International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031

INTERNATIONAL JOURNAL OF INNOVATION AND INDUSTRIAL REVOLUTION (IJIREV)
www.ijirev.com

MAPPING THE GLOBAL RESEARCH LANDSCAPE OF CRYPTOCURRENCY PRICE: A BIBLIOMETRIC AND THEMATIC ANALYSIS

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Article Info:

Article history:
Received date: 26.06.2025
Revised date: 22.07.2025
Accepted date: 28.08.2025
Published date: 18.09.2025

To cite this document:

Rashid, N. A., Ismail, M. T., Aziz, A. A., Ahmad, A. M., Azizan, N. H., & Abdul Rahim, A. H. (2025). Mapping The Global Research Landscape of Cryptocurrency Price: A Bibliometric and Thematic Analysis. *International Journal of Innovation and Industrial Revolution, 7* (22), 553-575.

DOI: 10.35631/IJIREV.722031

Abstract:

This study evaluates the evolution of cryptocurrency price research through a bibliometric network analysis and a thematic review of publications from 2014 to 2022. Three main themes are identified: cryptocurrency behavior, predictive modeling techniques, and factors influencing cryptocurrency prices. The findings reveal inconsistencies in the literature regarding predictive models and contributing factors, highlighting significant theoretical gaps. Future research directions are proposed, including the development of hybrid forecasting models that integrate machine learning, behavioral factors, and macro-financial indicators. This review offers valuable insights for scholars, investors, and policymakers aiming to enhance forecasting accuracy, manage risk, and better understand the complexities of the digital asset ecosystem.

Keywords:

Bibliometric; Cryptocurrency; Models; Predictive; Thematic; Volatility

International Journal of Innovation and Industrial Revolution
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Introduction

The resurgence of interest in digital currencies has been driven by escalating economic and geopolitical uncertainties, which have led to depreciating currency values, declining stock markets, and heightened investor apprehension (Ibrahim, 2020). In response to these instabilities, digital assets, particularly cryptocurrencies such as Bitcoin (BTC), have emerged as attractive alternatives due to their decentralized architecture, significant volatility, and strong performance over the past five years (Corbet, Larkin, et al., 2020; Corbet et al., 2019; Kristoufek, 2015). These assets operate as peer-to-peer payment systems facilitated by blockchain technology, which enables secure and transparent transactions without reliance on traditional financial intermediaries (Gowda & Chakravorty, 2021; Roy et al., 2018; Lee et al., 2015).

However, the rapid growth of the cryptocurrency market has sparked concern among regulatory bodies, particularly regarding financial stability and the potential misuse of these assets for illicit activities. These regulatory challenges, combined with the volatile and speculative nature of cryptocurrencies, have prompted a surge in academic interest. Research has increasingly focused on the classification of cryptocurrencies, specifically whether they function as currencies or speculative assets, as well as the inherent complexities of price forecasting in a highly dynamic and non-linear market environment (Yermack, 2024; Corbet, Cumming, et al., 2020; Corbet, Meegan, et al., 2018; Fry, 2018; Dyhrberg, 2016).

Despite the growing volume of literature, much of the research remains fragmented across disciplines, methodologies, and market scopes. This underscores the need for a comprehensive synthesis that can consolidate existing findings, trace thematic developments, and highlight emerging directions. To address this gap, the present study adopts a two-stage methodological approach. First, a bibliometric network analysis is conducted to identify key publication trends, influential authors, and keyword co-occurrences. Second, a thematic review is undertaken, comprising 149 curated articles, to explore conceptual patterns and model performance in forecasting cryptocurrency prices.

By integrating these methods, this study aims to provide a structured and in-depth overview of the cryptocurrency price prediction literature. The objective is not only to map the evolution of scholarly work but also to support researchers, practitioners, and policymakers in navigating the complexities of model selection and market behavior analysis in the cryptocurrency domain.

Literature Review

Over the past decade, scholarly interest in cryptocurrency price behavior has evolved significantly, moving from basic volatility analysis to more sophisticated predictive modeling. Early research primarily utilized traditional econometric frameworks such as GARCH, EGARCH, and VAR to examine short-term market dynamics and speculative characteristics. For instance, Kristoufek (Kristoufek, 2013, 2015) analyzed the interplay between macroeconomic indicators and investor sentiment, while Lahmiri and Bekiros (Lahmiri &

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EISSN: 2637-0972
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Bekiros, 2019, 2020) employed hybrid GARCH-ANN models to detect non-linear and chaotic structures in crypto price movements. While foundational, these studies often fell short in addressing the abrupt regime changes and deep non-linearities characteristic of digital asset markets.

