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A Review: Predictive Models and Behaviour of Cryptocurrencies Price

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ABSTRACT

This study aims to assess the knowledge flow within the research field and provide recommendations for further investigation. Specifically, this study conducts a thematic analysis of articles published in peer-reviewed journals between 2014 and 2022. Two primary themes emerge from the co-occurring keywords: (1) cryptocurrency behaviour and (2) cryptocurrency price prediction models. The findings reveal the use of various methods for predicting cryptocurrency prices, including econometric and statistical approaches, machine learning (ML), deep learning (DL), and hybrid models. The overarching objective of all these models is to achieve optimal results in addressing the various challenges associated with predicting cryptocurrency prices. However, it is important to note that no single model can effectively address all the behavioural nuances within cryptocurrency price prediction datasets. To bridge this gap, we recommend that future researchers explore the development of a hybrid model that combines a statistical model with deep learning. Such a hybrid model has the potential to accurately address the behavioural challenges encountered in cryptocurrency price prediction data series.

1. Introduction

Due to the recent rise in economic and geopolitical concerns, which has resulted in declining stock markets, declining currency values, and investors losing wealth, there has been a resurgence of interest in digital currencies [1]. Among the most well-known digital currencies, cryptocurrency has been in the headlines. Because of its consistent success over the past five years, investors want a piece of it, and businesses are considering it as a method of payment [2]. Note that virtual currencies or cryptocurrencies are peer-to-peer, decentralised payment systems that may be transmitted, stored as well as traded online. The original purpose of cryptocurrencies, which is now widely recognized as a phenomenon on a worldwide scale, was to facilitate electronic payments between individuals without the need for a middleman [3]. In fact, cryptocurrency transactions are built on decentralised computer networks or blockchain technology, which allows for the evolution of the money supply and independence from central banks [4]. Aside from that, the extraordinary growth

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of currencies has caught the attention of governmental organisations concerned regarding the funding of crime and its effect on the national financial systems' stability. Because of this, many academic studies have been performed on cryptocurrencies, particularly Bitcoin (BTC), to determine if it is a currency or a speculative asset [5-7].

Given cryptocurrencies are still in their infancy, our research will assist traders, and investors in choosing the right model for predicting cryptocurrency prices accurately. Indirectly it can reduce the cryptocurrency investment advantages and risks. There are some review papers on cryptocurrency conducted in the previous study. For instance, Guo and Donev [8] provide Bibliometrics and Network Analysis of Cryptocurrency. Meanwhile, Bariviera and Merediz-Solà [9] developed a dual analysis bibliometric evaluation, while the second one gave a detailed literature review with respect to all the scientific production involving cryptocurrencies performed in economics. Nevertheless, Almeida and Gonçalves [10] focus on a systematic literature review. In their evaluation of the literature from 2009 to 2021, they list the contributions made in the last ten years to the understanding of risk management and volatility in cryptocurrency investment. Alsmadi *et al.,* [11] conducted the cryptocurrency on bibliometric analysis that focused on the Scopus database only. Subsequently, García-Corral *et al.,* [12] examined a bibliometric analysis of cryptocurrency growth that combined the unified metadata from the Scopus and Web of Science (WoS) databases. Similar to this, Jeris *et al.,* [13] performed a systematic review of the relationship between the stock market and cryptocurrency. As far as we are concerned, most past research focuses on a wide scope of cryptocurrency, and there is no review study focusing on cryptocurrencies' prices with a theme so far.

The limitation of this research is that it only concentrates on the Scopus database, the constraint of the time frame, and selected keyword interests. The contribution of this study is to provide the most thorough and current literature review on the behaviour and prediction model of cryptocurrency price. The remaining part of the article is organised as follows: In Section 2, this study highlights how this review has been carried out. Subsequently, the research theme is presented in Section 3. This research evaluates the literature analysis of the knowledge it has learned about behaviour of the cryptocurrency price as well as predictive models. Finally, in Section 4, this study gives conclusions and future research.

2. Research Methodology

This study begins by identifying the keyword for searching by focusing on access to the Scopus scientific database. The coverage and scope of this research, in terms of the keyword “cryptocurrency price,” was utilised when querying the Scopus database for data on publications titles, abstracts, and keywords. Note that the search was conducted on September 24, 2022. This study retrieved each and every year in the core compilation Scopus database and selected all the document types available in that database. From the keyword searching, Scopus yielded 1088 documents, from which no documents were removed. These documents are used for the bibliometric analysis phase and are not described in this paper. The search strategy is depicted in a schematic in Figure 1.

