Research Landscape of Artificial Intelligence in Financial Disciplines: A Bibliometric Perspective

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Abstract

The last 20 years have seen the artificial intelligence make considerable progress, especially in the finance field. By 2021, AI has become ubiquitous and the activity in the field of research has increased significantly. This project aims to engage in a systematic review of the existing research, see what has already been done, and what gaps that still exist in this field, namely in the area of finance. In this regard, I investigated a wide range of published articles that were published between 1992 and March 2021. The literature reviewed was divided into ten major research topics, which included: AI on stock market, algorithmic trading, volatility estimation, portfolio management, performance, risk and default analysis, cryptocurrencies, derivatives, bank credit risk, investor sentiment, and the foreign-exchange markets. Nevertheless, there are significant gaps in these endeavours, especially when it comes to the risk posed by recent technological upheavals on finance; this offers prospects of research in the future. I used both a bibliometric and content analysis methodologically to compile a global picture. These results indicate that, most of the studies on various applications of AI in the financial sector have a sharp rise since the beginning of the 21 st century around the world. Predictive and forecasting systems, classification and early-, warning model, and big-, data-, data-, and text-mining based analytical methods are the most common ones.

Introduction

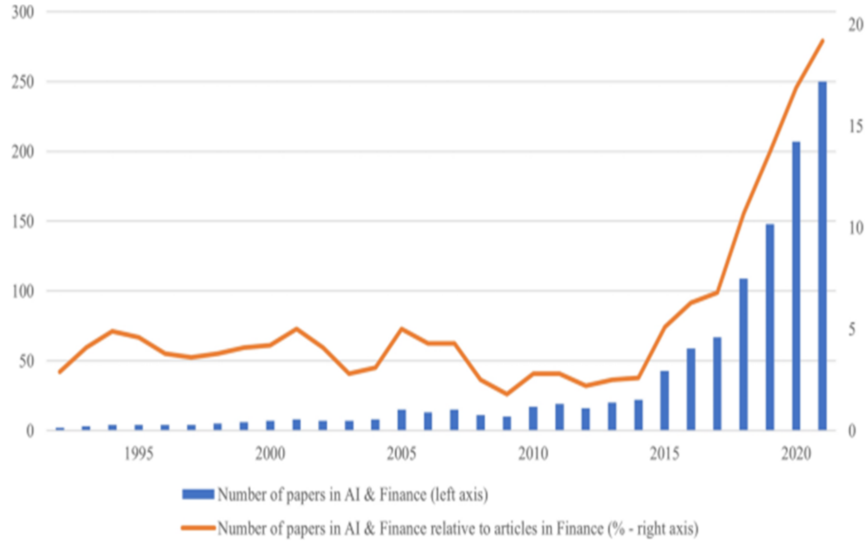
The importance of artificial intelligence was introduced by John McCarthy in 1956 in a conference at Dartmouth College and defined it as a science of thinking machines (Buchanan 2019). Nevertheless, storage capacity and the insufficiency of the capability to perform calculations limited development of technologies in the sphere until the millennium turn. This resulted in the lack of interest by the government and the investors in the period between 1974 and 1980 and the same between 1987 and 1993 which scholars call as the ais winters (1).

The broad adoption of the AI is set to have massive consequences on both adopters and the economy as well as the rest of the society. Specifically, it is expected to lead to the increase in the global GDP, which by 2030 is expected to reach 14% according to Price Waterhouse Coopers (PwC, 2017). In actuality, statistical data show that organisations that have embraced the use of AI applications have often recorded improved operational performance (Van Roy et al., 2020).