As methodological capabilities advanced, the literature saw a shift towards machine learning (ML) and deep learning (DL) applications. Models such as Random Forests, Support Vector Machines (SVM), and Long Short-Term Memory (LSTM) networks began to dominate forecasting studies, demonstrating superior performance in capturing complex temporal relationships and market irregularities (Lamothe-Fernández et al., 2020; Kumar & Anandarao, 2019). These approaches, particularly when incorporating blockchain-specific metrics and sentiment analysis, offer enhanced accuracy. However, they also introduce challenges, including issues of interpretability and model transparency, which are especially pertinent in financial decision-making contexts.

Recent developments have focused on hybrid frameworks and explainable artificial intelligence (XAI) tools, aiming to strike a balance between predictive accuracy and interpretability. Khedr et al. (A. E. Khedr et al., 2021), for example, compared ARIMA and LSTM models to assess the integration of transparent, human-interpretable components into forecasting systems. Meanwhile, literature has expanded thematically to include multi-dimensional factors influencing price movements, encompassing media sentiment, macroeconomic policy, and cross-asset spillovers (Kraaijeveld & De Smedt, 2020; Corbet, Meegan, et al., 2018;). These studies collectively reflect an evolving consensus that cryptocurrency prices are shaped by a convergence of technical, behavioral, and macro-financial variables.

Despite this progress, the literature remains diffuse. Previous review efforts, such as those by Guo and Donev (Guo & Donev, 2020), Bariviera and Merediz-Solà (Bariviera & Merediz-Solà, 2021), and Almeida and Gonçalves (Almeida & Gonçalves, 2022), have provided valuable insights into cryptocurrency-related research, covering aspects such as risk management, volatility, and economic modeling. Others, including Alsmadi et al. (Alsmadi et al., 2022) and García-Corral et al. (García-Corral et al., 2022), have employed bibliometric techniques using Scopus and Web of Science data, while Jeris et al. (Jeris et al., 2022) explored the relationship between crypto assets and stock markets. Nevertheless, a focused synthesis addressing the thematic and methodological evolution of cryptocurrency price prediction remains absent.

To fill this void, the present study offers a comprehensive review that combines bibliometric network analysis with a thematic exploration of cryptocurrency price forecasting literature. This dual-method approach facilitates a nuanced understanding of research trajectories, model developments, and underexplored areas. Ultimately, this review aims to unify existing knowledge, identify future research opportunities, and provide a strategic framework for advancing predictive analytics in the context of digital currency markets.

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Methodology

This study adopts a mixed-methods research design, integrating bibliometric analysis with thematic content review to examine the evolution of cryptocurrency price research. The methodological process is outlined in Figure 1, which illustrates the search strategy and analytical steps taken.

Data Collection and Search Strategy

On September 24, 2022, a comprehensive search was conducted in the Scopus database using keywords such as *"cryptocurrency price prediction," "Bitcoin forecasting,"* and *"digital asset volatility"*. The search targeted titles, abstracts, and keywords, and included all document types without restriction. A total of 1,088 documents were retrieved and used as the initial dataset.

Stage 1: Bibliometric Analysis

The first phase involved bibliometric mapping to understand publication trends, research structures, and scholarly impact. Tools used in this stage include VOSviewer for generating visualizations of:

- Keyword co-occurrence, to identify prominent research themes and evolving trends.
- Author co-citation networks, to uncover intellectual linkages and key contributors.
- Thematic clustering, to group related studies and provide structure to the literature.