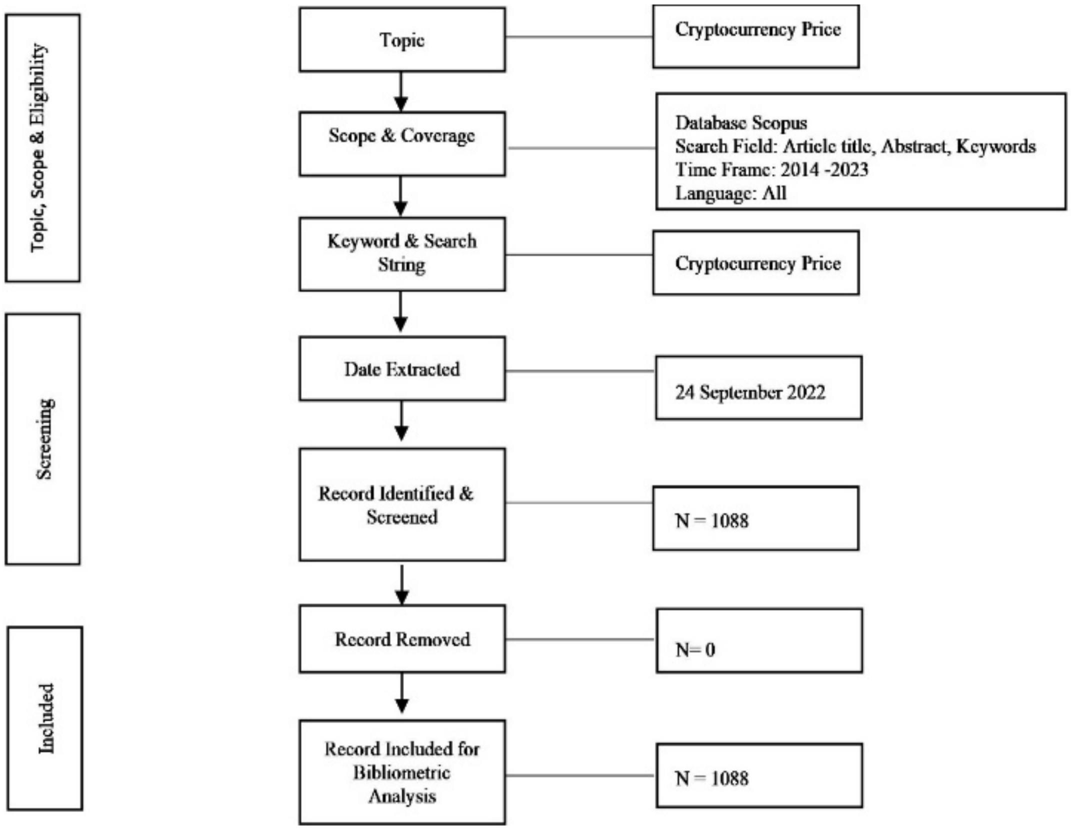

Fig. 1. Search strategy

3. Thematic Review

In the thematic review phase, we analysed the bibliometric data (N=1088) for the co-occurrence of the keyword's cryptocurrency behaviour and cryptocurrency price prediction models. After we described the exclusion and inclusion criteria, we screened the documents, and it was reduced to 149 documents. Note that we exclude some keywords and focus on the English language and source documents such as journals and proceedings. The searching string is stated in Appendix A. The process of review is shown in Figure 2.

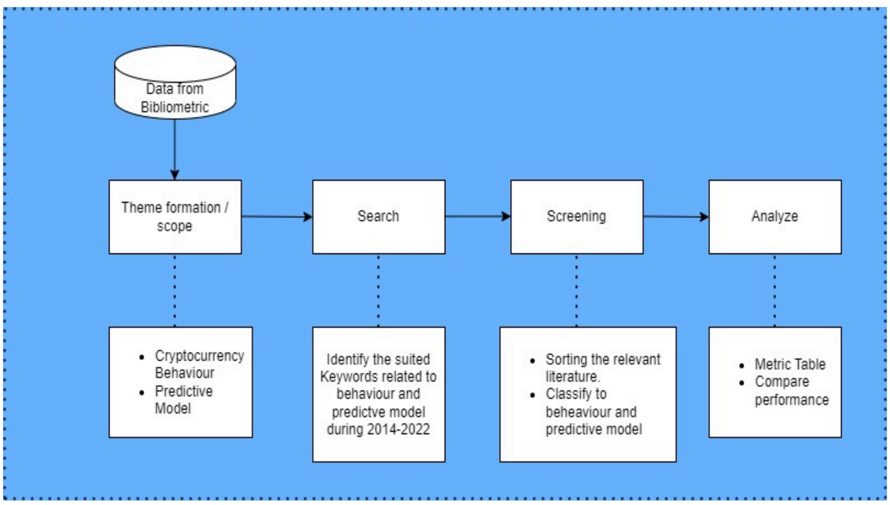

Fig. 2. Process of thematic review

3.1 Cryptocurrency Behaviour

In recent times, cryptocurrencies have garnered significant attention from both the media as well as investors. Bitcoin, introduced to the market in 2008 at a modest $0.0001, remained relatively obscure for years. However, in the 2017-2018 period, Bitcoin underwent a substantial bull market, soaring to an unprecedented peak of $66,002.23 in October 2021, according to Coinmarketcap reports. This surge in interest has led to the emergence of numerous new cryptocurrencies facilitated by Initial Coin Offerings (ICOs). Presently, there are more than 22,163 tradable cryptocurrencies, collectively contributing to a market capitalization surpassing $1.1 trillion. The rapid expansion of the cryptocurrency market suggests an increasingly pivotal role within the broader financial system.

Due to rising interest in cryptocurrencies and their connections to the foreign and stock exchange markets, they just appeared as a key investment tool [14]. Bitcoin (BTC) is one of the rising cryptocurrencies and has emerged as an appealing investment for traders. Contradictory with stocks or foreign exchange, cryptocurrency prices fluctuate primarily due to its 24-hour-a-day trading time without close time, which is a very challenging task [15]. Furthermore, the main and challenging work is to deal with the behaviour of datasets such as dynamic nonlinear dependency, high volatility, heavy tail distribution, outliers, and long memory temporal dependency structural [16-24]. Other than that, similar to the price changes of traditional stocks, cryptocurrency price swings are non-stationary and incredibly volatile [25]. Another study by Kristoufek [26] examined short- and long-term connections with various types of elements, revealing a substantial connection between fundamental economic conditions and times when the price of BTC increases.

