FORECASTING CRYPTOCURRENCY PRICES: AN OVERVIEW OF THEORETICAL AND EMPIRICAL LITERATURE

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ABSTRACT:

Since the inception of Bitcoin in 2008, numerous different crypto assets have been established and are currently regarded as being at the forefront of financial innovation. Given the complex nature of cryptocurrency prices and the various factors that may influence them, there is a need for a comprehensive study that utilizes advanced techniques to investigate the determinants of cryptocurrency prices and improve forecasting accuracy. This study aims at enriching the debate surrounding the determinants of cryptocurrency prices and the best methods used to ensure good forecasting. A recent theoretical and empirical literature review is presented, based on the main research on forecasting cryptocurrency prices. The goal of this paper is to explore which variable the most affects Bitcoin prices, Ethereum prices, and other cryptocurrency prices, and what is the most effective method for predicting their future movements. The studies reviewed in our literature review highlight the potential of incorporating Blockchain information in cryptocurrency price prediction models and suggest that this information can improve the accuracy of these models. However, there is still much room for further research to fully exploit the potential of this unique data source and to develop more effective methods for incorporating Blockchain information in cryptocurrency price prediction models. We hope that the key findings of this study will contribute to the expansion of knowledge in the field of cryptocurrency research.

Key-words:

Cryptocurrency prices forecasting, DeFi Trading, Econometric methods, Artificial Intelligence techniques, Blockchain information.

JEL Classifications: *B27, C61, C82, G12.*

1. INTRODUCTION

The world of cryptocurrencies has brought many new things in its wake: programmable currencies, Non-Fungible Token, metavers, etc. Yet, one of the most important innovations for businesses in the long run could be DeFi. DeFi, or decentralized finance, is an alternative system to traditional finance. It is becoming more democratic, and many crypto enthusiasts are taking a keen interest in this new field. While Bitcoin has paved the way for the exchange of value on the Internet without a centralized third party, DeFi wants to go further by offering users a whole range of decentralized financial services through borrowing and lending, insurance, exchange platforms or even liquidity providers. Djoufouet and Tonmo (2022) identify six broad categories of DeFi services - stablecoins, exchanges, loans, derivatives, insurance, and asset management - as well as ancillary services such as wallets and oracles. While centralized finance relies on intermediaries to manage and process financial services, DeFi operates in a decentralized environment. Services are typically encoded in open source software protocols and smart contracts (Lee et al., 2018).

Artificial Intelligence (AI) and DeFi are two technological developments that have gained tremendous traction in the last couple of years (Sadman et al., 2022). Made possible through the smart contracts functionality of the Ethereum protocol or other Blockchains, this new form of finance offers the possibility of moving valuable assets in a more fluid and transparent way using the Blockchain directly (Centobelli et al., 2021). Behind DeFi is the idea that citizens could regain control of their financial destiny, giving them freedom from large financial structures that often impose their terms (Bahga & Madisetti, 2016). Blockchain is a peer-to-peer public ledger managed by a distributed network of computers that requires no central authority or third-party intermediary. The benefits of Blockchain through the creation of smart contracts have already attracted many financial institutions. This is because the smart contract can help reduce uncertainty and speculation. A Blockchain-based system can be used as a reliable solution to manage various financial contracts and will help financial institutions work more productively and efficiently. Blockchain proposes, therefore, a new paradigm, decentralized, unmediated and dematerialized (Schär, 2021). Thus, the transparency, traceability, and immutability characteristics of Blockchain technology allow it to be applied in a variety of transactions (Rabbani et al., 2020).

When talking about Blockchain, the first instinct is to think of Bitcoin, which is a crypto asset that sees itself as an alternative to the current monetary system. Since the inception of Bitcoin, numerous different crypto assets have been established and are currently regarded as being at the forefront of financial innovation.

Cryptocurrencies have been volatile for several years, but the last four years have been a particularly wild ride for millions of investors around the world. Successful investing is based on making accurate price predictions for cryptocurrencies since doing so enables investors to develop risk management plans and optimization techniques that take unpredictability and the prospect of loss into account. Accurate price prediction might also be used to support investing methods like portfolio management to attain stability and maximum earnings (Nanayakkara et al., 2021). It is challenging for investors and stakeholders to effectively turn a profit, though, because the market has a dynamic structure that is governed by numerous forces. To construct successful investing strategies, an accurate price prediction model must be developed (Kim et al., 2022).

Recent research has focused on three main sets of factors that drive cryptocurrency price formation. A first set of factors related to traditional currency and related to market forces, a second set of factors specific to cryptocurrency and related to its attractiveness, and a final set of factors are economic in nature related to macroeconomic and financial development (Van Wijk, 2013; Bouoiyour & Refk, 2016; Kristoufek, 2018).

To date, several studies have attempted to predict the price of cryptocurrencies, utilizing various methods such as traditional statistical techniques, machine learning, and deep reinforcement learning. Studies have shown that traditional statistical methods have been widely used to predict the price of cryptocurrencies, but they suffer from limitations such as the lack of incorporating external factors. Machine learning methods have been used to improve the prediction accuracy of cryptocurrency prices by incorporating external factors, but they suffer from limitations such as the lack of interpretability. Deep reinforcement learning techniques have been used to improve the prediction accuracy of cryptocurrency prices by incorporating external factors and providing interpretability, but they suffer from limitations such as the need for large amounts of data. Thus, there remains a gap in understanding the factors that drive the price of cryptocurrency and the most effective methods for predicting its future movements.