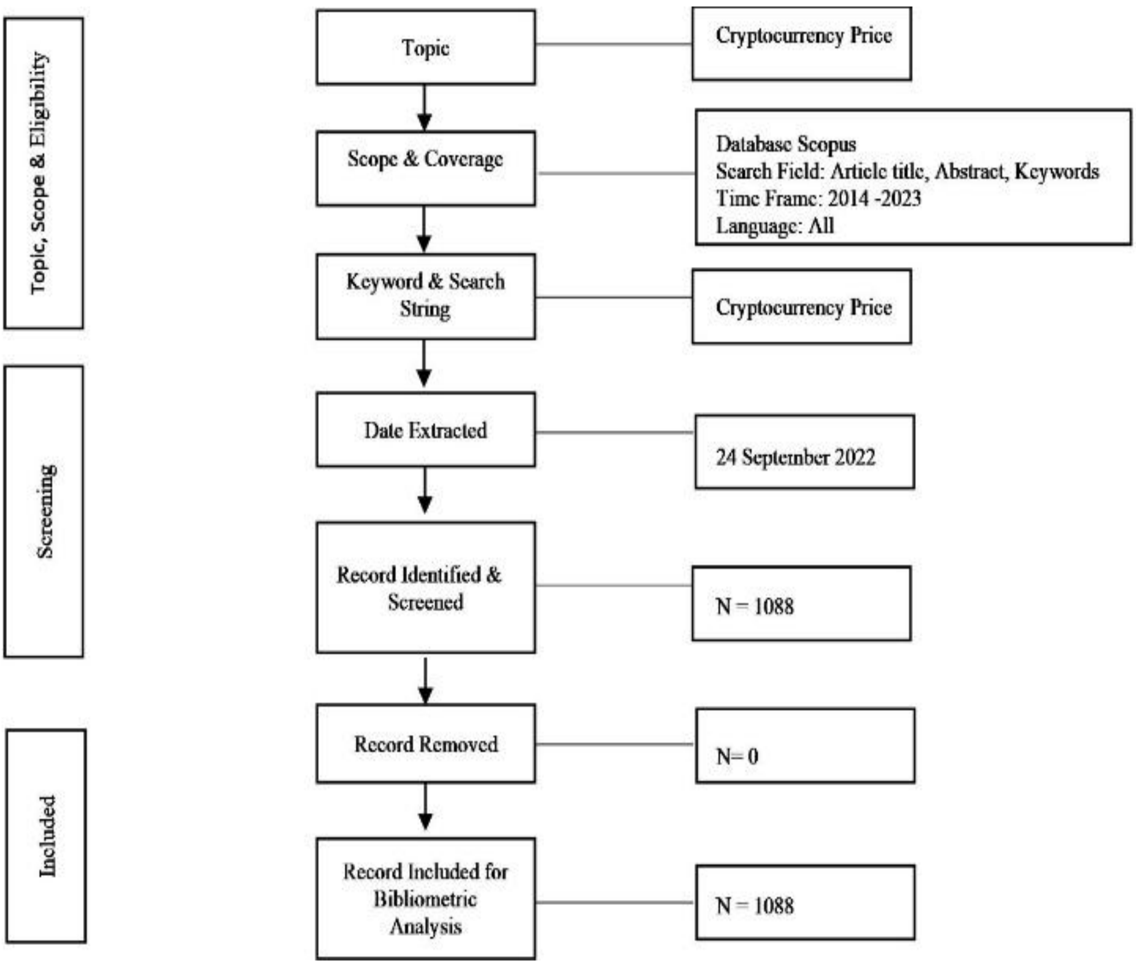

Figure 1: Search Strategy for Bibliometric and Thematic Review

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Additionally, Harzing's Publish or Perish software was employed to extract and analyze citation metrics, offering insight into the academic influence of the selected works.

Stage 2: Thematic Content Review

In the second phase, a refined sample of 149 documents was selected based on citation frequency, thematic relevance, and methodological rigor. These documents were subjected to a qualitative thematic analysis aimed at synthesizing:

- Research focus areas
- Theoretical frameworks
- Methodological approaches
- Identified gaps and future research directions

Documents were grouped into emergent thematic clusters to facilitate a structured interpretation of the literature and to align with the overarching objectives of the study.
Integration of Methods

By combining bibliometric mapping with thematic content analysis, this dual-method approach provides both macro-level structural insights and micro-level conceptual understanding of the cryptocurrency price prediction literature. This integrated methodology ensures a comprehensive and rigorous assessment of the field's development and scholarly discourse.

Results and Discussion

This section presents the evolution of academic research on cryptocurrency price prediction, highlighting publication trends and mapping intellectual structures using bibliometric network techniques.

Research Growth and Publication Trends

Figure 2 illustrates the annual growth in publications related to cryptocurrency price research. While the field began to emerge gradually around 2014, a sharp increase in academic output occurred from 2018 onward, coinciding with major market events such as Bitcoin's substantial price rallies and the rising institutional adoption of digital assets. The number of publications peaked in 2021, reflecting a period of intensified scholarly engagement.

The surge in research mirrors broader market developments, where the valuation of major cryptocurrencies like Bitcoin and Ethereum experienced rapid appreciation. Bitcoin remains the most studied digital asset, though research on Ethereum, Ripple, and other altcoins has also gained traction. Key themes driving this interest include sentiment analysis, price volatility, investment behavior, machine learning-based prediction models, and the influence of external factors such as social media and global events like the COVID-19 pandemic.

