new model combines feature selection algorithm and ensemble learning classifier to enhance credit scoring accuracy. - The Hybrid model delivers more precise outcomes than single classifiers.
Stream 9: AI and Investor Sentiments Analysis						
Houlihan & Creamer, (2021)	- Can sentiment from social media predict the direction of asset prices?	- Sentiment analysis, Natural language processing	- Messages on StockTwits and stocks - 2009-2012 - CRSP, StockTwits	- Asset price direction	- Message volume, sentiments, past returns	- Message volume and sentiment can be used as features to predict asset price movements and as risk factors in asset pricing models. - Message information needs a period of diffusion before being absorbed into the share price

Articles	What is Research Question/ Purpose?	How is AI or Aspect of AI used in the paper?	Sample (Period, Source of Data, Country)	Dependent Variables	Independent Variables	Findings
Yin, Wu, & Kong, (2020)	- Does investor sentiment affect stock Market liquidity?	- Data mining,sentiment analysis	- CSI 300 Index - 2015-2019 - WIND, RESET, eastmoney.com - China	- Stock liquidity	- Investor sentiment(pos-neg) - Order flow imbalance	- Investor sentiment correlates positively with stock liquidity through order flow imbalance - This positive correlation is stronger in a bear market than in a bull one. - Liquidity sensitivity is higher for firms with a higher book-to-market ratio, larger size, and lower risk, in less regulated market
Heston & Sinha, (2017)	- Can news predict stock returns?	- Text mining, Sentiment analysis, Neural Network	- News articles - 2003-2010 - Thomson Reuters NewsScope Data - USA	- Stock returns	- Positive/negative sentiment of news	- Daily news predicts stock returns for only one to two days. Weekly news predicts stock returns for one quarter. - Positive news increase stock returns quickly, but negative stories trigger a delayed reaction: much of the delayed response occurs around the earnings announcement.
Renault, (2017)	- Forecasting stock index returns based on investor sentiment	- Sentiment analysis, text mining	- S&P 500 index ETF and social media data - 2012-2016 - StockTwits platform - USA	- Intraday stock returns	- Investor sentiment indicators	- Online investor sentiment helps forecast intraday stock index returns. - Intraday sentiment effect is driven by the shift in the sentiment of novice traders: there is empirical evidence of sentiment-driven noise trading at the intraday level.
Stream 10: AI and Foreign Exchange Management						
Amelot, Subadar Agathee, & Sunecher, (2021)	- Prediction of currency rates and volatility in Mauritius	- Predictive/ forecasting systems	- EUR/MUR, GBP/MUR, CAD/MUR, and AUD/MUR - 2014-2018 - Mauritius Commercial Bank (MCB) - Mauritius	- Exchange rate in five years - Volatility of foreign exchange rates	- Time series of spot exchange rates	- Overall, the study deduced that the NARX topology achieves better prediction performance results compared to time series and statistical parameters.
Galeshchuk & Mukherjee, (2017)	- Can Deep NN effectively predict the direction of change in forex rates?	- Deep learning, Predictive/ forecasting systems	- Eur/Usd, Gbp/Usd, Usd/Jpy - 2014-2015 - http://www.global-view.com/forex-trading-tools/forex-history; (https://www.tensorflow.org;	- change of direction in forex rate	- moving averages of currency rates	- CNNs[17] are significantly better at predicting directions of change in forex rates than time series models and shallow networks when raw exchange rate data are used as inputs to the models. - Deep networks outperform traditional machine learning classifiers, such as shallow networks and SVMs, that are trained on derived features.

[17] Deep Convolution Neural networks

Dunis, Laws, & Sermpinis, (2010)	- Forecasting and trading the euro/dollar (EUR/USD) exchange rate	- Predictive/ forecasting systems	- Eur/Usd - 1999-2007 - ECB	- Rate of return	- exchange rate return and moving averages of Eur/ Usd - volatility	- Sophisticated models as HONN network produces better results and outperform all other NN and traditional statistical models in terms of annualized return

Note: Summary of key papers

CHAPTER 4 – GOING FORWARD: PRIORITIZATION OF POTENTIAL RESEARCH TOPICS

4.1 FUTURE RESEARCH QUESTIONS

The literature on Artificial Intelligence in finance is vast and rapidly growing as technology advances. There are, however, aspects of AI in finance to be explored yet.