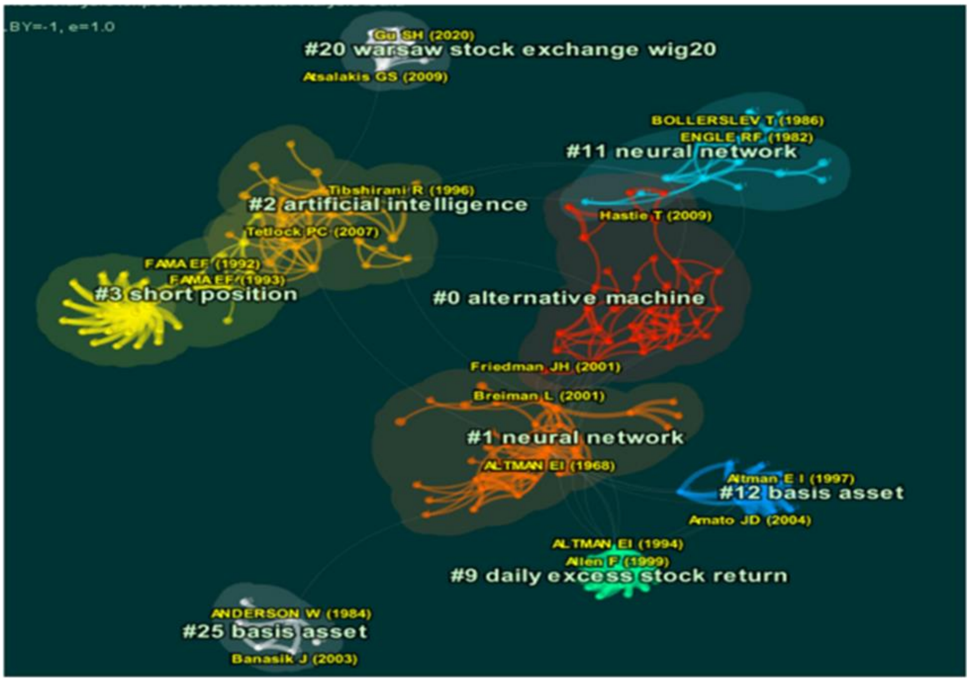
Finance is one of the fundamental fields to apply AI, and the field is not an exception to the overall technological revolution. AI finds its way into the economic leaders and the wide-ranging application of big data and automation of processes have placed financial institutions in the centre of AI implementation (PwC, 2020). In production, e.g. in the automation process, it increases efficiency and productivity; in prediction analytics and trade optimization, AI removes human error and bias. AI also leads to transformations in the business model, which fundamentally relates to reinventing the relationship with the clients through personalised digital finance and the solution to the service productivity and cost effectiveness achieved through the integration of AI with process automation (Cucculelli & Recanatini, 2022). Additionally, AI will be instrumental to the financial and prudential regulators as it will allow them to identify the possible violations and clarify the consequences of the regulatory changes (Wall, 2018). State-of-the-art AI and machine-learning models enable fintech issuers to deliver fast credit decision projects within only a matter of seconds, which benefits both the issuers and customers (Jagtiani and John, 2018). Smart technology is used in finance fields such as fraud identification, algorithmic and high-frequency trading, portfolio management, credit approval modelling, bankruptcy prediction, risk management, behavioural analysis should it be sentient, and regulation compliance.

The past few years have witnessed growing momentum of researchers exploring the premises of AI technologies in a variety of financial applications. However, the literature that does exist is diverse and wide ranging, with differing research questions, a geographic context, an industry area, analysis levels and methodology. As a result, it is difficult to produce strong conclusions and clarify the new research directions. It is in this spirit that I am offering a review of the application of AI in finance presented in a comprehensive way as I am trying to give a very comprehensive assessment of the state of the art and also outline some of the research problems which have not been addressed comprehensively. This review, though not exhaustive can be the guide on the way of newcomers in the field in order to de-confusion those who face the intricate interconnections that characterize this sphere. Specifically, it provides a helpful reference point to be used in future empirical studies, as it outlines currently existing best practices and places the issues that are contentious and require additional research. The work is complementary to new systematic reviews, including the ones by Hentzen and others (2022b) and Biju and others (2020). The latter does not cover the customer-facing environments and financial services related specifically to the retail sector, but the former is not the subject of this study since it focuses on the technical literature and the effectiveness and predictability of machine-learning, AI, and deep-learning algorithms in the financial industry.

As part of our analysis we can note that since the beginning of the twenty-first century research on AI in the finance discipline has grown significantly. Breadth, diversity are not the only characteristics of the literature, which also cover the world, consisting of a range of AI applications in the financial sector, such as predictive, forecasting systems, classification/detection/early-warning mechanisms, and big-data analytics, data mining, and text mining. In addition, we demonstrate that the works gathered can be structured into ten large streams of research, namely: AI in the stock market, trading model development, volatility forecasting, portfolio management, performance assessment, risk and default evaluation, cryptocurrency studies, derivatives analyses, bank credit risk, investor sentiment analysis, and foreign-exchange management.



