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Received: 1 January 2022 | Revised: 30 April 2022 | Accepted: 21 June 2022

DOI: 10.1002/for.2886

RESEARCH ARTICLE

WILEY

# Cryptocurrencies trading algorithms: A review

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**Funding information**
Conselho Nacional de Desenvolvimento Científico e Tecnológico, Grant/Award Number: 305199/2019-6; Coordenação de Aperfeiçoamento de Pessoal de Nível Superior

**Abstract**

This study conducts a bibliometric analysis and systematic review of cryptocurrency trading algorithms to identify existing gaps in the area. From our standpoint, this is the first study to carry out a deep analysis of price forecasts and portfolio management in cryptocurrencies in addition to analyzing the most relevant studies and authors, trend topics of the area, and identifying countries with the most published studies. During our research, we identified some gaps that can be used for further research. Currently, there are approximately 16,000 cryptocurrencies; however, in majority of the papers, the authors have only used the top 10 ranking market capitalization cryptocurrencies, leaving aside potential minor cryptocurrencies. Thus, trading strategies using Big Data can be a potential research topic, considering the greater number of emerging cryptocurrencies.

**KEYWORDS**

bibliometric analysis, cryptocurrencies portfolio, cryptocurrency trading, systematic review

## 1 | INTRODUCTION

The cryptocurrency market has been a relatively new topic since the first cryptocurrency (Bitcoin) was created in 2008 by the pseudonym Satoshi Nakamoto (Nakamoto, 2008). Since the creation of Bitcoin, several currencies such as Ethereum (Buterin et al., 2014) have appeared with different functionalities (smart contracts), and with that, a new economic model is rising with a diverse range of opportunities. It is a decentralized world in which there are no intermediaries or custodians of money, everything is based on the code and trust in the computing code (Nakamoto, 2008).

Although there has been growth in cryptocurrency research since 2017 according to our research, we have not found any review studies on trading strategies and forecasting the price of cryptocurrencies to date. To address this gap in research, we analyzed and studied the existing literature on cryptocurrency and determined future potential areas of implementation for advanced research. For this research, we used bibliometric analysis to identify certain features, such as the main authors and the countries that publish the most, and used a systematic review to identify the methods used to forecast prices with an analysis of cryptocurrencies.

The remainder of this paper is organized as follows. Section 1 presents the methodology of the bibliometric analysis and systematic review. Section 2 presents the systematic review. Section 3 presents the discussion and conclusion.

## 2 | METHODOLOGY

The main objective of this paper is to provide a quantitative (bibliometric analysis) and qualitative review (literature review) of the most relevant research on trading algorithms with cryptocurrencies from 2008 until 2021. For this review, a selected number of papers from databases were used for both analyses. The bibliometric review aims to construct quantitative knowledge of authors, countries, and relevant areas. However, the

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literature review seeks to deeply analyze the papers to determine the gap in the research on cryptocurrency trading. As a result, the following research question was raised: *Is it possible to design a portfolio or intelligent fund of cryptocurrencies that works in real time with econometric models or machine-learning models?* This section presents the structure of the methodology used to implement the bibliometric analysis and literature review of cryptocurrency trading. The study was divided into six steps: Steps 1 to 4 represent the filters selected to find the ideal papers; step 5 describes the bibliometric analysis; and step 6 describes the systematic literature review.Step 1: Selection of databases for review: Web of Science (WoS) and Scopus databases were chosen because of their relevance and quality in the scientific domain.

Step 2: Selection of keywords for research. To delimit the number of papers and enhance the quality of the results, a filter was implemented from the most used keywords in related papers: *(cryptocurrency OR "cryptocurrencies") AND ("trading") OR "digital cash"*. In this step, 966 papers were obtained.

Step 3: Other filters were implemented. For this step, only papers written after the creation of Bitcoin (2008) were selected. In addition, irrelevant papers were excluded, resulting in 843 papers. Table 1 presents a delimitation of this study.

Step 4: Duplicate and unrelated papers were excluded. After removing duplicate and unrelated papers, 560 papers remained after the initial filters from step 3. To enhance the quality of the review, only journals and periodic papers were considered. After the initial reading of the introduction, abstract, and conclusions of the papers, papers which were not within the scope of this research were excluded. In this step, only 158 papers remained.