The number of academic studies on cryptocurrencies has grown exponentially in recent years. Given the unpredictable nature of a highly volatile market impacting individual users, companies, countries, and international relations alike, cryptocurrencies occupy the center of researchers' attention. In this context, our study aims at **enriching the debate surrounding the determinants of cryptocurrency prices and the best methods used to ensure good forecasting.** To reach conclusions on the subject at hand, we first located and examined all relevant literature on the subject for our systematic review method. A recent theoretical and empirical literature review is presented, based on the main research on forecasting cryptocurrency prices. The goal of this paper is to explore which variable affects cryptocurrency prices the most, and what is the most effective methods for predicting its future movements. The structure of this paper is as follows: the first section will provide a literature and empirical review of the main drivers of Bitcoin prices, Ethereum prices and other cryptocurrency prices. The second section will review the literature on various methods that have been used to predict the price of cryptocurrencies, including traditional statistical and econometric methods, as well as more recent machine learning and artificial intelligence techniques. Finally, we will conclude with a summary of our main findings and recommendations for future research.

2. LITERATURE AND EMPIRICAL REVIEW

This part of the study analyzes and withdraws valuable information from previous research looking at the determinants of cryptocurrency prices. About our research methodology, we only included scholarly journals written in English. The flow of information through our systematic review approach is based on the PRISMA protocol, which was adapted from Page et al. (2021). First, during the identification step, we identified 1.019 articles. Then, using *rayyan* and our quality standards, we deleted 43 duplicates and removed 680 articles. Second, during the screening step, we evaluated 296 papers, deleting 33 that did not meet our qualifying requirements. Finally, throughout the inclusion step and because of our procedure, our final sample showed 90 articles.

2.1 Overview of Main Drivers of Bitcoin Prices

Bitcoin, which was introduced in early 2009, began trading at $0.50 in December 2010. Its value has now skyrocketed, reaching $40,040 in January 2021 and over $50,000 in February 2021. On the 19th of the same month, Bitcoin's market capitalization surpassed $1 trillion for the first time. In February 2022, the global cryptocurrency market capitalization exceeded $1.7 trillion. By market capitalization, Bitcoin is the most valuable cryptocurrency, followed by Ethereum (Naifar et al., 2023). Bitcoin and Blockchain technologies are shaping and defining new areas of computer science and information technology. The need for decentralized money has been explored more as a theoretical concept, but in the last decade, it has become a reality, owing to Satoshi Nakamoto's renowned paper in 2008, which introduced Bitcoin and Blockchain technology (Vujičić et al., 2018). As stated by Li et al. (2022), some natural questions about Bitcoin price forecast arise: *Is the price of Bitcoin predictable*? *What variables influence its market value*? Previous research has identified several kinds of potential factors influencing Bitcoin price movements: internal parameters such as Bitcoin market volume, Bitcoin transaction patterns, and hash rate (Chen et al., 2020; Jang & Lee, 2018), external factors such as external commodities, investor mood, and foreign currency exchange rates (Li et al., 2022; Buchholz et al., 2012), investor sentiment in financial markets (Kristoufek, 2018; Ortu et al., 2022; Sapkota, 2022; Glaser et al., 2014; Naifar et al., 2023), macroeconomic factors (Poyser, 2019; Palombizio & Morris, 2012; Van Wijk, 2013; Dimitrova, 2005), the Ukrainian crisis (Boubaker et al., 2022; Boungou & Yatié, 2022; Appiah-Otoo, 2023; Khalfaoui et al., 2022; Theiri et al., 2022). **Table 1** summarizes the various studies that have been conducted, using different methods, to identify potential factors affecting Bitcoin prices, as documented in the literature.

2.2.Overview of Main Drivers of Ethereum Prices

Transactions via Ethereum have become even more important in the wake of the DeFi explosion. By 2023, Ethereum, or its token ETH, is one of the major digital decentralized currencies today and is the second biggest one (Coinmarketcap, 2022), with a market capitalization of over $200 billion, making it one of the most sought-after and valuable cryptocurrencies. Ethereum price forecasting enables investors to make informed decisions when buying and selling Ethereum. After a significant price increase in 2021, Ethereum consolidated its place among other cryptocurrencies, and for the first time, new investors began buying Ethereum instead of Bitcoin. **Table 2** summarizes the various studies that have been conducted, using different methods, to identify potential factors affecting Ethereum prices, as documented in the literature.