Consequently, to maximize capital gain and minimize the risk involved, investors and traders need to precisely forecast the cryptocurrency price trend with more information on the history of data relationship behaviour [27]. This is particularly crucial in predicting cryptocurrency prices. Therefore, in this section, we present the behaviour and trend of predictive techniques related to cryptocurrency prices that scholars have studied.

3.1.1 Volatility behaviour

The mechanics of the volatility of cryptocurrency returns has been the subject of several recent empirical research. Understanding the volatility of the cryptocurrency market is a topic that has been the subject of several investigations. Cryptocurrencies display significant volatility, as shown by Chu *et al.,* [28], and are appealing to risk-taking investors. This is corroborated by research from Trimborn *et al.,* [19] who examined 39 cryptocurrencies and discovered that they are more volatile compared to traditional assets. It follows the same conclusion by Nikolova *et al.,* [29] who discovered that cryptocurrencies exert extreme volatility. They discovered that cryptocurrencies are more volatile in comparison to traditional assets, Apple Inc. equity, the S&P 500, as well as foreign exchange pairs.

Since the Generalised Autoregressive Conditional Heteroscedasticity (GARCH) is the popular model for handling volatility in traditional assets, indirectly numerous studies apply the GARCH model in the cryptocurrency market, as shown in Table 1 [30,31]. On the other hand, Dyhrberg [5] delves into the financial asset capabilities of BTC employing GARCH models. Besides that, the GARCH analysis revealed that BTC might be helpful in risk management and fitting for risk-averse investors in advance of adverse market shocks. Chu *et al.,* [28] and Katsiampa [32] examine the goodness of fit of distinct GARCH models to the cryptocurrency returns time series. According to the results obtained, no model comes to the same conclusion. Subsequently, Corbet *et al.,* [7] utilised a multivariate GARCH (1,1) introduced by Bollerslev [33] to find out how the volatility of cryptocurrency markets changes right after a significant cybercrime. Hence, the results are reliable because they estimate GARCH calculated volatility over the whole time period, which can identify cybercrime episodes.

Table 1
GARCH Model

Reference	Model	Finding(s)
Katsiampa [32]	AR-CGARCH	The AR-CGARCH is the greatest model in terms of how well it fits the data, a finding that highlights the significance of having both a short- and a long-run component of conditional variance.
Akcora *et al.,* [34]	GARCH	This study uses high-fidelity graphs to model the Bitcoin blockchain transaction history. Empirical evidence demonstrates that extreme chainlet activity, as evaluated by occurrences and transaction amounts, is correlated with a higher loss probability and a significant increase in volatility.
Guo *et al.,* [35]	GARCH and BEGARCH	The errors of EWMA, GARCH, BEGARCH, and STR are relatively similar
Kristjanpoller and Minutolo [36]	Hybrid Artificial Neural Network-Generalised AutoRegressive Conditional Heteroskedasticity (ANN-GARCH)	To lessen the exposure to risk, models might incorporate volatility.
Katsiampa *et al.,* [37]	Multivariate GARCH	Both the prior squared errors and the prior conditional volatility have a major impact on all of the conditional variances.
Matkovskyy [38]	GARCH	It demonstrates participants' lack of trust and consensus during a period of price increases by showing trade volume increasing as prices decline.
Ječmínek *et al.,* [39]	GARCH, EWMA model, historical VaR, and Monte Carlo simulation (Geometric Brownian Motion).	Conclusion: Due to the robustness of the findings and the high diffusion (stochastic) process, Monte Carlo simulation is the best approach for estimating the value-at-risk for cryptocurrencies.
Venter *et al.,* [30]	GARCH	The market-proposed bid-ask spreads may be accurately priced using the GARCH option pricing model.
Azman *et al.,* [40]	SS, NNAR, GARCH (1,1,1)	The state space model provides a significant match out of the three. Out of the three models, the state space model's estimates for volatility and value at risk had the tightest confidence intervals.
Bruhn and Ernst [41]	GARCH-EVT	From this study, it can be inferred that there are extremely high chances of loss while investing in both individual cryptocurrencies and a portfolio.
Christopher *et al.,* [42]	Autoregressive Conditional Heteroscedasticity (ARCH) and Generalised Autoregressive Conditional Heteroscedasticity (GARCH)	The outcome demonstrates that the data from the ARCH and GARCH models are not appropriate for daily use.
Maitra *et al.,* [43]	ARMA-GARCH	The results also show that using cryptocurrencies to mitigate stock market risk during the COVID-19 pandemic would not result in incremental returns.

However, Christopher *et al.,* [42] apply the ARCH (Autoregressive Conditional Heteroscedasticity) and GARCH models in predicting cryptocurrency volatility for BTC, ETH, Binance Coin, Dashcoin, and LTC. They found that these models are not suitable for forecast volatility on a daily cryptocurrency basis. It is the same conclusion as Ječmínek *et al.,* [39], as they performed comprehensive volatility and Value-at-Risk (VaR) of the three primary digital assets, such as BTC, Ether, and Ripple (XRP).

Exponentially Weighted Moving Average (EWMA) and GARCH (1,1) models were employed to estimate the volatility. Because of the unique characteristics of the cryptocurrency market, the outcome showed that GARCH is not the best strategy for predicting VaR. As a result, single GARCH models have constraints that make it difficult to describe complicated fluctuation, including skewness, non-normal distribution data, and nonlinear correlation of time series data [44]. The ability to identify asymmetric impacts on cryptocurrency volatility is backed by Fakhfekh and Jeribi [45].