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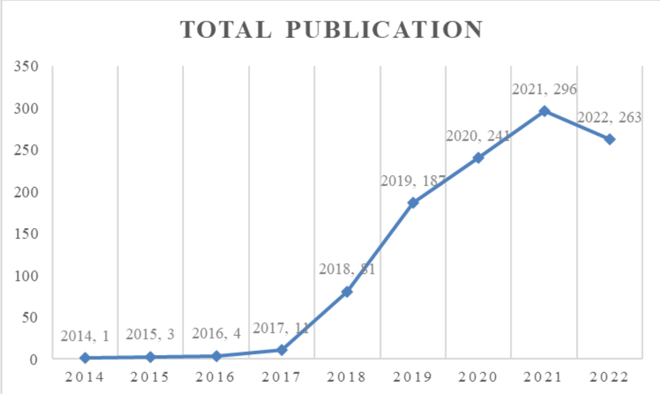

Figure 2: Annual Growth of Publications Related to Cryptocurrency Price Research

Bibliometric Network Analysis

To further explore thematic patterns and intellectual linkages in the field, a bibliometric network analysis was conducted using VOSviewer software. Two techniques were employed: keyword co-occurrence analysis and author-level co-citation analysis, both based on a dataset of 1,088 documents retrieved from the Scopus database.

Keyword Co-Occurrence Analysis

Figure 3 presents the results of the keyword co-occurrence analysis. From 4,859 unique keywords, 121 met the inclusion threshold of appearing at least 10 times. After filtering out non-relevant terms such as "cost" and "learning algorithm," 66 keywords directly related to cryptocurrency pricing were selected.

The co-occurrence mapping revealed three dominant thematic clusters:

- Cluster 1 – Cryptocurrency Behaviour: Includes studies focusing on market dynamics, volatility, and investor sentiment.
- Cluster 2 – Predictive Models: Encompasses research utilizing machine learning, time series analysis, and AI-based forecasting techniques.
- Cluster 3 – Influencing Attributes: Covers external and intrinsic factors affecting cryptocurrency prices, such as macroeconomic indicators, regulations, and social media.

The color-coded visualization (Figure 3) indicates that recent research has increasingly emphasized predictive modeling, especially using machine learning tools and the analysis of market responses during significant events like the COVID-19 pandemic. Bitcoin consistently appears as the central focus across all clusters, underscoring its dominant role in cryptocurrency research.

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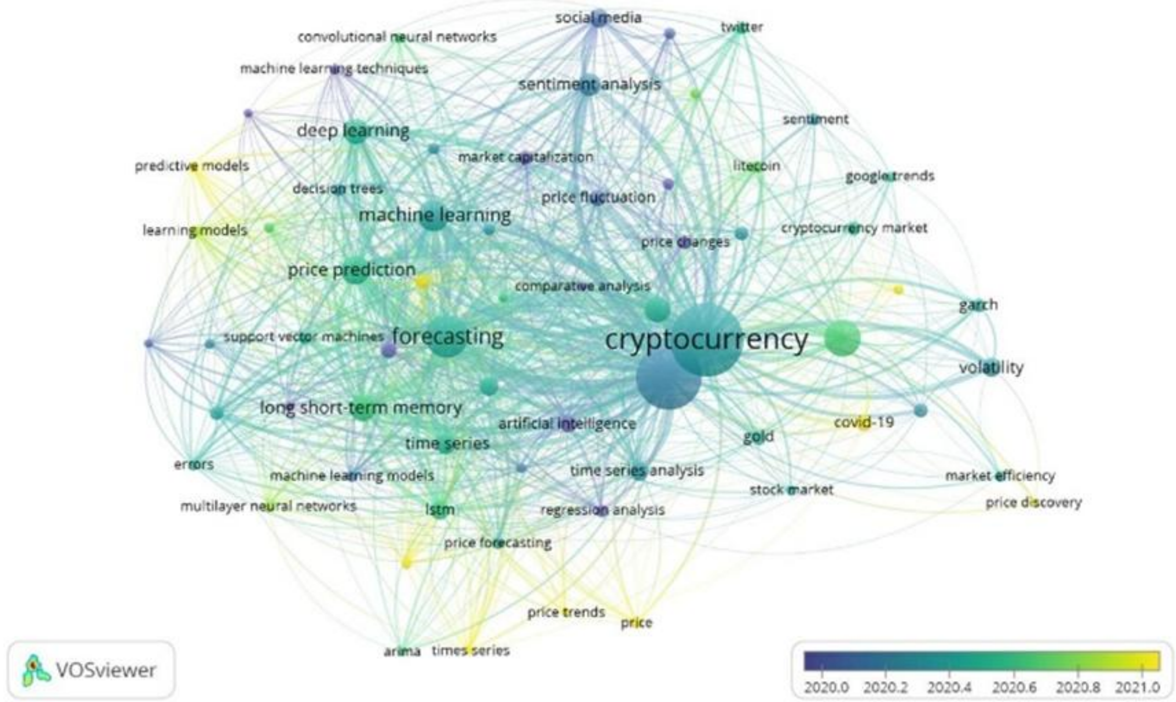

Figure 3: VOSviewer Visualization of Keyword Co-Occurrence Network.