Publication Trend, 1992–2021



Source: authors' elaboration of data from Web of Science; visualisation produced using CiteSpace. Citation Mapping and identification of the research streams

Methodology

To perform a thorough literature review of the topic under consideration, we will use the two widely adopted methodologies which are the bibliometric analysis and content analysis. The bibliometric analysis is a broad and solid method of investigation and analysis of a large amount of scientific data, providing an opportunity to clarify the nuances of evolutionary processes in a specific area of study and determine the current trends or hotspots (Donthu et al.

2021). The bibliometric analysis in this work is conducted with the help of the known software package, the HistCite that helps scholars to enlarge and visualize the results of literature review obtained in the Web of Science. Particularly, we use HistCite to access into the volume of publications, forward citations (which we will use subsequently to identify the most impactful journals and articles) and co-citation network (e.g. all citations a journal received, as well as all citations a journal issued) corresponding to each calendar year. These data aid the determination of larger currents of discovery of research elaborated by the part entitled Discovery and analysis of mainstreams of research. Later, to analyze the contents of the most relevant studies on artificial intelligence in the field of finance we depend on the traditional content analysis which is a research methodology which provides a systematic and objective way of making inferences about the contents of the verbal, written, or visual expressions in addition to seeking to give us insight and understanding about the phenomenon being studied (Downe 1992:117).

A detailed account of the literature on AI in Finance

We provide a narration of the literature in the field of artificial intelligence in finance to identify common themes and trends, hence providing concise but exhaustive mapping of the existing state of the art. In particular, we determine some bibliographic features made by bibliometric analysis. Next, we use a snowballing technique of a part of the studies and further do the initial analysis of the chosen papers using content analysis, and thus, define the leading AI applications in finance. Last but not least, we conclude this paper and briefly comment on ten streams of research.

The identified main areas of research are (1) AI and the stock market; (2) AI and trading models; (3) AI and volatility forecasting; (4) AI and portfolio management; (5) AI and investor sentiment analysis; (6) AI and Bitcoin, cryptocurrencies; (7) AI and derivatives; (8) AI and bank credit risk; (9) AI and foreign exchange management. Several streams of research could be broken down to smaller sub-streams since they deal with different aspects of the same fundamental research subject.

Stream 01: AI and stock market

The stream of AI and the stock market has two sub- streams, which are the algorithmic trading feature and AI driven stock price forecast. The former sub-stream tries to look at the impact of the algorithmic trading (AT) on financial markets. In that regard, Herdershott et al. (2011) believe that AT has a beneficial impact on the liquidity of the market by minimizing the spreads, adverse selection, and trade-based price discovery. As a result, the cost of equity on the listed companies decreases in the long-run and medium-term, especially in the developing economies (Litzenberger et al. 2012). In comparison with human traders, AT is much faster at responding to information and being more profitable around news announcements because it has a better timing capability and faster execution in the market (Frino et al. 2017). Even though a particular form of algorithmic trading, high-frequency trading, has compounded volatility in reaction to news or fundamentals and propagated it across markets, in general, the amount of variance in return volatility was decreased through AT and market efficiency was enhanced (Kelejian and Mukerji 2016; Litzenberger et al. 2012).

Stream 02: AI and trading models

Judging by the literature review deployed by this stream, one can conclude that the creation of intelligent automated trading systems is based on the neural network and machine learning systems. To illustrate the point, Creamer and Freund (2010) build a machine learning algorithm in a stock-price sequence and buys the most attractive stocks by approving short- or long-term holdings by making tangible predictions. The other component of the model is the overlay of risk-aversion which disallows trading upon the unprofitability of strategies. Likewise, Creamer (2012) writes about high-frequency trading futures: the rationale is that it is recommended on futures to choose progressively more profitable and risk-averse investments and enable the model to take a long or short position on the future. To achieve more effective trading model, Trippi and DeSieno (1992) combine several neural networks into a single decision-rule system which is more effective than individual NNs; Kercheval and Zhang (2015) use a semi-supervised learning approach (i.e., multi-class SVM) that more accurately predicts even in the high-frequency limit order books, the movement of mid-prices, based on the category of low-stationary-up; and incorporates such prediction into trading strategies to produce positive returns under controlled risk.

Stream 03 Artificial intelligence and volatility forecasting.