Consequently, various hybrid GARCH models have been proposed by scholars in predicting cryptocurrency. For example, Kristjanpoller and Minutolo [36] and Seo and Kim [46] utilize the ANN-GARCH models for precisely forecasting BTC's realised volatility. Conrad *et al.,* [47] suggested GARCH-MIDAS retrieve the short- and long-term volatility components of cryptocurrencies. As per Peng *et al.,* [48] which utilized daily and hourly data to study the volatility prediction of cryptocurrencies employing a hybrid model of GARCH and support vector regression (SVR), the suggested SVR-GARCH strategy accomplished noticeably better than all existing GARCH-based alternatives. Nevertheless, a potent decomposition technique and a straightforward forecasting model have outperformed more advanced competitors [49]. In order to foresee extremely volatile and noisy BTC price time series, they thus devised a hybrid forecasting strategy that combines the Theta decomposition method with SVR. Meanwhile, Bruhn and Ernst [41] suggested a GARCH-EVT to examine the return for extreme tail risks by implementing Extreme Value Theory (EVT). However, since EVT does not meet the assumption of independent and identically distributed data, they affirmed that the method covers the drawback of the result.

Based on the aforementioned literature, most empirical literature dominates GARCH as a volatility process estimator. However, this model cannot handle asymmetric data very well, and strict stationarity suffices for asymptotic normality [50,51]. Other than that, in order to accurately simulate the volatility of cryptocurrencies, Dutta and Bouri [52] argue that time-varying leaps and significant shocks must be taken into consideration. According to their research, cryptocurrencies are characterized by time-varying volatility and price movements that are more dramatic than the existing market. Consequently, other than the GARCH model hybrid, some researchers have started exploring the family of state space (SS) or known as the structural time series model. This model handles the cryptocurrency volatility and other behaviours it may cater to, such as non-stationary, time-varying, and outliers that retain the information instead of removing it [53]. For instance, Neslihanoglu [54] utilised linear SS with a Kalman filter. Note that the advantage of this model is that it can cater for the behaviour of cryptocurrency prices via time-varying. The model performed better than other models in predicting cryptocurrency values during the pre-COVID-19 and COVID-19 eras, according to the results. On the contrary, Jalan *et al.,* [55] employ a Bayesian structural time-series model to analyse the influence of the BTC spot market in terms of five characteristics: liquidity, kurtosis, skewness, volatility, and returns. The analysis retains the information of behaviour data to predict the BTC market.

Furthermore, Azman *et al.,* [40] analysed the volatility behaviour for cryptocurrency prices, implementing the SS model framework for volatility, including the Kalman filter. It's found that this approach accurately predicts the conditional volatility of five cryptocurrency prices: ETH, BTC, LTC, XRP as well as Bitcoin Cash (BCH). Additionally, according to mean absolute error (MAE), root mean square error (RMSE) as well as the volatility plot, the efficiency of this model is contrasted with that of the GARCH (1,1) model, which is the neural network autoregressive (NNAR), and other models. The Kalman filter may be employed in the SS model to filter out extraneous noise throughout the forecasting process, improving forecast accuracy and yielding more accurate volatility estimates. Meanwhile, a SS model was employed by Raimundo Júnior *et al.,* [56] to measure the herding phenomena over time in the cryptocurrency market. According to the market volatility, market index as well as volatility index, herding toward the market exhibits strong movement and tenacity regardless of market conditions. Therefore, we can conclude that based on the prior literature mentioned above, other than the popular GARCH model, SS can predict cryptocurrency volatility time-varying very well.

Examining the period from April 2018 to June 2020, Ftiti *et al.,* [57] delves into the investigation of the primary cryptocurrency markets—Ripple, Ethereum, Ethereum Classic, as well as Bitcoin. The aim is to evaluate the impact of crisis periods, with a particular focus on the COVID-19 pandemic, on the dynamics of cryptocurrency volatility. The study involves the computation and decomposition of the realized volatility measure into distinct components, including discontinuous versus continuous, negative and positive semi-variances, as well as signed jumps. Several heterogeneous autoregressive (HAR) models, encompassing various components, have been created. This allows for the evaluation of different modeling assumptions, such as persistence and asymmetric dynamics, for both in-sample and out-of-sample forecasting strategies in the context of modeling as well as forecasting volatility. The outcomes of the analysis unveil three principal findings. Initially, it seems that the extended HAR model, encompassing both positive and negative jumps, proves to be the most effective in forecasting future volatility across non-crisis as well as crisis periods. Secondly, exclusively during the crisis period, the statistically significant component is the negative jump. Lastly, concerning volatility prediction, the outcomes indicate that the extended HAR model incorporating negative and positive semi-variances outperforms alternative models.

In other studies, Chen *et al.,* [58] attempt to calibrate an option pricing model adapting the high volatility and jump properties. Hu *et al.,* [59] find that the jump estimator separated from Realized Variance (RV) suffers from the consecutive jump phenomenon, which causes the jump estimator biased. RV, accounting for intraday information from high-frequency data, is essentially the sum of squared returns over the period [60]. The Bitcoin market is extremely risky in the sense of volatility, entangled jumps, and extensive consecutive jumps, which reflect the major incidents worldwide. Empirical study by Hu *et al.,* [59] shows that the lagged realized variance increases the future realized variance, while the jumps, especially positive ones, significantly reduce future realized variance. The out-of-sample forecasting model reveals that, in terms of forecasting accuracy and utility gain, investors interested in the long-term realized variance benefit from explicitly modelling the jumps and signed estimators, which is unnecessary for the short-term realized variance forecast.