Co-Citation Analysis of Authors

To identify intellectual foundations and key contributors in the field, an author-level co-citation analysis was performed. From the dataset, 60 authors met the minimum threshold of 100 citations. The resulting network, shown in Figure 4, is categorized into three clusters:

- Group I – Bitcoin-focused Studies (Red Cluster): Comprising 31 authors, this group includes foundational researchers investigating Bitcoin's role in digital markets.
- Group II – Behavior and Volatility (Green Cluster): With 15 authors, this cluster explores the behavioral economics of cryptocurrency markets, including sentiment and volatility.
- Group III – GARCH and Econometric Modeling (Blue Cluster): Consisting of 14 authors, this group is centered around econometric modeling approaches such as GARCH and its variants in forecasting cryptocurrency volatility.

These clusters collectively reflect the interdisciplinary nature of cryptocurrency price research, blending economics, computer science, and finance. They also highlight the field's evolution from traditional econometric analysis to more advanced predictive frameworks incorporating AI and data-driven modeling.

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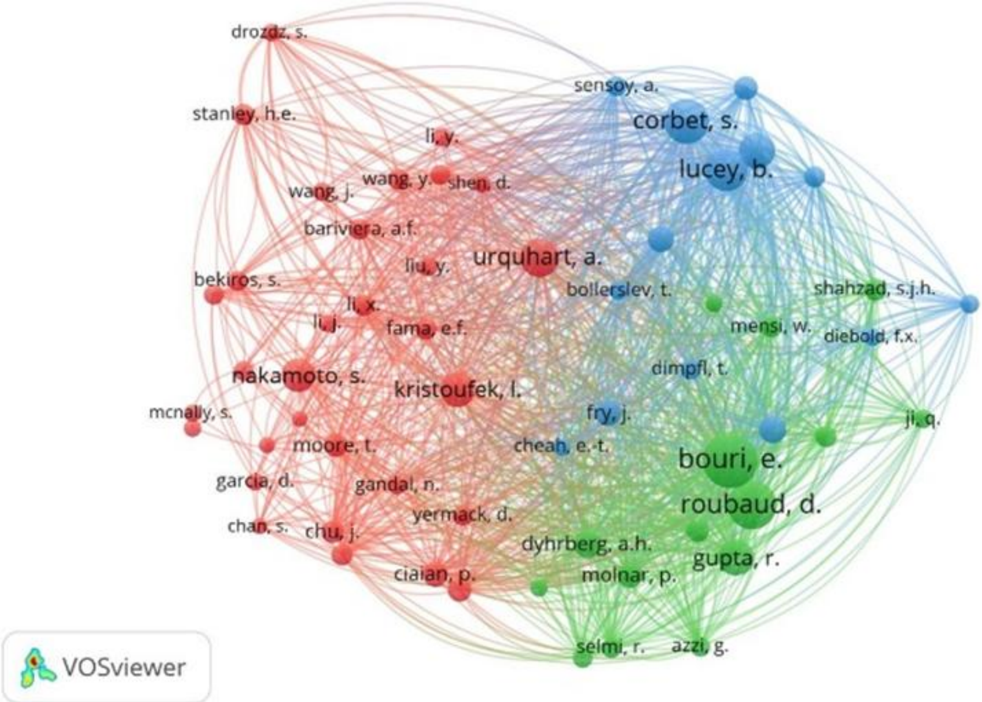

Figure 4: VOSviewer Visualization of Author-Level Co-Citation Network.

Table 1: Comparative Summary of Top 20 Cryptocurrency Forecasting Studies

Author(s)	Asset(s)	Methodology	Dataset Period	Forecast Horizon	Notable Findings
(Kristoufek, 2015)	BTC	Wavelet Coherence	2012–2014	Short-term	Sentiment and macroeconomic links are dynamic and time-varying
(Lahmiri & Bekiros, 2019)	BTC	Deep Learning + GARCH	2014–2018	Multi-day	GARCH-DL outperforms traditional models in chaotic markets
(Kumar & Anandarao, 2019)	BTC	GARCH Variants	2015–2017	1–5 days	GJR-GARCH shows superior volatility modeling accuracy
(Kraaijeveld & De Smedt, 2020)	Multiple	Twitter Sentiment + OLS	2017–2019	Next-day	Sentiment significantly predicts BTC and LTC returns
(Lamothe-Fernández et al., 2020)	ETH	GARCH	2016–2018	1–10 days	ETH volatility is more sensitive to high-frequency fluctuations
(Makarov & Schoar, 2020)	BTC + Exchanges	Price Spread Analysis	2018	Intraday	Arbitrage gaps persist across global exchanges