2.3. Overview of Main Drivers of Other Cryptocurrency Prices

The vast majority of published cryptocurrency research focuses on Bitcoin. However, given the current era, many more cryptocurrencies have entered the Blockchain technology space. Investors are now pivoting their preference from Bitcoin to other cryptocurrencies, looking at the market's mood. However, according to Shahbazi and Byun (2021), the previous approaches in price prediction don't contain enough information and solution for forecasting the price changes, due to the real-time prediction of prices. Recent theoretical and empirical research indicates that the price dynamics of cryptocurrencies are driven by a variety of hidden factors (Derbentsev et al., 2020). These critical factors drivers are not well understood and identified (Selmi et al., 2018; Ciaian, 2016; Derbentsev et al., 2020). **Table 3** summarizes the various studies that have been conducted, using different methods, to identify potential factors affecting cryptocurrency prices, as documented in the literature.

Table 1. Recent studies using various approaches and main determinants for Bitcoin price prediction

References	Methodology	Study Period	Key Factors	Results
Rafi et al. (2023)	Bi-directional LSTM Implemented wrapper approach MDI approach CUSUM control charts	First test set: 1) April 01, 2013, to April 01, 2016 2) April 01, 2013, to April 01, 2017 3) April 01, 2013, to December 31, 2019 New test set: January 01, 2020, to January 01, 2022 ***Dataset:*** *Bitcoincharts*	Blockchain information	Bitcoin forecasting: The model achieved RMSE values 3.499 for interval 1, 5.070 for interval 2 and 6.642 for interval 3. Ethereum forecasting: RMSE of 0.094, 0.332, 3.027 are obtained for the three intervals respectively. On a new test-set collected for the two cryptocurrencies, results show an average RMSE of 9.17, with model bias correction. The performance evaluation metrics' outcomes demonstrate a notable advancement in the current literature's ability to predict daily closing price as well as price variation.
Mallqui and Fernandes (2019)	ANN SVM RNN and the *k*-Means clustering method	August 19, 2013, to July 19, 2016 ***Dataset:*** *Bitcoincharts, Quand, Investing*	Bitcoin's Blockchain information: volume of trades, total transaction fees, cost per transaction, number of transactions, hash rate. Macro-economic factors: Crude oil, Gold, S&P 500 NASDAQ 100, DAX index Google popularity index- Wikipedia search volume	The combination of Recurrent Neural Networks and a Tree classifier obtained the best results to predict the Bitcoin price direction.
Ortu et al. (2022)	*MLP* *CNN* *LSTM* *MALSTM-CNF*	January 1st, 2017, to January 1st, 2021 ***Dataset:*** *Crypto Data Download, Bitfinex*	Technical indicators (e.g. opening and closing prices), trading indicators (e.g. moving averages), and social indicators (e.g. users' sentiment) indicators.	Including *both* trading and social media indicators, results show a significant improvement in the prediction and accuracy consistently across all algorithms. In the cryptocurrency ecosystem, social communities and markets are closely connected.
Aggarwal et al. (2019)	CEEMD SVM	February 3, 2012 to October 3, 2018 ***Dataset :*** *Investing*	Economic events Market inefficiency	CEEMD is used to determine the short, medium, and long-term trend in the Bitcoin price series using daily Bitcoin prices from 2012 to 2018. The study used the SVM learning method to determine whether it can forecast Bitcoin prices and discovers that SVM predicts Bitcoin prices five steps ahead for the short term, medium term, long term, and overall Bitcoin price level.

Dixon et al. (2019)	GARCH	February 2015 to December 2018 ***Dataset:*** *Coinbase*	Blockchain information Extreme Chainlet	The authors fit GARCH models with and without the extreme chainlets using bars ranging from 15 minutes to a day, and they demonstrate that the former display greater Value-at-Risk Backtesting risk effectiveness. In general, extreme chainlets give a more granular depiction of the market than Bitcoin price information, allowing investors to make more informed portfolio allocation and hedging decisions.
Koo and Kim (2021)	MLP RNN LSTM FDS based on the copula theory	April 28th, 2013, to April 27th, 2020 ***Dataset:*** *Not indicated*	Volume of business, market capitalization, Prices of Bitcoin in terms of open, high, low, close (consider close price of Bitcoin to predict return direction)	The proposed algorithms based on FDS improve significantly the prediction accuracy of the return of Bitcoin price for each of the three architectures.
Dimpfl and Peter (2020)	ILS Traditional measures	March 8th, 2017, to November 8th, 2017 ***Dataset:*** *Coinmarketcap, Bitcoinity, Bitfinex, Kraken, Poloniex*	Market microstructure noise NYSE and NASDAQ stocks	The traditional measures suggest a lower information share compared to the information leadership share, which accounts for the noise component in the price series.
Li et al. (2022)	VMD-LMH-BiSTM model	April 29, 2013, to January 1, 2021 ***Dataset:*** *Quandl*	Transaction fees, Bitcoin volume, USD exchange volume, XAU exchange rate, hash rate and Google Trends	In terms of prediction accuracy throughout various forecasting periods, the suggested VMD-LMH-BiLSTM model surpassed all benchmark models.
Naifar et al. (2023)	Asymmetric framework based on the QQA approach	January 30, 2020, to April 26, 2021 ***Dataset:*** *Not indicated*	Investor sentiment, uncertainty indices (EPU, VIX, and GVZ), Bitcoin and Ethereum returns	Cryptocurrency behavior appears to be highly influenced by global uncertainty concerns. Investor attitudes can provide useful information for explaining cryptocurrency return behavior. Neither Bitcoin nor Ethereum can be used as a hedge against global financial and economic uncertainty during the COVID-19 epidemic. Bitcoin might be used as a hedge under particular gold uncertainty scenarios.
Jakubik et al. (2023)	LSTM Bi-LSTM CNN Random forest	June 6, 2011, to May 13, 2019 September 12th, 2013, to June 18th, 2019 ***Dataset:*** *Financial Times, Amazon, Yelp, Imdb, kraken*	Sentiment of the financial news, unstructured data in Bitcoin price	The LSTM predictions outperform random forest and the CNN model in terms of the MSE.nLSTM is capable of properly identifying financial news as well as accurately predicting prices in a highly turbulent market. Study highlights how combining deep learning and financial news offers investors and traders support for the monetization of unstructured data in finance.