Moreover, the Heterogeneous Autoregressive model of Realized Volatility (HAR-RV) introduced by Corsi [61] has demonstrated remarkable success in replicating key empirical characteristics of financial returns, such as, fat tails, long memory as well as self-similarity. This model provides an efficient and practical means of achieving this objective and has become a benchmark in financial econometrics. Its primary focus is on capturing the dynamic nature of high-frequency data, in which volatility can undergo rapid changes over brief time periods. Several investigations have employed the HAR model to predict cryptocurrency trends, as evidenced in Pham *et al.,* [62]. These investigations examine the dynamic volatility interconnections between cryptocurrency as well as other markets by analyzing their realized variances and semi-variances. A multivariate HAR model, incorporating considerations for long memory as well as structural breaks in realized volatility time series, is employed. The findings reveal a significant dependence of China's thermal coal futures market on cryptocurrency market volatility, while the influence of the energy market on the cryptocurrency market is deemed inconsequential. Furthermore, in Ming *et al.,* [63], the forecast accuracy of cryptocurrency rates is enhanced by proposing the calculation of Shannon entropy based on the probabilities of a decrease in cryptocurrency market prices.

In contrast to Bollerslev *et al.,* [64], they enhance the predictive capacity of the existing HAR model by integrating the scaled principal component analysis (SPCA) technique. The findings indicate a consistent enhancement in predictive performance with the HAR-SPCA model approach. Nonetheless, the drawback of using weekly data, which lacks the level of detail found in daily or intraday data, may not align well with the HAR model. The model, optimized for processing data with high frequency, could encounter difficulties when faced with lower granularity, leading to potential challenges in accurately capturing volatility nuances in less frequent observations. Furthermore, the HAR model's assumption of stationary time series may be compromised by trends or seasonality evident in weekly data, potentially affecting the precision of the model. As a result, it may be more advisable to explore alternative models better tailored for lower-frequency data when analyzing weekly data.

3.1.2 Nonlinear dependency and long memory behaviour

Cryptocurrencies market behaviour forecasting is rather challenging. Another crucial behaviour in cryptocurrency price data to be accounted for predicting accuracy is the way to handle nonlinear and long memory behaviour. It is a stylised empirical fact from statistical analysis of financial time series. Other than that, the correlation between a long-memory market and the inefficiency of cryptocurrencies was examined by Cheah *et al.,* [65]. Long-range dependent traits may manifest as a result of structural breakdowns altering the parameters of processes generating conditional volatility and returns, according to Diebold and Inoue [66], and Mensi *et al.,* [67]. The Hurst exponent approach, a well-liked estimator of long memory, is a common way of calculating long memory, as explained by Bariviera [68]. It is appropriate and reliable under tail distribution in BTC [69]. Other studies corresponding to the occurrence of long memory in the cryptocurrency market are discussed in Bariviera [24], Wu and Chen [69], Al-Yahyaee *et al.,* [70], and Phillip *et al.,* [71].

On the other hand, Jang and Lee [72] used Bayesian neural networks since the log volatility of BTC data is unsuitable for linear analysis due to the violation of the assumptions. According to Liashenko *et al.,* [17] neural networks are modern data science methods suitable for nonlinear dependency approximation cases, which are successfully applied in many fields. Bejaoui *et al.,* [73] tried to examine the possible nonlinear structure in the cryptocurrency market cycle relying on the Markov Switching – Autoregressive Moving Average (MS-ARMA) model, displaying proof of nonlinear behaviour in cryptocurrencies' returns in terms of mean and variance. Corresponding, Loh *et al.,* [74] stated that BTC price prediction is difficult and hard for investors to determine due to the nonlinearity property of the BTC price. In order to estimate the price of BTC, they utilized the ML training techniques, which are the Scaled Conjugate Gradient (SCG) backpropagation algorithm and Levenberg-Marquardt (LM) backpropagation algorithm utilizing Feedforward Neural Network (FNN). Here, the outcome showed that employing the FNN-LM model improved the performance of BTC price predicting. Keep in mind that non-statistical techniques are effective resources for predicting nonlinear time series. For example, two extensively used non-statistical techniques for forecasting nonlinear time series are ANN and grey system theory [75]. Brockett *et al.,* [76] showed that the ANN methodology accomplishes better financial prediction than statistical and traditional approaches. Alouaret [77] performed a comparison of recurrent neural networks (RNN) and vector autoregression (VAR) to forecast the price of BTC, demonstrating that RNN models outperform the VAR approach.

Given the nonlinear dynamics, which include the inherent chaoticity and fractality of digital currencies, Altan *et al.,* [78] suggested a hybrid model. Numerous academic studies have shown that a single model is insufficient for making highly accurate predictions about digital currency. Since, many models used to forecast digital currencies, each have flaws and strengths of their own, they could not always provide the best forecasting accuracy under all circumstances. Recently, studies applied a hybrid model due to the limitation of a single model. For instance, Du *et al.,* [79] compare various hybrid models depending on integration techniques as well as complex systems methodology. The result revealed that the hybrid process could enhance forecasting accuracy more efficiently than a single model.