International Journal of Innovation and Industrial Revolution
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(A. E. Khedr et al., 2021)	BTC	ARIMA vs. LSTM	2016–2019	Daily	LSTM yields lower RMSE and MAE than ARIMA
(Corbet et al., 2019)	BTC	Meta-Review	2013–2018	N/A	Highlights thematic fragmentation and model limitations
(Yermack, 2024)	BTC	Economic Theory	2009–2012	N/A	Argues BTC lacks classical currency functions
(Bouri et al., 2017)	BTC	Quantile Regression	2011–2016	Weekly	BTC is weak hedge but may act as safe haven in some markets
(Cretarola et al., 2020)	BTC, ETH	Stochastic Volatility	2015–2018	Short-term	SV models capture volatility clustering effectively
(Jeris et al., 2022)	Multiple	Copula + GARCH	2017–2020	Multi-asset	Dependency between cryptos increases during downturns
(Huynh et al., 2020)	BTC	Wavelet + Quantile	2014–2018	Medium-term	Strong nonlinear effect of uncertainty on prices
(Shahzad et al., 2020)	BTC, ETH	DCC-GARCH	2015–2017	Short-term	BTC and ETH show dynamic correlation post-shocks
(Liu & Tsyvinski, 2021)	Multiple	Panel Regression	2015–2017	Weekly	Risk-return profile differs sharply from stocks/bonds
(Ji et al., 2021)	BTC, ETH	Bayesian VAR	2016–2020	Daily	Crypto prices are affected by both internal and global shocks
(Sun, 2024)	BTC	XGBoost	2018–2021	Short-term	XGBoost shows high accuracy with sentiment + macro data
(Goodell & Goutte, 2021)	BTC	Structural Break Tests	2016–2020	Event-based	COVID-19 altered BTC's volatility permanently
(Qureshi et al., 2025)	BTC, ETH	Ensemble Learning	2017–2019	Short-term	Stacking improves predictive robustness
(McNally et al., 2018)	BTC	ANN + LSTM	2013–2017	Daily	LSTM outperforms traditional ANN in RMSE and MAPE

Comparative Summary of Top 20 Studies
To provide a more comprehensive understanding of cryptocurrency forecasting literature, Table 1 presents a comparative analysis of 20 influential studies, evaluating each based on asset type, methodological approach, dataset period, forecast horizon, and key findings. A significant number of these studies focus on Bitcoin (BTC), though analyses of Ethereum (ETH) and multi-asset portfolios are increasingly emerging. Traditional econometric models, such as GARCH and its variants (e.g., GJR GARCH and DCC GARCH), remain widely used for short

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IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
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to medium term volatility modeling, as demonstrated by Kumar and Anandarao (Kumar & Anandarao, 2019), Lamothe-Fernández et al. (Lamothe-Fernández et al., 2020), and Bouri et al. (Bouri et al., 2019). However, a clear methodological shift is observed with the growing use of machine learning (ML) and deep learning (DL) techniques, including LSTM, XGBoost, and ensemble learning, which consistently outperform conventional models in predictive accuracy (Qureshi et al., 2025; Sun, 2024; A. M. Khedr et al., 2021).

Several studies, including Kristoufek (Kristoufek, 2015) and Kraaijeveld and De Smedt (Kraaijeveld & De Smedt, 2020), underscore the importance of sentiment and macroeconomic variables, while others such as Huynh et al. (Huynh et al., 2020) and Sun (Sun, 2024) highlight the value of integrating economic uncertainty and social signals for improved robustness. In contrast, conceptual and structural contributions from Yermack (Yermack, 2024) and Corbet et al. (Corbet et al., 2019) critically evaluate the theoretical positioning of cryptocurrencies within modern financial systems. Furthermore, market structure analyses by Makarov and Schoar (Makarov & Schoar, 2020) and Goodell and Goutte (Goodell & Goutte, 2021) provide insight into arbitrage inefficiencies and the impact of exogenous shocks such as the COVID-19 pandemic.

Overall, the comparative review reflects the evolution of cryptocurrency forecasting from classical statistical approaches to more dynamic, hybrid, and AI-enhanced frameworks. It also illustrates the field's growing complexity, with expanded research scopes encompassing diverse assets, behavioral drivers, and systemic market events, all of which contribute to a deeper and more nuanced understanding of cryptocurrency price behavior.