In this section, we provide a roadmap for future studies involving AI applications in the financial sector. For this section, we use the papers published between 2015 to 2021 to consider only the most recent research directions. Then, we analyse these papers through content analysis and establish a future research agenda. Finally, we convert the potential research agenda into research questions, excluding those already addressed. The procedure results in 26 research questions, as illustrated in Table 10.

4.1.1 AI and Stock Market

This research stream focuses on algorithmic trading (AT) and stock price prediction. Future research in the field should study alternative AI-based market predictors (e.g., clustering algorithms and similar learning methods) in more detail and draw up a regime clustering algorithm to have a clear view of the potential applications and benefits of clustering methodologies (Law, & Shawe-Taylor, 2017). Litzenberger, Castura, & Gorelick, (2012) and Booth, Gerding, & McGroarty, (2015) recommend broadening the study to market cycles and regulation policies that may affect AI models' performance in stock prediction and algorithmic trading, respectively. This issue has not been addressed in the latest papers, which is why we take into consideration these two papers outside the established range period. Furthermore, forecasting models should be evaluated with deeper order book information that may lead to higher prediction accuracy of stock prices (Tashiro et al., 2019)

4.1.2 AI and Trading Models

This research stream builds on the application of AI in trading models. Robo advisors are the evolution of basic trading models: easily accessible, cost-effective, profitable for investors and, unlike human traders, immune to behavioural biases. Robo advisory, however, is a recent phenomenon and needs further performance evaluations, especially in times of financial distress as Covid-19 (Tao et al., 2021), or so-called "Black swan" events. Conversely, trading models based on spatial neural networks, an advanced ANN, outperform all statistical techniques in modelling limit order books and suggest an extensive interpretation of the joint distribution of the best bid and best ask. Given the versatility of such a method, future research should use it to analyse whether neural networks with more order book information (i.e., order flow history) yield better trading performances (Sirignano, 2018)

4.1.3 AI and Volatility Forecasting

As said in the previous section, volatility forecasting is a challenging task. Despite recent studies show solid results in the field (see Sermpinis, Laws & Dunis, 2013; Vortelinos, 2017), future works could deploy more elaborated recurrent NNs by modifying the activation function (of processing units composing the ANNs) or adding hidden layers and then evaluate their performance (Bucci, 2020). Since univariate time series are commonly used for realized volatility prediction, it is interesting to inquire about the performance of multivariate time series.

4.1.4 AI and Portfolio Management

This research stream examines AI in portfolio selection strategies. Past studies have developed AI models able to replicate the performance of stock indexes (as known as index tracking strategy) and construct efficient portfolios with no human intervention. To this end, Kim & Kim, (2020) suggest focusing on optimizing AI algorithms to boost index-tracking performance. Soleymani & Vasighi, (2020) recognize the importance of clustering algorithms in portfolio management and propose a clustering approach powered by a membership function, also known as fuzzy clustering, to further improve the selection of less risky and most profitable assets. For this reason, analysis of asset volatility through deep learning should be embedded in portfolio selection models (Chen & Ge, 2021).

4.1.5 AI and Performance, Risk, Default Valuation

Bankruptcy and performance prediction models rely on binary classifiers that only provide two outcomes, e.g., risky-not risky, default-not default, good-bad performance. These methods may be restrictive as sometimes there is not a clear distinction between the two categories (Jones, Johnstone, & Wilson, 2017). Therefore, future research could focus on multiple outcome domains and extend the research area to other contexts such as bond default prediction, corporate mergers, reconstructions, takeovers, and credit rating changes (Jones, Johnstone, & Wilson, 2017). Corporate credit ratings and social media data should be included as independent predictors in credit risk forecast to evaluate their impact on the accuracy of risk predicting models (Uddin et al., 2020). Moreover, it is interesting to see the benefits of a combined human-machine approach where analysts contribute to variables' selection alongside data mining techniques (Jones, Johnstone, & Wilson, 2017).

Future research should also address black box and over-fitting biases (Sariev & Germano, 2020), as well as provide solutions for the manipulation and transformation of missing input data relevant to the model (Jones, Johnstone, & Wilson, 2017).

4.1.6 AI and Cryptocurrencies

The use of AI in the cryptocurrency market is in its infancy, as are the policies regulating it. As the digital currency industry becomes increasingly important in the financial world, future research should study the impact of regulations and blockchain progress on the performance of AI techniques applied in this field (Petukhina, Reule, & Härdle, 2021). Cryptocurrencies, Bitcoins particularly, are extensively used in financial portfolios, hence new AI approaches should be developed to optimize cryptocurrency portfolios (Burggraf, 2021).