3.1.3 Tail distribution

Recent studies have explored the interdependence and contagious influences witnessed in the relationships between cryptocurrencies as well as their engagements with conventional financial markets. A specific focus lies in the transfer of negative risks among different cryptocurrencies. The findings of a study by Borri [80] indicate that crypto assets are notably exposed to tail risk within crypto markets, a vulnerability that does not have a parallel in traditional asset markets. Expanding on the findings of this study, Ahelegbey *et al.,* [81] investigated the connections among crypto assets in times of market turmoil, utilizing two econometric modeling approaches to assess tail risk: extreme downside correlation (EDC) as well as extreme downside hedge (EDH). The results revealed a categorization of cryptocurrencies into two groups: speculative assets, like Bitcoin, mainly serving as origins of tail contagion, while technical assets, for instance, Ethereum, primarily serving as recipients of contagion.

Another aspect of study delves into exploring the connections between cryptocurrencies as well as traditional financial markets. To confirm a flight-to-quality trend from Bitcoin to gold in times of crises, Klein *et al.,* [82] applied a BEKK-GARCH model, challenging the notion of Bitcoin serving as a "virtual gold." However, GARCH-based models have inherent limitations as they only capture average correlations, neglecting crucial information about the entire distribution, especially in the tails. Additional studies have identified spillover effects of downside risk between Bitcoin as well as conventional assets through pairwise correlation analysis [83-85]. Expanding on this research, Jiang *et al.,* [86] quantified the intricate network effects in play.

They primarily focused on spillovers of left-tail risk, rather than the spillovers of average volatility, between Bitcoin as well as traditional assets in their research. Despite observing evidence of tail risk contagion between cryptocurrency as well as traditional markets, there is a noticeable absence of robust mathematical or economic evidence linking tail-event contagion to systemic risk. Thus, Wang *et al.,* [87] investigates the interdependencies among tail events (TE) in cryptocurrency markets and introduces a new measure of systemic risk using the FRM framework, which is built upon the TENET Quantile LASSO Regressions [88]. The fundamental framework of FRM is derived from CoVaR. The FRM employs quantile regression to identify the transmission of TE risk and systemic risk in cryptocurrencies. Through empirical tests based on simulation, Härdle *et al.,* [89] reveals that the index relies on three key factors: the error term's variance, the correlation structure of the covariates, as well as the count of non-zero coefficients in the model. Building upon this, Ren *et al.,* [90] and Wang *et al.,* [91] enhance the model by incorporating Lagrange interpretation. FRM@Crypto showcases strong predictive abilities in foreseeing future systemic risk, addressing a significant gap in the market.

Moreover, a contemporary framework for assessing the value of cryptocurrencies recognizes the existence of various equilibria in cryptocurrency markets. According to Cong *et al.,* [92], these equilibrium fluctuations are rooted in network externalities, implying that the advantages of employing cryptocurrency in transactions rise with the overall efficiency of the platform. Consequently, external shocks to productivity have a magnified impact. Furthermore, Pagnotta and Buraschi [93] contribute the notion of demand-supply spirals, enhancing the consequences delineated in Cong's model. Biais *et al.,* [94] enhances our comprehension by underscoring that the advantages associated with cryptocurrency use, as opposed to conventional stock dividends, hinge on the purchasing power of the cryptocurrency, inherently connected to its price. This opens up the potential for situations in which the cryptocurrency price experiences a swift decline to zero. Such occurrences are prompted by external events, commonly labeled as 'sunspots,' which induce a shift in perceptions regarding future prices and transactional benefits, leading to a sharp drop in the present price. In the Biais *et al.,* [94] framework, the variable probability of these sunspot events can also contribute to unwarranted fluctuations in cryptocurrency prices.

If these mechanisms are indeed operating in cryptocurrency markets and we examine these markets within the larger network they function in, the relationships among various elements in this network can influence significant returns. As noted in Cong *et al.,* [92], crucial aspect of connectivity is the interplay between the on-chain and off-chain segments of the cryptocurrency market. Moreover, the Biais *et al.,* [94] model suggests that media influence plays a part in shaping connectivity, impacting the coordination of expectations among market participants. If this expectation coordination, especially across the entire cryptocurrency market, takes place, indicators of connectivity among various cryptocurrency markets could also demonstrate the ability to predict extreme returns.

The relationship between network connectivity in the cryptocurrency ecosystem as well as the prediction of Bitcoin returns at various quantiles of the return distribution is investigated by Caferra *et al.,* [95]. The study utilizes quantile autoregressions of Bitcoin returns, incorporating metrics related to the activity and connectivity of cryptocurrency markets, as well as media coverage of these markets. The findings highlight the efficacy of several connectivity measures in forecasting both downward as well as upward price movements. Notably, the impact varies before and during the COVID-19 outbreak.

3.2 Predictive Model

Chaim and Laurini [21] claimed that the apparent long memory in volatility, large abrupt price swings, and high volatility causes nonlinear dependence in cryptocurrency markets, creating unpredictable market fluctuations and making prediction difficult. Figure 3 depicts the category predictive model reviewing the distribution of the article. Out of the 98 considered works, 44 articles applied ML models, 47 used statistical or econometric models and the remaining for the hybrid model to forecast cryptocurrency price or to complement their technique by contrasting it to other models. Apart from that, the details of some techniques were applied by previous studies presented. Several researchers looked at the cryptocurrency market's effectiveness level over time, and their conclusions were published. The most often used conventional method for multiple time series cryptocurrency prediction strategies is autoregressive integrated moving average (ARIMA) [96]. These models, nevertheless, are unable to represent the nonlinear patterns found in challenging prediction issues. According to reports, time series models have been employed to examine seasonality trends in BTC trading [97]. Furthermore, in the presence of considerable volatility, defining the cryptocurrency market feature due to the nature of the market itself, the traditional time series approaches were unable to capture long-term interdependence.