Sapkota (2022)	HAR-RV	January 2012 until August 2021 ***Dataset:*** *99bitcoins*	Psychological and discourse sentiment dictionaries, Harvard-IV general-purpose psychological dictionary (GI), Quantitative Discourse Analysis Package (QDAP) dictionary, Finance-specific sentiment dictionaries, Henry's (2008) finance-specific dictionary (HE), Loughran and McDonald (2011) finance-specific dictionary (LM)	Psychological sentiments have medium-term and financial sentiments have long-term effects on Bitcoin volatility.
Gillaizeau et al. (2019)	Generalised variance and a decomposition approach VAR models	March 12th, 2013, to January 31st, 2018 ***Dataset:*** *Bitcoincharts, Mt.Gox, Bitstamp, LocalBitcoins*	Spillover-effects, spillover returns, sentimental value	Bitcoin-USD has a high predictive power, while Bitcoin-Euro is the net receiver. Furthermore, increased uncertainty has been observed to accelerate spillover effects, with larger implications across markets.
Otabek and Choi (2022)	Q-learning algorithm	April 1, 2014, to November 14, 2018 ***Dataset***: *Twitter*	Tweet attributes (number of tweet poster's followers, number of comments, number of likes, and number of retweets)	Tweets with the most user-related attributes had the greatest effect on the future Bitcoin price.
Wang and Wang (2020)	Partial differential equation (PDE) model	January 1, 2017, to December 31, 2017 ***Dataset:*** *Bitcoin, Google trends*	Effect of bitcoin market sentiment	The study is the first attempt to apply a PDE model to the Bitcoin transaction network for forecasting. The PDE model can forecast the Bitcoin price movement.
Sujatha et al. (2021)	Levenberg-Marquard Bayesian Regularization Scaled Conjugate Gradient	The year 2019 ***Dataset:*** *Sentiment*	Price, volume, market capitalization, social dominance, development activity, market value to realized value and realized capitalization	The results of the error histogram and regression plots reveal that the Bayesian Regularized Neural Network performs well and so delivers a more accurate forecast.

Aghashahi and Bamdad (2023)	Feedforwardnet Fitnet and Cascade networks	January 1, 2018 to September 30, 2018	Price-related and lagged features	This paper assesses the models' performance and how specific setups produce principled and stable predictions for beneficial trading. The Fitnet network with trainlm function and 30 hidden neurons outweighs the others.
Poyser (2019)	Bayesian Structural Time Series Approach (BSTS)	January 2013 to May 2017 ***Dataset:*** *Blockchain, Quandl*	Blockchain information, attractiveness and adoption, and macro-financial factors	In terms of attractiveness as a currency or investment asset, this study discovered evidence of different effects between countries and deviations in time, with a significant consideration of Brazil and the United States during the first time Bitcoin's price skyrocketed and Russia's positive impact at the beginning of 2016. In terms of macro-financial aspects, this analysis discovered that Bitcoin price is more affected by exchange rates than a commodity like gold or a stock indication.
Ciaian et al. (2016)	Multi-variate vector auto regressive (VAR) model	November 2009 to September 2013 October 2013 to May 2015 ***Dataset:*** *Quandl, Bitcointalk, Wikipedia, Federal Research Bank of St.Louis*	Market forces of Bitcoin: number of Bitcoin transactions, number of Bitcoin addresses Bitcoin attractiveness for investors and users: new posts in Bitcoin community site, new members in Bitcoin community site	Market forces and Bitcoin's attractiveness to investors and users have a substantial impact on Bitcoin price, however this varies over time.

Source: Authors' Contribution.