Step 5: Bibliometric analysis of the remaining dataset of papers. Following qualitative analysis on the filtered dataset was performed using RStudio software and Bibliometrix and BiblioShiny packages: (a) annual scientific production of WoS and Scopus, (b) trend topics, (c) co-occurrence network map of the most cited keywords, (d) most relevant sources, (e) H-index from the main sources of papers, and (f) origin (country) of the papers.

Step 6: Systematic Literature Review. After analyzing the metrics of the dataset, a systematic literature review was conducted to identify gaps in the research on trading algorithms.

**TABLE 1** Applied filters for the bibliometric and literature review

| Description | Filter |
|---|---|
| Research Period | 2008–2021 |
| Year of Research | 2021 |
| Type of Paper | Conference Papers/Journal |
| Concentration Areas | Computing, finances, mathematics and engineering |
| Number of Resulting Papers | 843 papers (390 Web of Science and 453 Scopus) |

## 3 | BIBLIOMETRIC ANALYSIS

According to Donthu et al. (2021), bibliometric analysis can be implemented to map the scientific knowledge of a specific topic. In step 5, using the final dataset of 158 papers, a bibliometric analysis was conducted to build the knowledge of the dataset. Figure 1 shows annual scientific publications from 2015 to 2021. As can be seen in the figure, between 2017 and 2020, the number of papers with cryptocurrencies as a main topic grew; in 2017, after a bull run in market, Bitcoin became the center of media attention, which can a reason of researchers starting to publish papers in this area after the initial curiosity.

Figure 2 shows the trending topics in the research of our sample. We can see a high frequency of terms such as neural networks, long short-term memory (LSTM), learning algorithms, and deep learning. In this case, we can highlight some main topics to categorize the results of our research: Deep Learning, Big Data, Machine-Learning Algorithms (artificial intelligence, learning algorithms, and learning systems), Technical Analysis, and Portfolio Management, all of which focus on finding the most profitable trading strategy.

As a complementary study of the main topics, Figure 3 presents the co-occurrence map of the most cited keywords in the filtered 158 papers. In this figure, the link between finances and machine-learning algorithms can be seen.

As shown in Figure 4, most papers were from finance or economics journals. In addition, most relevant sources for the research had a high scientific impact (H-index), as shown in Figure 5, and can be potential target journals for publishing future findings.

Among the 10 countries that published the most cryptocurrency studies, the United States, Italy, France, and Brazil are on the top of the list, as can be seen in Figure 6.

Apart from the country and source metrics, an analysis of the authors and papers was conducted to identify the most cited papers (Table 2). As can be seen in Table 2, most authors prefer to work with deep learning and machine-learning algorithms to forecast the prices of cryptocurrencies and manage smart portfolios.

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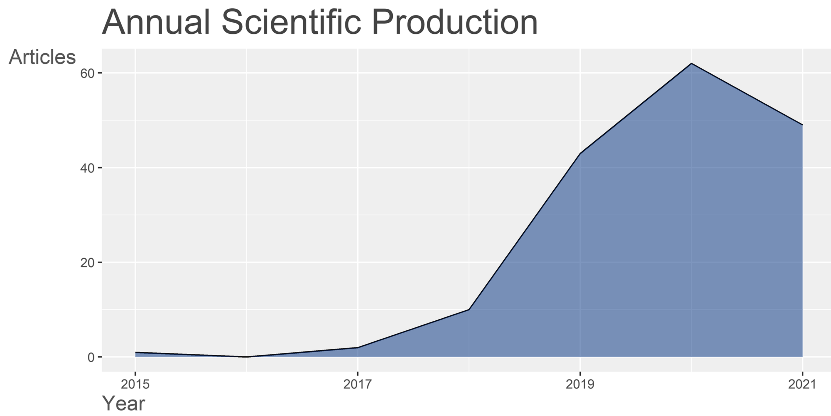