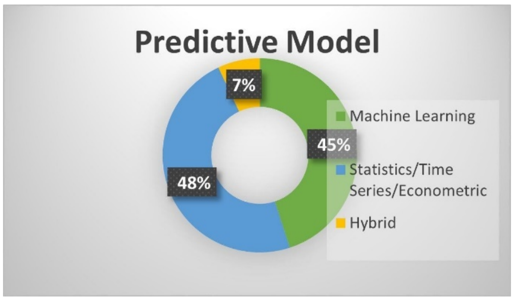

Fig. 3. Paper distribution by category

Other than that, traditional methods of predicting financial data, including cryptocurrency, are typically statistical and econometric models [98]. Using a combination of statistical and economic theory, these techniques could significantly assess and predict the econometrics variables. Statistical and econometric analysis are likely to explain cryptocurrency returns as a well-established approach to assessing return-predictive signals that have been utilised for many years [73,99]. Apart from that, several studies have been done on predicting or estimating BTC price movements. Regression modelling is the most popular technique for predicting the price of BTC by considering probable price-affecting variables [18,100]. In some occurrences, statistical-model-based approaches may offer adequate models [101]. Moreover, the advantage of the linear statistical model-based approach is that it can define the fundamental and technical how prices and an explanatory variable are linked in relationship with each other. Throughout the time period, Dahham *et al.,* [102] are able to decipher the intricate connection between cryptocurrency prices and socio-political circumstances. Nevertheless, linear regressions may take into account the impact of several factors. Furthermore, they set rigid assumptions on the functional form of how signals indicate market movements and are rigid in their inclusion.

On the contrary, machine learning (ML) methods are becoming more popular for predicting cryptocurrency markets and other disciplines because they do not have these limitations [103]. ML techniques like neural networks-based approaches employ iterative optimisation techniques like "gradient descent" in conjunction with hyperparameter tuning to determine the best answer that fits the data [104]. Because of this, ML methods were employed to estimate asset prices and returns in recent years by incorporating nonlinearity, showing more accurate predictions than traditional time series models [105-107]. In another study, researchers also apply ML to predicting cryptocurrency prices. Other than that, Shintate and Pichl [108] work provides a benchmark of how efficient the modern ML algorithms are, in accordance with their applicability to high-frequency trading data on the minute scale. Ji *et al.,* [109], Livieris *et al.,* [110], Lamothe-Fernández *et al.,* [111], and Cocco *et al.,* [112] utilised different ML-based frameworks to predict BTC prices. They discovered that these network variables had limited predictive potential, most likely because the behaviour of exchanges technically determines the price of BTC. From our survey, we can say that ML is a good predictive model primarily focused on technical aspects of prediction based on input-output mapping. However, this model has not examined and interpreted the impacts of individual variables on output because of irrelevant input variables included in the model, and hence overfitting or underfitting occurs.

Therefore, deep learning (DL) refers to potent ML algorithms that specialize in resolving complicated, nonlinear issues. These techniques make use of the massive volumes of data available today to develop effective prediction models. Furthermore, the model is a powerful methodology that has been efficiently applied for time series or forecasting. Recent research initiatives have utilised DL techniques for cryptocurrency price forecasting. For example, Saxena *et al.,* [113] compared Long-Short Term Memory (LSTM) and ARIMA models in estimating BTC price, which resulted in the RMSE of the ARIMA and LSTM models of 700.69 and 456.78, respectively. Lamothe-Fernández *et al.,* [111] and Lahmiri and Bekiros [114] conducted a comparison of DL methodologies for forecasting cryptocurrency prices. Note that Lahmiri and Bekiros [115] used DL approaches to estimate the three cryptocurrencies' prices: XRP, Digital Cash, as well as BTC. They demonstrated that DL was quite good at predicting the naturally chaotic behaviour of cryptocurrency markets. On the other hand, Indera *et al.,* [116] present a Multi-Layer Perceptron (MLP)-based Nonlinear Autoregressive with Linear Autoregressive with Exogenous Inputs (NARX) BTC price estimating model employing the closing, opening, maximum, and past minimum prices along with Moving Average (MA). The outcomes showed that the model was capable of making accurate BTC price predictions and passing every model validation test. Furthermore, Liashenko *et al.,* [17], Zhengyang *et al.,* [117], Cherati *et al.,* [118] revealed their results that LSTM showed slightly better accuracy in contrast to other models for price movement prediction.

Nevertheless, the result contradicts [119]. In their study, they utilized LSTM, bi-directional LSTM as well as convolutional layers to create an intelligent forecasting model that is thought to be crucial for decision-making and portfolio optimization because of the high volatility and significant price fluctuations over time. Moreover, the result revealed that the combination of DL cannot achieve high performance. It is supported by Livieris *et al.,* [120]. They found that a prediction of a DL model does not ensure the establishment of a reliable prediction model in cryptocurrency caused by its chaotic and very complex nature.

Furthermore, some of the most effective and extensively applied DL algorithms for forecasting cryptocurrency values are evaluated by Pintelas *et al.,* [121]. The outcomes demonstrate that DL models are unable to resolve this issue effectively and efficiently. Their findings show that cryptocurrency values mostly follow a random walk process, even if there may be a few underlying trends. To resolve this issue effectively and efficiently, accurately forecasting cryptocurrency prices. Thus, they lack the knowledge necessary to make reliable and accurate forecasts about the future.