4.1.7 AI and Derivatives

This research stream examines derivative pricing models based on AI. An interesting future research area is the incorporation of text-based input data, such as tweets, blogs, and comments for option price prediction (Jang & Lee, 2019). As derivatives pricing is an utterly complicated task, Chen & Wan, (2021) suggest studying advanced AI designs that minimize computational costs. Funahashi, (2020) recognizes a typical human learning process (i.e., recognition by differences) and applies it to the model, significantly simplifying the pricing problem. To this end, future research should investigate other human learning and reasoning paths that can improve AI reasoning skills.

4.1.8 AI and Credit Risk in Banks

Bank default prediction models often rely solely on accounting information from bank's financial statements. To enhance default forecast, future work should consider market data as well (Le & Viviani, 2018). Credit risk includes bank accounts fraud and financial systemic risk. Fraud detection based on AI needs further experiments in terms of training speed and classification accuracy (Kumar et al., 2019). Early warning models, on the other hand, should be more sensitive to systemic risk. For this, future studies should provide a common platform for modelling systemic risk and visualization techniques to enable interaction with both model parameters and visual interfaces (Holopainen & Sarlin, 2017).

4.1.9 AI and Investor Sentiment Analysis

Sentiment analysis builds on text-based data from social networks and news to identify the investor sentiment and use it as a predictor of asset prices.

Further research could analyse the effect of investor sentiment on specific sectors (Houlihan & Creamer, 2021) as well as the impact of diverse types of news on financial markets (Heston & Sinha, 2017). This is important for understanding how markets process information. Xu & Zhao, (2020) propose a deeper analysis of how social networks' sentiment affects individual stock returns. They also believe the activity of financial influencers, such as financial analysts or investment advisors, potentially affects market returns and needs to be considered in financial forecasts or portfolio management.

4.1.10 AI and Foreign Exchange Management

This research stream investigates the application of AI models in the Forex market. Deep networks, in particular, efficiently predict the direction of change in forex rates thanks to their ability to "learn" abstract features (i.e., moving averages) through hidden layers. Future work should study whether these abstract features can be inferred from the model and used as valid input data to simplify the deep network structure (Galeshchuk & Mukherjee, 2017). Moreover, the performance of foreign exchange trading models should be assessed in financial distressed times. Further research should also compare the predictive performance of advanced times series models such as genetic algorithms and hybrid NNs for forex trading purposes (Amelot, Subadar Agathee, & Sunecher, 2021).

Table 10. Future Research Questions

Research streams		Future research questions	Authors (s) / Year
AI and Stock Market	1.	Which AI-based technique (e.g., ML, clustering algorithms) is the best for Stock market prediction?	Law, & Shawe-Taylor, (2017)
	2.	Which kind of order book information best improves the accuracy of AI-based models for stock market prediction?	Tashiro, et al., (2019)
	3.	How does policy and regulation impact Algorithmic trading?	Litzenberger, Castura, & Gorelick, (2012)
	4.	What effect have market cycles on the accuracy of intelligent stock price prediction models? Can it be leveraged to improve the model's performance?	Booth, Gerding, & McGroarty, (2015)
AI and Trading Models	5.	How do Robo advisors perform during major unexpected financial crisis such as Covid-19?	Tao et al., (2021)
	6.	Can limit order books data embedded in AI-based techniques boost trading models accuracy?	Sirignano, (2018)
AI and Volatility Forecasting	7.	Do more elaborated neural network architectures enhance realized volatility prediction? What are the benefits and results of using NNs multivariate time series in forecasting realised volatility?	Bucci, (2020)
	8.	Which AI optimizing algorithms most improve index-tracking portfolio strategy?	Kim & Kim, (2020)
AI and Portfolio Management	9.	Which machine learning approach (e.g., fuzzy clustering) best improves portfolio construction?	Soleymani & Vasighi, (2020)
	10.	How can deep learning techniques contribute to volatility forecasting for portfolio selection?	Chen & Ge, (2021)
AI and Performance, Risk, & Default Valuation	11.	How would multiple classifiers based on AI technology perform compared to binary classifiers in predicting corporate bankruptcy, bond default, corporate mergers, reconstructions, and takeovers? What are the benefits of combining sophisticated data mining techniques with experts' opinion in corporate default forecasts? What are possible solutions for transforming and manipulating missing data in AI predictive models?	Jones, Johnstone, & Wilson, (2017)
	12.	What impact have corporate credit ratings and social media data on the accuracy of AI-powered risk predictors?	Uddin et al., (2020)
	13.	Which AI tools help overcome ANNs limitations (e.g., overfitting, black box)?	Sariev & Germano, (2020)
AI and Bitcoin, Cryptocurrency.	14.	Which AI techniques are best for the optimization of a cryptocurrency portfolio?	Burggraf, (2021)
	15.	What are future developments in the crypto market in terms of AI-based trading methods and blockchain? What impact has regulation and blockchain on crypto markets and AI models performance?	Petukhina, Reule, & Härdle, (2021)
AI and Derivatives	16.	What are potential deployments and results of text-based input data and sentiment analysis in option pricing?	Jang & Lee, (2019)
	17.	What are the best designs of AI models that minimize computational cost?	Chen & Wan, (2021)
	18.	Are there further human learning paths to be implemented in AI technology?	Funahashi, (2020)
AI and Credit Risk in Banks	19.	What type of data (e.g., bank market data) best improves the result of bank default forecasting models?	Le & Viviani, (2018)