**FIGURE 1** Annual Scientific Production since 2008. Source: BiblioShiny

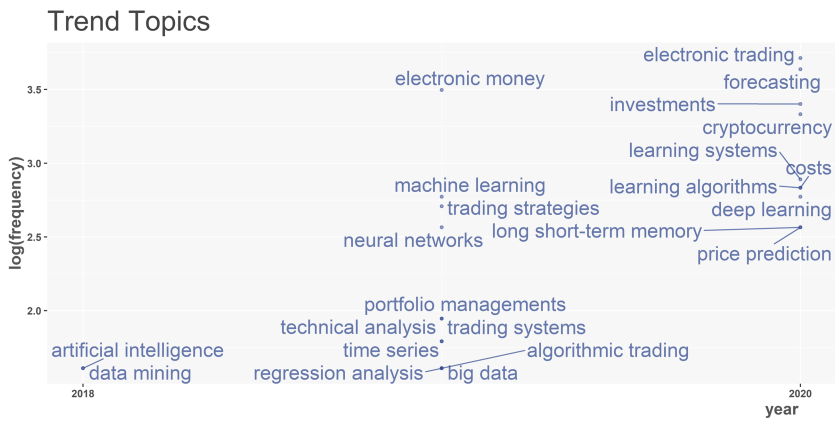


**FIGURE 2** Trend Topics of the final sample. Source: BiblioShiny

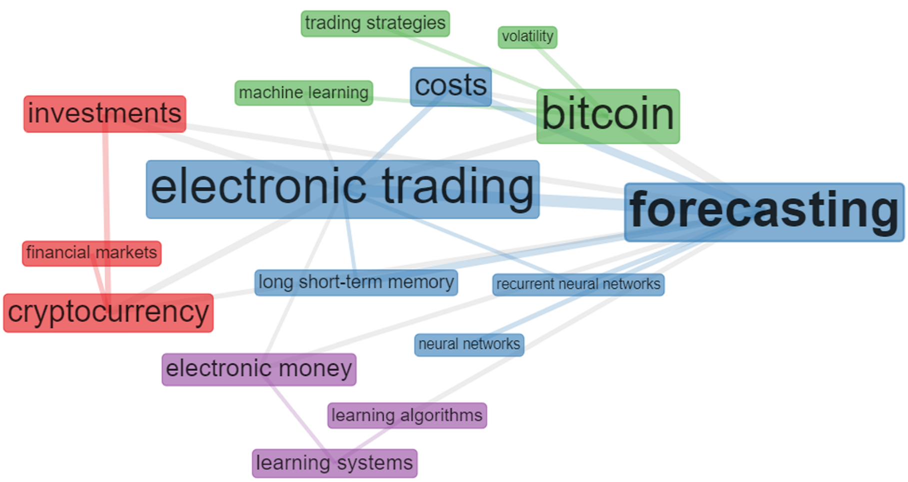


**FIGURE 3** Co-occurrence map between the most cited keywords. Source: BiblioShiny

Most of the studies have only analyzed less than 10 cryptocurrencies, except for the study by Alessandretti et al. (2018).

## 4 | SYSTEMATIC REVIEW

### 4.1 | Price forecasting

Since the creation of Bitcoin, social networks and the Internet have contributed to the dissemination of knowledge about investment in cryptocurrencies even before the introduction of exchanges which now facilitate in investing coins or tokens. Several researchers have studied how information or news published on social networks, such as Twitter and Reddit, is related to people's feelings and affects the price of Bitcoin (Balfagih & Keselj, 2019; Dipple et al., 2020; Garcia & Schweitzer, 2015; Guégan & Renault, 2021; McCoy & Rahimi, 2020; Phillips & Gorse, 2017, 2018; Poongodi et al., 2021; Tamura & Matsuo 2020) and other coins (Dipple et al., 2020; Garcia & Schweitzer, 2015; McCoy &