Table 2. Recent studies using various approaches and main determinants for Ethereum prices

References	Methodology	Study Period	Key Factors	Results
Kim et al. (2021)	Time-series analyses and advanced machine-learning techniques	August 11, 2015 to November 28, 2018	Macro-economic development indices, global currency ratios, generic Blockchain information (on Ethereum, Bitcoin, Litecoin, and Dashcoin), and Ethereum-specific Blockchain information.	Macro-economy factors, Ethereum-specific Blockchain information, and the Blockchain information of other cryptocurrency play important roles in the prediction of Ethereum prices. Practitioners should use macro-economic factors and the Blockchain information of Ethereum and Bitcoin actively to accurate forecast Ethereum prices.
Angela and Sun (2020)	The Autoregressive Distributed Lag (ARDL) test model	January 2016 - 28 December 2018 ***Dataset:*** *Coinmarketcap*	Macroeconomic aspects, such as EUR/USD exchange rate and the price of gold, as well as Bitcoin and other altcoins prices.	Only in the near term does EUR/USD affect Ethereum prices, whereas gold prices have no effect on Ethereum pricing. The values of Ethereum are heavily influenced by Bitcoin, Litecoin, and Monero. Nonetheless, Ripple and Stellar have no discernible impact on Ethereum prices.
Hansson (2022)	GARCH (1,1) model	Daily data between the time period 2017-08-17 and 2022-01-18	Google trends, hash rate, S&P 500, address count, trade volume, hash rate and S&P 500.	The variables Google trends, hash rate, S&P 500, address count, and trade volume impacted the volatility. With only the hash rate and S&P 500 lowering the volatility.
Zoumpekas et al. (2020)	CNN-2L, CNN-3L, LSTM, SLSTM, BiLSTM and GRU	August 8, 2015, to May 28, 2018 ***Dataset:*** *Poloniex*	Endogenous price data	The recurrent neural network, LSTM, achieved the best values in the performance metrics from the predictive models constructed and evaluated on the data, while the GRU, which came second in forecasting performance, is less computational expensive than the previous. Experiment results indicate that many of the aforementioned models can be used to predict the Ethereum closing price in real time with promising accuracy and empirically proved profitability.
Nimbark (2022)	Deep Coin Cap Algorit	April 2020 to April 2021 ***Dataset:*** Coinmarketcap	BTC dataset Coinmarketcap dataset	The proposed methodology can provide the optimum precision for Ethereum price prediction using incidence logging.

Source: Authors' Contribution.

Table 3. Recent studies using various approaches and main determinants for other cryptocurrency prices

References	Methodology	Study Period	Key Factors	Results
Shahbazi and Byun (2021)	A proposed system contains the Blockchain framework for secure transaction environment and Reinforcement Learning algorithm for analysis and prediction of price. The main focus of this system is on Litecoin and Monero cryptocurrencies.	Litecoin 2016-2020 Monero 2015-2020 ***Dataset:*** *A market statistic, Network information of Blockchain, Google trends and volume of tweets*	Timestamp, open price, high price, low price, close price, currency volume, price weight, size of block, hash rate, trades per minute, transaction numbers, confirmed transaction records, and estimated value for transactions.	The results show the presented system accurate the performance of price prediction higher than another state-of-art algorithm.
Torres et al. (2020)	A dynamic linguistic decision-making approach for building decision models to support cryptocurrency investors in buy/hold/sell decisions.	March 1st, 2018, to May 27, 2018 ***Dataset:*** *Coinmarket*	Day-profitability, day-variability, and market capitalization	The approach exhibits a good computational performance for obtaining recommendations based on quantitative data. The procedure can identify some inefficient cryptocurrency behaviors which are not captured by traditional econometric techniques. Results uncover arbitrage opportunities that outperform buy-and-hold or random strategies.
Ghosh et al. (2023)	GARCH-models	24th January 2018 - 2nd August 2022	Return and volatility properties	The returns of both NFTs and cryptocurrencies have fat tails, with evidence of tail exponents following the inverse cubic-law, along with clear persistence behavior. All returns exhibit volatility clustering, albeit to varying degrees, and the detected absence of inverse volatility-asymmetry challenges the safe-haven property often documented for cryptocurrencies. Return-based long-memory is slightly more intense than volatility-based long-memory, especially for NFTs, which demonstrate a predictability contesting market efficiency.