Table 2: Top Cited Studies in Cryptocurrency Price Forecasting Literature

Author(s) & Year	Asset Focus	Methodology	Key Contribution
(Kristoufek, 2015)	Bitcoin	Wavelet Coherence	Analyzed macroeconomic drivers and sentiment in price formation
(Lahmiri & Bekiros, 2019)	Bitcoin	Deep Learning + GARCH	Modeled chaotic behavior in cryptocurrency time series
(Kumar & Anandarao, 2019)	Bitcoin	GARCH variants	Compared volatility models for BTC under different windows
(Lamothe-Fernández et al., 2020)	Ethereum	GARCH models	Modeled ETH volatility with a focus on variance behavior
(Kraaijeveld & De Smedt, 2020)	Multiple	Twitter Sentiment + Regression	Demonstrated predictive value of public sentiment
(Corbet et al., 2019)	Bitcoin	Literature Review	Provided a meta-review of crypto as financial assets
(Makarov & Schoar, 2020)	Bitcoin & exchanges	Arbitrage analysis	Studied cross-exchange price efficiency and flow
(Gandal & Halaburda, 2016)	Multiple	Market Design	Assessed long-run competition and dominance in crypto
(A. M. Khedr et al., 2021)	Bitcoin	ARIMA vs LSTM	Compared traditional vs DL forecasting accuracy

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(Yermack, 2024)	Bitcoin	Conceptual analysis	Argued Bitcoin lacks currency properties in classical economics

Table 2 offers a concise yet insightful overview of seminal and high-impact studies that have significantly shaped the field of cryptocurrency price forecasting. These works reflect a broad spectrum of research approaches, asset focuses, and analytical tools, underscoring the multidisciplinary nature of this domain. A clear pattern in the top-cited studies is the dominance of Bitcoin (BTC) as the primary focus of analysis. Seminal works by Kristoufek (Kristoufek, 2015), Lahmiri and Bekiros (Lahmiri & Bekiros, 2019), Kumar and Anandarao (Kumar & Anandarao, 2019), and Yermack (Yermack, 2024) highlight BTC's central role in cryptocurrency forecasting research, reaffirming its status as the most extensively examined digital asset. However, more recent studies, such as Lamothe-Fernández et al. (Lamothe-Fernández et al., 2020) and Kraaijeveld and De Smedt (Kraaijeveld & De Smedt, 2020), signal a growing academic interest in Ethereum (ETH) and multi-asset analyses, indicating a broadening scope of inquiry in the field.

In terms of methodology, the literature reveals a high degree of diversity in modeling approaches. Traditional econometric frameworks such as GARCH remain widely used for volatility estimation (Kumar & Anandarao, 2019; Lamothe-Fernández et al., 2020), while more advanced models leveraging deep learning (DL) and LSTM architectures (e.g., Lahmiri & Bekiros; Khedr et al.) have gained traction for capturing nonlinear dynamics. Some studies integrate sentiment analysis and social media indicators (Kraaijeveld & De Smedt, 2020) to reflect behavioral patterns in market activity, whereas others offer conceptual or qualitative insights into the economic nature of cryptocurrencies (e.g., Yermack; Corbet et al.). This methodological plurality underscores the field's evolution from classical statistical models toward hybrid and AI-enhanced forecasting techniques.

Moreover, there is an increasing integration of non-traditional data sources, particularly sentiment-driven indicators. Kristoufek (Kristoufek, 2015) and Kraaijeveld and De Smedt (Kraaijeveld & De Smedt, 2020), forinstance, demonstrate the predictive value of public sentiment and online behavior, which are often excluded from conventional financial models. These studies reflect the speculative and psychologically influenced nature of cryptocurrency markets, where news flow and investor emotion can drive substantial short-term price movements.

Some contributions, such as those by Makarov and Schoar (Makarov & Schoar, 2020) and Gandal and Halaburda (Gandal & Halaburda, 2016), pivot from direct price prediction to market microstructure and exchange-level analysis. These studies examine cross-exchange price differences, arbitrage potential, and competitive dynamics, offering deeper insights into how market design affects price efficiency and long-run competition among digital currencies. Finally, several works provide foundational and theoretical perspectives. Yermack (Yermack, 2024), in particular, challenges the classification of Bitcoin within classical economic frameworks, arguing that it lacks the core properties of traditional currencies. Meanwhile, Corbet et al. (Corbet et al., 2019) contribute a comprehensive literature review, helping to synthesize the field's fragmented insights and positioning cryptocurrency as a distinctive asset class within modern finance.