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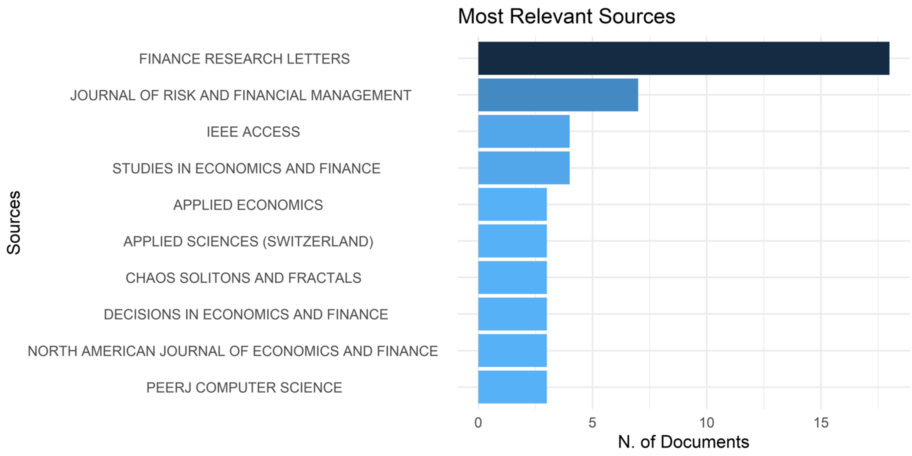


**FIGURE 4** Top 10 most relevant journals of the research. Source: BiblioShiny

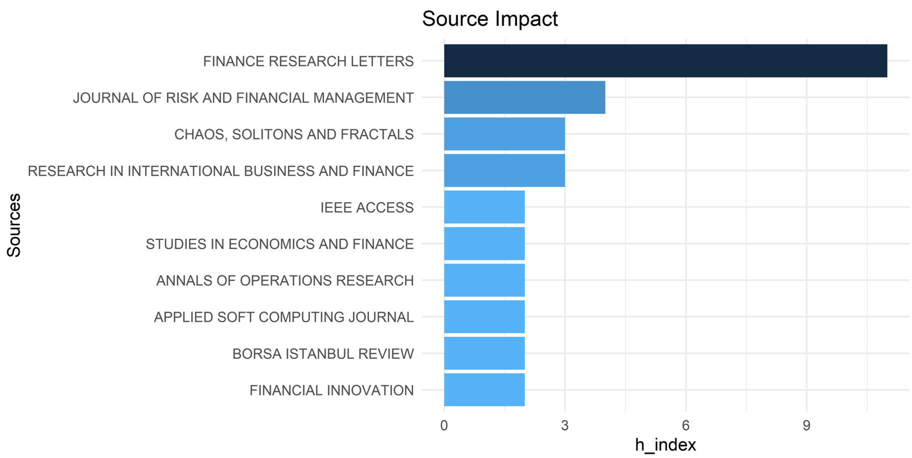


**FIGURE 5** H-index (source impact) of the journals. Source: BiblioShiny

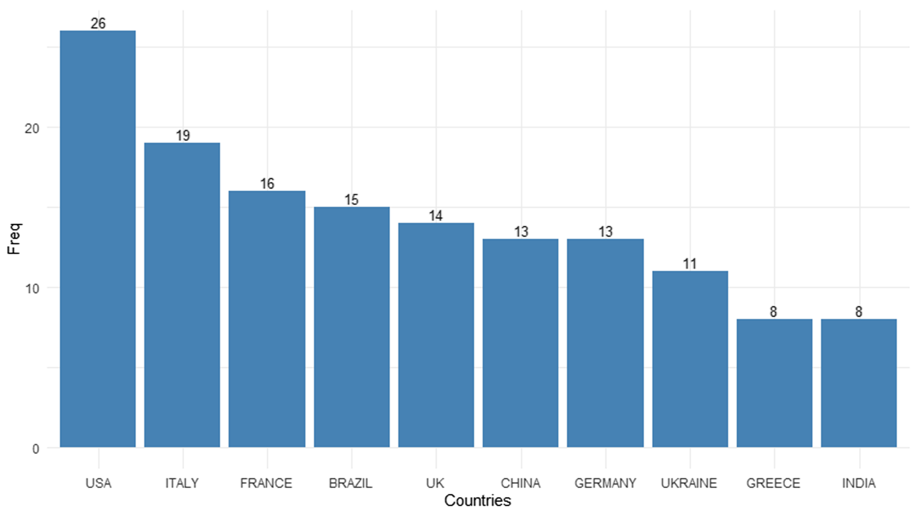


**FIGURE 6** Top 10 countries that publish the most

Rahimi, 2020; Phillips & Gorse, 2017; Poongodi et al., 2021; Tamura & Matsuo, 2020).