Fung et al. (2022)	ARMA-GARCH models GARCH models	1st March 2019 to 1st March 2021	Cryptocurrency daily returns, traded volume, and usage categories	Heavy-tailed VaR specifications outperform all normally distributed alternatives. Authors find long memory, volatility clustering, heavy tails, and negative leverage effects to be common features of cryptocurrencies' return behavior. GARCH models accounting for these features provide the best goodness-of-fit properties. About 80% of cryptocurrencies are well described by Student's t GARCH specifications with the TGARCH-stud chosen for about 20% of the sample.
Nayak et al. (2023)	eAEFA, eAEFA+RVFLN, ARIMA (MLP), RVFLN, SVR, LSTM, GA trained RVFLN, and AEFA trained RVFLN.	April 17, 2017, and May 6, 2021 ***Dataset:*** *Cryptodatadownload*	Historical prices	The proposed eAEFA+RVFLN findings outperform the comparator models in terms of performance and statistical significance tests. A number of additional elements affecting crypto data, including social media trends, laws, investor mood, and the interdependencies among the currencies that are now available, could be included in addition to past pricing.
Jiang et al. (2021)	Rolling window quantile regression	August 10th, 2015, to June 30th, 2020 ***Dataset:*** *Policyuncertainty, Economicpolicyuncertaintyinchina.weebly, Coingecko*	EMV, EPU, and cryptocurrencies returns	Cryptocurrencies act as good hedging tools against high EPU, but not during periods of moderate or low EPU and that their hedging properties don't remain all the time. Several kinds of cryptocurrencies, XRP and XLM specifically, can serve as hedging assets during such period of extreme financial market panic.
Fruehwirt et al. (2021)	Wavelet analysis	January 11, 2017, to April 5, 2018 ***Dataset:*** *Bittrex exchange*	Critical events, market capitalization, 24-hour trade volume, and circulating supply	The findings emphasize the benefits of researching cryptocurrencies in time-frequency space and employing data with high temporal resolution. This result adds to a growing body of literature showing that the dependence between the parts of a complex system increases, when instability increases.
Panagiotidis et al. (2022)	Traditional and Markov-switching GARCH models	Not indicated	Closing prices	For a wide range of cryptocurrencies, time-varying models outperform traditional ones.
Haykir and Yagli (2022)	PSY methodology CSAD approach Panel and time-series probit estimations	January 1, 2020, to March 31, 2021 ***Dataset:*** *Coinmarketcap, Google trends, Crypto Currencies Index*	Lagged returns, volatility, volume, market returns, and Google trends	Results indicate that each cryptocurrency covered in the study presented bubbles. Explosive behavior in one currency leads to explosivity in other cryptocurrencies.
Müller et al. (2022)	GARCH model	September 8, 2017, until November 5, 2021	Daily closing prices	The main driver for the RVaR of cryptocurrencies is the conditional standard deviation and not the distribution of the stochastic term. The Value at Risk (VaR) and Expected Shortfall (ES), non-normal distributions present the best performance.
Pessa et al. (2023)	Bayesian linear model Clauset-Shalizi-Newman method	29 April 2013 to 25 July 2022 ***Dataset:*** Coinmarketcap	Daily closing prices	Changes in the tail exponents are very often simultaneously related to cryptocurrency age and market capitalization or only to age, with only a minority of crypto assets being affected just by market capitalization or neither of the two quantities. Trends in power-law exponents usually point to mixed directions, and that large price variations are likely to become less frequent only in about 28% of the cryptocurrencies as they age and grow in market capitalization.

Şoiman et al. (2023)	Time series and panel regressions	From March 2018	Cryptocurrency market, network effect, and valuation ratio	The impact of the cryptocurrency market on DeFi returns is stronger than any other considered driver and provides superior explanatory power.
Azqueta-Gavaldón (2020)	Latent Dirichlet Allocation (LDA) Convergent Cross Mapping (CCM)	April 2013 to December 2018	Financial investment, technological innovation, security breaches, and regulation	The research explores the causal relationship between the narratives embedded in conventional media-articles describing cryptocurrencies and prices: Two positive narratives (investment and technology), and two defeatist narratives (security and regulation). Results indicate a strong bi-directional causal relationship between narratives and cryptocurrency prices.
Stosic et al. (2018)	Random matrix theory Minimum spanning trees	August 26, 2016, to January 18, 2018 ***Dataset:*** *Coinmarketcap*	Price change	Results reveal the presence of multiple collective behaviors in the market of cryptocurrencies, which can be useful when constructing cryptocurrency investment portfolios.
Enoksen et al. (2020)	VIX-index EPU-index	December 27, 2013, to February 15, 2019 ***Dataset:*** *Coinmetrics, Coinmarketcap, Economic Policy Uncertainty, FRED database*	Uncertainty measures	Higher volatility, trading volume and transactions are positively associated with the presence of bubbles across cryptocurrencies. Regarding the uncertainty variables, the VIX-index consistently demonstrates negative relationships with bubble occurrence; the EPU-index mostly exhibits positive associations with bubbles.
Khalfaoui et al. (2022)	Quantile cross-spectral analysis	February 24, 2022, to June 21, 2022	Public sentiment toward the Russia-Ukraine conflict (Google Trend Russia-Ukraine war index)	Russia-Ukraine war public attention has a strong negative causal effect on the four cryptocurrencies (BTC, XRP, ETC, LTC) and G7 stock market returns.

Source: Authors' Contribution.

3. Main Methodologies used to Forecast Cryptocurrency Prices

This section will review the literature on various methods that have been used to predict the price of cryptocurrencies, including traditional statistical and econometric methods (**Table 4**), as well as more recent machine learning and artificial intelligence techniques (**Table 5**).

Table 4: Methodologies used to forecast cryptocurrency prices using traditional statistical and econometric methods