Therefore, hybrid models, which may record numerous behavioural features, have increased popularity as predicting techniques. Their developed frameworks have been extensively applied in several investigations and have successfully improved predicting performance. To accomplish accurate time series forecasting, which includes BTC price forecasting, exchange rate forecasting, and stock price forecasting, several academics have developed hybrid models [36a,122,123]. Gao *et al.,* [124] suggest a hybrid method combining the benefits of non-stationary parametric models like GARCH with the nonlinear modelling potential of LSTM neural networks due to the nonlinearity and extremely volatile dynamics of the price data of cryptocurrencies. The findings show that, in the case of extremely volatile data, a combination of deep neural networks and parametric models like GARCH may yield improved predictions of cryptocurrency prices. Aside from that, model integration can maximize each model's benefits.

4. Conclusions and Future Research

Based on the aforementioned literature, the various methods utilised in predicting cryptocurrency prices, whether econometric, statistical approach, ML and deep learning (DL) or hybrid model. All models' objective is to obtain the optimum result in handling the various behaviour while at the same time predicting cryptocurrency price. However, no single model can cater to all the behaviour of data series. Apart from that, the different methods have their ability or advantages in handling the characteristics of the dataset. However, traditional statistical methods are a powerful tool for linear, easy to interpret and implement. Even so, they depend on a number of statistical hypotheses that could be unfounded, whereas ML, the most advanced technology currently, can anticipate prices depending on historical data. This method's shortcoming prevents it from properly identifying and interpreting the majority of variables that influence cryptocurrency price. Recently, the trend of the hybrid model has been the best technique and option for most researchers. Since cryptocurrencies are still novel, the future needs more hybrid models between traditional and ML in predicting cryptocurrency prices in handling the various behaviour without eliminating the information. To comprehend the peculiar behaviour of cryptocurrencies and their pricing, it would be necessary to include all pertinent market-influencing aspects and track them over a longer time frame.

From this survey, there is limited discussion of seasonal effects in cryptocurrency and if they exist, causing it to be challenging to estimate utilising a statistical approach. Rathore *et al.,* [125] concluded that a seasonal pattern exists in historical cryptocurrency data. They utilised the FB Prophet, Long-Short Term Memory (LSTM) models and Autoregressive-integrated moving average (ARIMA) in comparing the result. The same goes with Ebenezer *et al.,* [96]; the Prophet model's output performs best when used with daily periodicity data that include at least a year's worth of historical data. It should be noted that it is built on an additive model where nonlinear trends suit seasonality on a weekly, annual, and holiday basis. The prophet is resilient to missing data, changes in the trend, and significant outliers outside of that. The model’s shortcoming is that it cannot handle non-stationary data. Hence, the suggestion for the next research is due to a limited study and a contradictory report about the seasonality in cryptocurrencies Khedr *et al.,* [126]. We suggest applying the structural time series model to prove the seasonality effect and non-stationary cryptocurrency price data exist or not.

Future research needs more exploration of the investigation of the hidden pattern because, in time series, that component is one of the crucial assumptions to get an accurate prediction. Furthermore, most studies applied a daily price data approach in predicting cryptocurrency prices instead of other time frames. As far as we are concerned, at the time this study was written, there had not yet been any studies using statistical, neural network, or hybrid models as predictive models to forecast changes in cryptocurrency prices via weekly datasets. Thus, no comparison in investigating the hidden pattern for different time frames. Nevertheless, this information is important to the investor or traders trading weekly.

Future researchers are recommended to develop a hybrid model of state space (SS) with DL to combine the advantage of SS and DL. Note that SS can model the hidden component and retain the information and non-stationary data; meanwhile, DL can handle nonlinear behaviour. By developing this hybrid model, it can handle the non-stationary and nonlinear problem of predicting cryptocurrency prices accurately. As mentioned by Livieris *et al.,* [110] and Pintelas *et al.,* [121], there are two difficulties in cryptocurrency forecasting. First, as a result of being non-stationary, the cryptocurrency time series is very similar to the random walk process, suggesting that the prediction issue is excessively difficult and intricate. Particularly non-stationary series have strong volatility and trend, typically exhibit heteroscedasticity, and exhibit changing major features, including mean, frequency, variance, and kurtosis. Secondly, the errors' autocorrelation and the absence of stationarity are the key causes of DL models' ineffectiveness [127,128].

Nevertheless, although extremely nonlinear time-series issues may be addressed by advanced DL models, it has been shown that these models give incorrect and ineffective cryptocurrency projections. Hence, we suggest these hybrid structural time-series models because of the ability of the hybrid model in comparison to a single model, given the advantages of each model. Furthermore, since there has been no study of hybrid linear structural time series so far, we advise that researchers explore that model more because of the advantages of linear structural time series.

Furthermore, ML and DL are good prediction models when the data is nonlinear or chaotic; however, they cannot accurately interpret the hidden pattern. For example, Ho *et al.,* [100] studied and understood the cryptocurrency market characteristics as well as the dynamic evolution. Nevertheless, they removed the trend and seasonal before model LSTM, causing information loss. In other studies, Pintelas *et al.,* [121] suggest that researchers need to incorporate and invent new strategies, techniques, as well as alternative strategies to obtain a highly accurate prediction in cryptocurrency without eliminating the hidden information. For example, more sophisticated predictions due to cryptocurrency prices resemble a random walk process. To ensure that a prediction model produces reliable and accurate predictions, several underlying patterns could be present simultaneously. To find these patterns, an intelligent framework is required.

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