With evolution in cryptocurrency and advances in the creation of centralized and decentralized exchanges, accurate information on prices has become accessible and therefore studies are emerging in this line of research using Neural Networks and Deep Learning to analyze market volatility (Bu & Cho, 2018; Miura et al., 2019), forecast future prices (Betancourt & Chen, 2021b; Bu & Cho, 2018; Ji et al., 2019; Lahmiri & Bekiros, 2019, 2021; Lee, 2020; Li et al., 2020; Livieris et al., 2021; Loh & Ismail, 2020; Lucarelli & Borrotti, 2019; Miura et al., 2019; Nithyakani et al., 2021; Sattarov et al., 2020; Sun et al., 2021; Zanc et al., 2019), and managing portfolios

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**TABLE 2** Top 10 most cited papers. Source: BiblioShiny

| Paper | Year | Method | Number of cryptocurrencies |
|---|---|---|---|
| Altan et al. (2019) | 2019 | LSTM and EWT decomposition | 4 |
| Lahmiri and Bekiros (2019) | 2019 | LSTM | 3 |
| Bouri et al. (2019) | 2019 | GARCH | 7 |
| Garcia and Schweitzer (2015) | 2015 | VAR, IRF | 1 |
| Atsalakis et al. (2019) | 2019 | Neuro-fuzzy controller | 1 |
| Mallqui and Fernandes (2019) | 2019 | ANN, SVM, ensemble algorithms, and *k*-means | 1 |
| Alessandretti et al. (2018) | 2018 | LSTM and recurrent neural networks | 1681 |
| Caporale and Plastun (2019) | 2019 | Student's *t*-test, ANOVA, and Kruskal–Wallis test | 4 |
| Troster et al. (2019) | 2019 | GARCH and GAS | 1 |
| Lukáš and Taisei (2017) | 2017 | Feed-forward neural network | 1 |

with Bitcoin in an automated way (Betancourt & Chen, 2021a; Jiang & Liang, 2016; Ren et al., 2021; Shi et al., 2019; Sun et al., 2021).

Other studies (Pintelas et al., 2020) have shown that pure deep learning models are not sufficient to forecast cryptocurrency prices; however, when combined with other advanced machine-learning algorithms (Al-Ameer & AL-Sunni, 2021; Borges & Neves, 2020; Chen et al., 2020; Dutta et al., 2020; Pintelas et al., 2020), deep learning models can better forecast prices of the largest currencies through market capitalization and understanding of the herd effect (Chu et al., 2020). Anghel (2020) studied some models of machine learning and concluded that even the most advanced models in the data science area can be problematic for predicting prices; however, models based on technical analysis, such as moving averages, are less biased (Anghel, 2020).

## 4.2 | Portfolio management

Some studies presented modeling to build a smart portfolio: Leung and Nguyen (2019) were the only ones to not use machine learning or deep learning in the process of building the cryptocurrency portfolio. They conducted a study on the co-integration of four main currencies, Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC), and Bitcoin Cash (BCH), using the CryptoCompare API between December 2017 and June 2018, and set up a strategy using an econometric model called ARMA.

Jiang and Liang (2016) built a portfolio using the Poloniex API with 12 currencies with the highest volume at the exchange and used data updated every 30 min to assemble their strategy using convolutional neural networks and deep reinforcement. One disadvantage of this method is that it is not possible to simulate a portfolio in real time.

Sun et al. (2021) used the same database (Jiang & Liang, 2016) with the 12 largest cryptocurrencies compared with volume and combined reinforcement learning algorithms with deep learning. A comparison with the main portfolio selection strategies, such as Online Moving Average Reversion (OLMAR) and Weighted Moving Average Mean Reversion (WMAMR), and the strategy used in their study surpassed the others that did not have learning by reinforcement. In their study, the authors used only price, which can be a disadvantage as other metrics were ignored, such as investor sentiment.