	20.	What methods reduce AI training speed and enhance classification accuracy?	Kumar et al., (2019)
	21.	How can early warning models be further simplified to be widely implemented? Which AI technique is best for combining visual data or visual interfaces with systemic risk measurement to "visualize" and interact with future risk scenarios?	Holopainen & Sarlin, (2017)
AI and Investor Sentiments Analysis	22.	Can the combination of both textual data and market data improve AI predictive models in specific sectors and industries?	Houlihan & Creamer, (2021)
	23.	How do diverse types of news and "social" data impact financial markets? How does the market process that information?	Heston & Sinha, (2017)
	24.	Which AI model best captures the impact of social networks sites' sentiment (SNS) on individual stock for portfolio management? Does the increasing role of "influencers" in finance (e.g., investor advisors, expert analysts) affect market returns and how can AI technology use it for financial forecasts?	Xu & Zhao, (2020)
	25.	What are the strategies to simplify and make machine learning leaner and faster? Which AI-based trading strategy best performs in the forex market during a financial crisis?	Galeshchuk & Mukherjee, (2017)
AI and Foreign Exchange Management	26.	Which AI model based on advanced time series (e.g., genetic algorithm (GA), hybrid genetic algorithm optimized long short-term memory, ETS models or APGARCH or hybrid ANN Gravitational models) is most performing in foreign exchange rates or stock market forecasting?	Amelot, Subadar Agathee, & Sunecher, (2021)

Note: Table summarizes the future research agenda

CONCLUSION

Despite the only recent application, AI has revolutionized the entire financial system thanks to advanced computer science and big data analytics. This also owes to the increasing outflow of data generated by consumers, investors, business, and governments activities.

In this paper, we collected a total number of 304 articles taking into consideration publishing journals listed on ISI Web of Knowledge (WoS), their ranking and citation data. The papers are selected based on a keywords analysis to cover the complete literature on the topic. Through a content analysis, we critically examine the articles and exclude those addressing the main subject marginally. This process yields a total of 110 papers.

Based on our in-depth review, we highlight 10 research streams that apply AI to various financial purposes.

First, AI presents itself as an excellent market predictor and contributes to market stability by minimizing information asymmetry and volatility, overall. This results in profitable investing systems and accurate performance evaluations.

Second, the superiority of intelligent methods eliminates human errors and psychological biases, responsible of market inefficiencies.

In the risk management area, AI aids with bankruptcy and credit risk prediction in both corporate and financial institutions. Since firm default differs from bank default, they are treated separately. Fraud detection and early warning models monitor the whole financial system and raise expectations for a future artificial market surveillance. This implies that global financial crises or unexpected financial turmoil can be anticipated and prevented.

Finally, we provide a roadmap for future research which should mostly focus on improving and simplifying machine learning algorithms and the structure of ANNs. Considering that the development of AI started only few years ago, we can safely affirm that this technology is still at its beginning and needs further research.

Whilst AI is undeniably the future of the financial world, the continuous use of customer data for financial purposes raises the question upon data privacy regulation and cybersecurity to prevent improper use or misappropriation of confidential information (Hermes Investment Management, Marsh, Oliver Wyman, & Bryan Cave Leighton Paisner LLP., 2019).

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