The third one deals with AI and volatility forecasting. CBOE volatility index (VIX): CBOE volatility index is a measure of the market sentiment and expectations. Volatility is very persistent thus making it difficult to predict (Fernandes et al. 2014). Fernandes et al. (2006) found that VIX is also negatively related with the return of the S&P 500 index, and positively related to the volume of the index. The HAR model does the best out-of-sample predictions in comparison with conventional feed-forward networks (Vortelinos 2017). Some more recent modeling methods, like LSTM and NARX (nonlinear autoregressive exogenous network), can also be considered alternatives (Bucci 2020). The other type of neural networks is known as higher-order neural network (HONNs); it predicts the 21 days ahead realised volatility of FTSE 100 futures. HONNs have strong statistical accuracy and trading efficiency by virtue of their ability to model higher-order correlations when compared with those of multi-layer perceptrons (MLP) and recurrent neural networks (RNN) (Sermpinis et al. 2013).

Stream 04: AI and investment portfolios management.

The current direction of research is on the use of artificial intelligence in the process of selecting a portfolio. Soleymani and Vasighi (2020) exemplify using this application with a clustering-based approach, which is later fitted with Value-at-Risk analysis, and comes to allocate the assets in a better manner; by concentrating on low-risk, high-return equities within the portfolio. More detailed allocation structures include a model of bankruptcy-detection and an enhanced utility-optimisation system: a more advanced neural network estimates the default risk of companies and the marginal utility of a single asset to the optimal portfolio (Loukeris , Brigade Eleftheriadis, 2015). Index tracking that is based on deep learning has been revealed to mitigate tracking error, as well as, provide positive risk-adjusted performance (Kim & Kim, 2020). Besides, the returns dependence, obtained by asymmetric copula techniques, are also estimates used as further input in portfolio-optimisation processes (Zhao et al., 2018). Overall, the collection of empirical research analyzed in this paper shows that prediction models that rely on machine-learning can be applied in portfolio selection to accurately predict the performance of each security (Zhao et al, 2018).

Stream 05: AI and performance, risk, default valuation

This stream of research is further divided into three thematic strands which are as follows: (i) AI and corporate performance, risk and default valuation; (ii) AI and real-estate investment performance, risk and default valuation; (iii) AI and bank performance, risk and default valuation. The former strand evaluates the financial status of firms to foresee troubled entities in regard to finances just like the case of Altman _et al. (1994). Jones _et al. (2017) and Gepp et al. (2010) provide the estimates of the probability of corporate default, whereas Sabău Popa et al. (2021) forecast business performance based on a composite financial index. The findings support the argument that AI-based classifiers have higher predictive and interpretability rates compared to traditional linear models. One interesting addition also measures the relationship between CEOs as masculine and the riskiness of the firms through image processing; it finds that companies with CEOs who are masculine in terms of face show higher risk- and leverage- and MER ratios (Kamiya _et al., 2018).

The second one is focused on the mortgage and loan default prediction (Feldman & Gross, 2005; Episcopos, Pericli, & Hu, 1998). Chen _et al. (2013) evaluates returns on real-estate investments determining the index of the REIT which show that the index is forecasted depending on the industrial-production, lending rates, stock indices, dividend yields etc. The implemented forecasting methods, including supervised machine-learning and artificial neural nets, are productive in terms of efficiency and accuracy every time as compared to the linear models.

The third strand deals with performance in the banking industry. However, unlike antecedent research, a text-mining study argues that non-financial risk factors associated with banking are the most salient ones and include regulatory, strategic, and managerial factors (Wei _et none, 2019). However, conclusions made using a textual analysis are limited to the revelations made in the papers under analysis.

Stream 06: AI and cryptos

The current algorithms and AI advisors are developed to a significantly higher level; the cryptocurrency market, however, is still mainly human-controlled (Petukhina _et al, 2021). Therefore, large arbitrage windows continue to exist in Bitcoin, at USDCNY and EURCNY (Pichl 12 and Kaizoji, 2017). As far as the volatility prediction (realized) is concerned, HAR model proves to be effective, and a feed-forward neural network serves to effectively model the BTCUSD daily returns and distribution (Pichl & Kaizoji, 2017). In addition, one of the most effective risk-management tools in regards to the extreme volatility of Bitcoin prices, the Hierarchical-Risk Parity (HRP), is a machine-learning-based process of allocating assets, a phenomenon that traditionally has been a powerful benefit of cryptocurrency traders (Burggraf, 2021).