References	Method	Main Results
Ghosh et al. (2023)	GARCH-models	Particularly for NFTs, which exhibit a predictability challenging market efficiency, return-based long-memory is marginally more intensive than volatility-based long-memory. These results are generally in line with earlier studies on stocks, suggesting that cryptocurrencies and NFTs behave more like traditional assets in terms of return and volatility.
Fung et al. (2022)	ARMA-GARCH models GARCH models	The findings have substantial implications for investors, politicians, and regulators in the cryptocurrency market in terms of understanding and evaluating market risk.
Jiang et al. (2021)	Rolling window Quantile regression	Evidence from China, the United States, and the United Kingdom demonstrates that early response to extreme outbreaks such as COVID-19 is critical to preventing the financial market and the economy from collapsing. Several cryptocurrencies, particularly XRP and XLM, can function as safe-haven assets during such a period of significant financial market panic.
Naeem et al. (2021)	A cross-quantilogram	The relationship between oil demand shocks, BTC and BNB suggests that cryptocurrencies are more stable than oil market shocks, making them an excellent hedge against sovereign risk and systemic instability.
Fruehwirt et al. (2021)	Wavelet coherence analysis	Following the high of the Bitcoin price in December 2017, there was a structural change in the links between cryptocurrencies toward instability, as indicated by increased interdependence.
Panagiotidis et al. (2022)	Traditional and Markov-switching GARCH models	Time-varying models beat traditional ones for a wide spectrum of cryptocurrencies.
Müller et al. (2022)	GARCH model	The conditional standard deviation, rather than the distribution of the stochastic factor, is the primary driver of cryptocurrency RVaR.
Haykir and Yagli (2022)	PSY methodology CSAD approach	Volume and volatility among cryptocurrency-specific characteristics are positively correlated with bubbles, and Google Trends is the sole market-related indicator that is positively connected with bubbles. Investors can use these indicators to forecast bubbles in a certain digital currency and profit from volatile price changes.
Şoiman et al. (2023)	Time series and panel regressions	The Bitcoin market has a greater impact on DeFi results than any other investigated driver and provides superior explanatory power.
Azqueta-Gavaldón (2020)	Latent Dirichlet Allocation (LDA) Convergent Cross Mapping (CCM)	A substantial bidirectional causal link between narratives and Bitcoin prices.
Stosic et al. (2018)	Random matrix theory Minimum spanning trees	There are numerous collective behaviors in the Bitcoin market that can be advantageous when developing cryptocurrency investment portfolios.
Enoksen et al. (2020)	VIX-index EPU-index	In terms of uncertainty variables, the VIX-index constantly shows negative links with bubble incidence, whereas the EPU-index typically shows positive relationships with bubbles.
Naifar et al. (2023)	The Quantile-on-Quantile approach	Cryptocurrency behavior appears to be highly influenced by global uncertainty issues, and investor opinions can provide vital insights into explaining cryptocurrency return behavior. This study implies that Bitcoin could be used as a hedge under particular gold uncertainty scenarios.
Dimpfl and Peter (2020)	ILS traditional measures	Poloniex's increased degree of microstructure noise overshadows its contribution to price discovery to the point that existing techniques cannot reliably discern the

		genuine contribution.
Sapkota (2022)	HAR-RV	The heterogeneous autoregressive model for realized volatility (HAR-RV), which uses the heterogeneous market concept to create a simple additive volatility model at different scales to learn which factor is influencing the time series, along with news sentiments as explanatory variables, demonstrated a better fit and higher forecasting accuracy.
Gillaizeau et al. (2019)	Generalized variance decomposition approach	The consequences for broad macroeconomic theory and investment decisions as imagined by islands with sticky pricing information: investors in a risky asset like Bitcoin require well-defined information set that determines - at least in part - their projected return value.
Wang and Wang (2020)	PDE model	Chainlet clusters with higher trading volumes do not always have a greater influence on the Bitcoin price. Bitcoin price prediction is based on the aggregate influence of all chainlet clusters.

Source: Authors' Contribution.

Table 5: Methodologies used to forecast cryptocurrency prices using artificial intelligence techniques.

References	Method	Main Results
Jang and Lee (2018)	Bayesian neural networks (BNNs)	BNN performs well in predicting Bitcoin price time series and explaining the high volatility of the recent Bitcoin price.
Nayak et al. (2023)	eAEFA, eAEFA+RVFLN, ARIMA (MLP), RVFLN, SVR, LSTM, GA trained RVFLN, and AEFA trained RVFLN.	eAEFA+RVFLN findings outperform the comparator models and a useful financial forecasting tool.
Kristjanpoller and Minutolo (2018)	Generalized Auto-regressive Conditional Heteroskedasticity (GARCH), Artificial Neural Network (ANN) and Principal Component Analysis (PCA)	The proposed model was effective in capturing price volatility, thus reducing financial risk exposure.
Chen et al. (2020)	Random Forest (RF), XGBoost, Quadratic Discriminant Analysis (QDA), Support Vector Machine (SVM), and Long Short-term Memory (LSTM).	The highest accuracy of 67.2% was achieved by the LSTM model.
Zoumpekas et al. (2020)	CNN-2L, CNN-3L, LSTM Slstm, BiLSTM, and GRU	GRU models outperform LSTM models in every way. GRU may be the superior strategy for short-term runoff predictions because model training takes less time.
Nimbark (2022)	DeepCoinCap algorithm	The proposed methodology may provide the highest precision for Ethereum price prediction utilizing incidence logging, and it can be utilized as a foundation for live data run using a deep learning model.
Rafi et al. (2023)	(MDI) features, Bi-directional LSTM, and CUSUM	This study provides the best performance scores with the MDI technique and the LSTM model. However, both feature selection approaches and classification models require additional research. Furthermore, ensemble learning approaches can be utilized to improve forecasting results in the future. The usage of CUSUM control charts in this study is confined to monitoring the changes impacting the model.
Ortu et al. (2022)	MLP, CNN, LSTM, and ALSTM	This study shows that including both trade and social media variables improves prediction and accuracy consistently across all algorithms.
Aggarwal et al. (2019)	(CEEMD) SVM (Support vector machine)	SVM predicts five steps ahead Bitcoin prices for the short term, medium term, long term, and overall Bitcoin price level.