Betancourt and Chen (2021a) proposed a dynamic portfolio management strategy using deep learning and learning by reinforcement on data from August 2017 to November 2019 from the Binance API with 85 cryptocurrencies and used buy and sell data of 30 min, 6 h, and 1 d. Compared with other strategies, this is the only one that presents a more dynamic approach to the market.

Ren et al. (2021) used a neural network with reinforcement learning and a set of characteristics such as traded volume, moving average, Elliot oscillator, and stochastic oscillator in 11 cryptocurrencies with the highest market volume of past 30 days before the backtesting strategy and compared them with traditional strategies such as OLMAR and CWMR, achieving better performance than all the strategies compared.

Shi et al. (2019) proposed in their paper a deep learning framework with a convolutional network with inception, a method already used in image analysis and applied to portfolio management. They obtained the database through the Poloniex exchange API for the largest cryptocurrencies in volume in three studied periods: DASH, LTC, XEM, XMR, XRP, ETH, FCT, ETC, ZEC, GNT, USDT, BTS, STR, VTC, and BCH, excluding Bitcoin. The performance of the framework was compared with that of other deep learning models and traditional strategies to obtain better results in all analyzed periods.

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Koker and Koutmos (2020) applied a machine-learning model of direct reinforcement in the five largest coins in circulation: BTC, ETH, LTC, XRP, and XRM between 26 August 2015 and 12 August 2019 in the 1-day period. Its performance was compared with the cumulative earnings versus the HOLD of the coins for the same period. For Bitcoin, the built model achieved better performance, tripling the value of Bitcoins in the portfolio. A disadvantage raised by the authors is the number of variables that can be used to improve the proposed model.

## 5 | DISCUSSION AND CONCLUSION

This review conducted a bibliographic and systematic review of 158 research papers involving trading strategies for price forecasting and portfolio management of cryptocurrencies. As per our findings, we can summarize the research interest in five main topics: Deep Learning, Big Data, Machine-Learning Algorithms, Technical Analysis, and Portfolio Management.

Several researchers used advanced computational models (LSTM, Recurrent Neural Networks, Reinforcement Learning) in their studies to achieve assertive results, while few of them used econometric models such as Vector Autoregression (VAR), GARCH, and technical analysis such as moving averages.

We noticed that most of the papers excluded analysis of cryptocurrencies with minor market capitalization, the ones that are not in the top ranking market capitalization. Therefore, this can be an opportunity for future studies on the aforementioned minor cryptocurrencies as the cryptocurrencies market is in constant expansion and new coins are created every day.

In addition, only a few studies have proposed a framework to deal with trading strategies in real time. According to CoinMarketCap, there are more than 16,000 cryptocurrencies in the cryptomarket, and studies that understand how to manipulate and create models with this amount of data using Big Data can be a valid topic for future investigations, especially in intraday price prediction.

The aim of this research is to identify gaps in the academic literature on trading strategies and contribute to the authors' interest in the topic.

## ACKNOWLEDGMENTS

IRRS thanks a PhD grant provided by Conselho Nacional de Desenvolvimento Científico e Tecnológico (CAPES), the Brazilian federal government agency under the Ministry of Education; PPB thanks the Brazilian agency CNPq (Conselho Nacional de Desenvolvimento Científico e Tecnológico) for the research grant 305199/2019-6. We also thank Editage (www.editage.com) for English language editing. And last, IRRS would also like to thank Dr. Nizam Omar for the years of mentoring and guidance during her PhD.

## CONFLICT OF INTEREST

There are no conflict of interests in this research.

## DATA AVAILABILITY STATEMENT

The data that supports the findings of this paper comes from CoinMarketData API and Web of Science and Scopus database.

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

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**How to cite this article:** Ruiz Roque da Silva, I., Junior, E. H., & Balbi, P. P. (2022). Cryptocurrencies trading algorithms: A review. *Journal of Forecasting*, *41*(8), 1661–1668. https://doi.org/10.1002/for.2886

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