Stream 07: AI and derivatives

Machine-learning algorithms and artificial neural networks are good tools in pricing financial derivatives. A machine-learning model introduced by Jang and Lee (2019) is better than classic American-option pricing models: a generative Bayesian neural network. Culkin and Das (2017) use a feed-forward deep neural network to recreate the Black-Scholes option-pricing formula with a great accuracy. A deep neural network to price American options and estimate their deltas in high dimensional situations is also suggested by Chen and Wan (2021). Conversely, Funahashi (2020) recommends not to use deep learning in making a decision on price because prices may fluctuate, and suggests a combination of an artificial neural network combined with an asymptotic expansion. Such a model does not predict option prices directly, but rather the difference between the target derivative price, and the approximation, which makes the ANN quicker, more precise as well as less burdensome in terms of layers and training information. The strategy works similarly to human learning as it concentrates on the variations that exist between a new object and an already known one (Funahashi, 2020).

Stream 08: AI and bank credit risk

The second stream of research, AI and Credit risk in Banks, has four sub-streams: AI and bank- credit risk; AI and consumer credit risk and default; AI and financial fraud detection / early warning system; AI and credit-scoring models. The former sub-Stream is focused on bank failure prediction. Machine-learning algorithms and artificial neural networks are superior to conventional ways of statistical analysis, but they deserve greater attention due to their black-box characteristics (Le &ʻViviani, 2018). In order to address this shortcoming, Durango-Gutierrez _et al. (2021) constructed logistic regression and AI-based multi-layer perceptrons (MLPs), which provide information about the explanatory variables. The entire banking industry is trying to prevent economic disasters on a worldwide level with the help of financial decision-support systems that are significantly improved with the assistance of AI-based models (Abedin _et al., 2019).

A second sub-stream involves traditional as well as sophisticated models of consumer credit risk. Controlled learning methodologies have become potent in identifying credit-card deviations and assigning a decision and a few can make even 12 months ahead of heartbreak (Lahmiri, 2016; Khandani _et al_, 2010; Butaru _et al_, 2016). Jagric et al (2011) presented an LVQNN especially better adapted to interactions among categorical variables, which yields a high classification accuracy between default and non-default. These are more effective than logit models and save the economy between 6 -25 percent of total lending losses collected (Khadani _et al- 2010).

The third group of articles deals with artificial intelligence and early warning systems. Within the retail setting, sophisticated random-forest models are effective in identifying credit card fraud cases on the basis of customer financial behavior and credit spending patterns to track the interest of the concerned authorities (Kumar et al., 2019). Likewise, Coats and Fant (1993) constructed an alert model of a distressed business using neural-networks, which is superior to a linear model. On the macroeconomic level, AI-based systemic risk monitoring models, including k -nearest neighbours and advanced neural networks, contribute to the macroprudential policy and issue warning signals when there is an indication of anomalous world order financial operations (Holopainen and Sarlin, 2017; Huang and Guo, 2021). Nevertheless, the use of such applications is not enough.

Lastly, the latter type is intelligent credit-scoring models, where machine-learning algorithms like AdaBoost and random forests can be used to perform best in credit-rating change predictions. These models are resistant to outliers, missing data, and overfitting, and have data flexibility (Jones and Di Matteo, 2015). As an example, Xu et al. (2019) designed a detailed framework, combining both data mining and machine learning, which eliminates the least relevant predictors and, thus, reduces the effect of noisy variables during prediction.

Stream 09 Artificial Intelligence and Investor Sentiment Analysis.

The psychology of investors is one of the key determinants in stock forecasting. Sentiment analysis is, therefore, used to obtain investor sentiment on social media sites like StockTwits, Yahoo Finance, Eastmoney and more using natural language processing (NLP) and data-mining methodologies and classify it into positive or negative (Yin et al., 2020). Subsequently, this feeling is reflected in asset-pricing models, as an instrument of orientation effects of prices, or as a proxy of intraday returns of indexes (Houlihan and Creamer, 2021; Renault and Dunston, 2017). Yin et al. (2020) in this regard show that investor sentiment is also positively related with liquidity of stock, especially during slow markets, and that firms that are larger size, book to market ratios and operate in a less regulated market, are more sensitive to liquidity conditions. Out-of-sample details imply that, the daily news have an ability to predict the stock returns within a period of a few days, whereas weekly news are able to predict the stock returns within a period of one month to one quarter. This relationship has the capability of creating a backlash effect on stock prices as there is a tendency of prompting delayed news to trigger large corporate events like earnings announcements; hence, investor sentiment could be a decisive factor when gauging the effects of AI in financial markets (Heston & Sinha, 2017).