Koo and Kim (2021)	MLP (Multilayer perceptron), RNN (Recurrent neural networks) and LSTM (Long short-term memory)	The authors propose flattening distribution strategy (FDS) based on copula theory as an approach for artificially modifying component distribution to better forecast of Bitcoin price return. To evaluate FDS's performance, authors used MLP, RNN, and LSTM. They discovered that the suggested FDS-based algorithms considerably increase the prediction accuracy of the return of Bitcoin price for each of the three architectures.
Li et al. (2022)	VMD-LMH-BiSTM model	The study offers a unique data decomposition-based hybrid bidirectional deep-learning model for anticipating daily price changes in the Bitcoin market and conducting algorithmic trading on the market. The proposed model outperforms other benchmark models, including econometric models, machine-learning models, and deep-learning models. Furthermore, the proposed model achieved higher investment returns than all benchmark models and the buy-and-hold strategy in a trading simulation.
Jakubik et al. (2023)	LSTM	The study demonstrates how merging deep learning and financial news provides investors and traders with help for monetizing unstructured data in finance and highlights how combining deep learning and financial news offers investors and traders support for the monetization of unstructured data in finance.
Otabek and Choi (2022)	Q-learning algorithm	Approach with a classic approach where all Bitcoin-related tweets without being attribute-filtering, are used as input data for the model, by analyzing the CPU workloads, RAM usage, memory, time, and prediction accuracy. The proposed approach has many advantages over the classic approach.
Aghashahi and Bamdad (2023)	Feedforwardnet Fitnet, and Cascade networks	This study evaluates the performance of the models and how specific setups create principled and stable forecasts for profitable trading. The Bitcoin price is predicted, and results are compared based on the amount of R to find out which ANN leads to a better prediction. This study concludes that the Fitnet network with trainlm function and 30 hidden neurons outweighs the others.
Sujatha et al. (2021)	Levenberg-Marquard, Bayesian Regularization, Scaled Conjugate Gradient	The Bayesian Regularized Neural Network performs well and consequently delivers a better forecast.

Source: Authors' Contribution.

CONCLUSION

Although financial market practitioners and researchers have recognized the importance of cryptocurrency price forecasting, the question of how best to predict cryptocurrency prices, given their extremely volatile nature, remains a thorny issue. The goal of this paper is to solve this problem focusing on Bitcoin, Ethereum and other cryptocurrencies. It explores which variables affect cryptocurrency prices level. The studies, reviewed in our literature and empirical review, propose different and somewhat similar factors over their own individual time periods and use a multitude of ways of analyzing the data. They highlight the potential of incorporating Blockchain information in cryptocurrency price prediction models and suggest that this information can improve the accuracy of these models. The use of Blockchain factors as drivers of cryptocurrency prices is an important and growing area of research. Additionally, various models have been applied to forecast cryptocurrency price, including traditional statistical and econometric methods (Time series, Panel regressions, ARMA-GARCH models, Quantile regression, Cross-quantilogram, Wavelet coherence analysis, etc.), as well as more recent machine learning and artificial intelligence techniques (ANN, PCA, RF, XGBoost, SVM, LSTM, QDA, etc.). According to the literature review presented in this paper, traditional approaches face the following challenges: (1) how to identify the potentially important factors that affect cryptocurrency price changes; and (2) how to design accurate forecasting models to deal with cryptocurrency's high price fluctuation. However, due to the high price fluctuation, these models have limited performance in forecasting accuracy and have failed to forecast price movement trends. In this way, artificial intelligence techniques prove to be more effective in terms of cryptocurrency price forecasting. In fact, considering all inputs in models, the literature review shows that machine learning and deep learning methods performs very well and are better than the statistical and econometric methods. The main implication of this result is that artificial intelligence methods prove to be a relevant cryptocurrency price forecasting tool, compared to statistical and econometric methods. However, this result cannot be definitive, as these methods also have their limitations. Machine learning and deep learning methods have been used to improve the prediction accuracy of cryptocurrency prices by incorporating external factors, but they suffer from the lack of interpretability and the need for large amounts of data. Thus, there remains a gap in understanding the most effective methods for predicting cryptocurrency future movements. It would be useful to develop other models in the future, to better understand the driving forces of the cryptocurrency market. Finally, it should be noted that all the studies presented in our theoretical and empirical literature review did not aim to predict the volatility of cryptocurrency prices. Although this review has identified a set of influential factors linked to the price movements of Bitcoin, Ethereum and other cryptocurrencies, this may be insufficient for traders who actually buy and sell cryptocurrencies. Thus, we believe that predicting the volatility of cryptocurrencies is crucial for providing important information to businesses using cryptocurrencies. Therefore, further research regarding the forecasting of cryptocurrencies volatility prices proves to be necessary.

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