Stream 10 Foreign-Exchange Management and Artificial Intelligence.

Another line of research is the AI use in foreign-exchange management. Accurate exchange-rate predictions are the key to cost-efficient operations and hedging in this market (Galeshchuk and Mukherjee, 2017). An example is the HONN model predicting and trading the EUR/USD exchange and ECB daily fixing series better than popular neural-network variants: multilayer perceptrons, recurrent neural networks, and the PSI-sigma models; trading profitability was better with the use of the HONN model (Dunis et al., 2010). Unlike, Galeshchuk and Mukherjee (2017) argue that the methods do not work well to predict the directional movement of forex rates and hence cannot facilitate profitable trading. Therefore, they use a deep convolutional neural network to forecast three leading exchange rates (EUR/USD, GBP/USD, and JPY/USD). The approach proves significantly better performance as compared to the classical models of time-series, including ARIMA and machine-learning classifiers. Finally, this collection of literature suggests that AI methods, such as NARX and algorithms presented in the current paper, can offer better predictive solutions than statistical and time-series models, which Amelot and company (2021) validate.

Conclusions

Although it is relatively new, artificial intelligence has transformed the whole financial system, thanks to progress in the field of computer science, big-data analytics, and the growing voluminous data generated by consumers, investors, businesses, and government activities. In line with this, it is surprising that an increasing literature has explored the application, advantages, and opportunities of AI applications in finance. The purpose of this paper was to give a correct account of the state of the art and thus act as a reference book to the scholars who may be interested in the same aspect and most importantly act as a stepping-stone in future research. In that respect, we gathered a significant amount of papers that were published in journals accepted in the Web of Science (WoS), and then we applied the methods of bibliometric and content-analysis. Specifically, we have examined various features of the studies that we analyze and have determined the key AI uses in finance as well as have introduced ten major research streams. Out of this comprehensive overview, it is quite clear that AI can be termed as an efficient market predictor and it helps in stabilising the market by decreasing information asymmetry and volatility; this, in turn, translates into profitable investing systems and sound performance analysis. Besides, regarding the field of risk management, AI enables the prediction of the bankruptcy and credit-risk of corporations and financial institutions alike, whereas fraud-detection and early-warning models keep a watch on the whole financial system and improve the future possibilities of artificial surveillance of markets. The results indicate that international financial crisis or any turbulent behaviour would be forecasted and avoided.

Overall, the spread of the artificial-intelligence (AI) application in the financial field has been growing very fast worldwide. Combined with the general evolution of technological advancement, this tendency implies the further development of AI usage in the sphere of finance in the regions and in the professions involved, and more precisely in the aspects of finances. Still, companies that have not managed to catch up with this new technological trend should be aware of this fact and willing to overcome the current barriers, thus, getting the potential AI integration effects and remaining competitive. As a result, stakeholders and policymakers must seek to ensure that organisations which are not already deploying AI or are still in the initial phases of such deployment modernize their practices, i.e. by offering funding schemes or apprenticeship schemes that will ensure more refined skillsets are in place when employees work with sophisticated tools and programming languages.

This research is limited in a number of ways. It, first, touches upon a very wide scope of interconnected issues, especially the key financial areas affected by AI those that have been defined as the main concern of the preceding studies and then provides brief descriptions of them. Other researchers can choose to focus on one or a limited number of topics and, in that way, offer a deeper depiction of the chosen domains. Second, we are appreciating the fact that technological change has been happening at a pace faster than any other. Even though we analyze a large time frame and incorporate a significant amount of research that was published within the first twenty years of the twenty-first century, we do not reflect the progress that has transpired since 2021, which is the last year to be covered by our sample. Indicatively, at least in recent years, AI experts, policy-makers, and an ever-increasing number of scholars have been discussing the opportunities and threats of AI-based technologies like ChatGPT, as well as the slightly amorphous so-called metaverse (see, e.g., Mondal et al. 2023 and Calzada 2023). Recent developments are likely to be further clarified in future on what their ramifications are to the field of finance, and other vital fields like education and health.

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