International Journal of Innovation and Industrial Revolution
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Thematic Clusters

The identified clusters are further summarized in Table 3 to provide an overview of key research focus areas. This section goes beyond description by critically examining each cluster's scholarly evolution, prevailing gaps, and interdisciplinary potential. Beyond summarizing, this section critically compares these clusters to explore overlapping themes, methodological progression, and theoretical divergence in the literature.

Table 3: Summary of Major Thematic Clusters in Cryptocurrency Price Research

Cluster	Focus Area	Methods	Topics
Cryptocurrency Behavior	Volatility, market efficiency	Sentiment analysis, econometrics	Herding, bubbles
Predictive Models	Price forecasting	LSTM, Random Forests, GARCH-ANN	Overfitting, non-stationarity
Factors Influencing Prices	External/internal drivers	Regression, sentiment mining	Macroeconomics, blockchain metrics

Cryptocurrency Behaviour

The rising popularity of cryptocurrencies and their growing correlations with traditional financial instruments have positioned them as a compelling asset class for investors and speculators alike (Chaudhari & Crane, 2020). Among them, Bitcoin (BTC) has emerged as the dominant digital asset, capturing the majority of academic and market attention. Unlike traditional stocks or forex, cryptocurrencies trade continuously 24 hours a day, which adds a layer of complexity in forecasting due to uninterrupted price fluctuation and increased market noise (Albariqi & Winarko, 2020).

Forecasting cryptocurrency prices is inherently challenging due to several structural characteristics of the data, including dynamic patterns (Agarwal & Muppalaneni, 2022), nonlinear dependencies (Liashenko et al., 2020), high volatility (Aloosh & Ouzan, 2020), heavy-tailed distributions (Trimborn et al., 2020; Chan et al., 2017), extreme outliers (Chaim & Laurini, 2019), and long-memory temporal dependencies (Wang et al., 2023; Ghazani & Jafari, 2021; Bariviera, 2017). Moreover, cryptocurrency price behavior is typically non-stationary and more volatile than traditional financial assets (Ammer & Aldhyani, 2022; Nikolova et al., 2020).

Price Bubbles, Sentiment, and Speculative Behavior

Several studies have explored the behavioral anomalies in cryptocurrency markets, particularly in relation to price bubbles and investor sentiment. Kristoufek (Kristoufek, 2015) demonstrated that fundamental economic factors often coincide with surges in BTC prices, suggesting speculative episodes. While some scholars label these instances as "bubbles" (Dreger & Zhang, 2013), others prefer the term price explosivity, which avoids definitional ambiguities and acknowledges the exponential price growth commonly observed (Agosto & Cafferata, 2020). Cheung et al. (Cheung et al., 2015) applied formal bubble detection methods to identify speculative behavior in BTC, whereas Corbet et al. (Corbet, Lucey, et al., 2018) found no bubble-like patterns in BTC or ETH, highlighting the influence of differing time frames and methodologies.

International Journal of Innovation and Industrial Revolution
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Investor sentiment and herding effects also significantly influence cryptocurrency pricing. Research has employed both traditional econometric models (e.g., EGARCH, Markov-switching) and newer sentiment-based proxies using alternative data sources like Reddit, Twitter, and Google Trends (Lahmiri & Bekiros, 2019). However, the field remains fragmented, lacking theoretical integration and cross-contextual validation across regulatory or cultural settings.

Predictive Models

Forecasting cryptocurrency prices poses substantial challenges due to their nonlinear dynamics, long-memory behavior, chaotic fluctuations, and extreme volatility. These challenges have driven researchers to explore a broad spectrum of models, from traditional econometrics to modern machine learning (ML), deep learning (DL), and hybrid approaches.

Volatility Modeling and the GARCH Framework

Volatility is one of the most studied features of cryptocurrency markets, with studies consistently confirming that digital assets such as Bitcoin (BTC), Ethereum (ETH), and Ripple (XRP) are significantly more volatile than traditional financial instruments like equities, indices, or foreign exchange pairs (Chu et al., 2017; Nikolova et al., 2020; Trimborn et al., 2020). The Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model and its extensions have been widely applied to capture these dynamics (Dyhrberg, 2016; Katsiampa, 2017).

Advanced variants, such as Multivariate GARCH (Corbet, Cumming, et al., 2020), GARCH-EVT (Bruhn & Ernst, 2022), and GARCH with Value-at-Risk (Ječmínek et al., 2020), have aimed to improve forecast performance. However, issues such as skewed distributions, heavy tails, and nonlinearity often limit their accuracy (Christopher et al., 2022; Mattera & Giacalone, 2018). Consequently, researchers have turned to hybrid models like ANN-GARCH (Kristjanpoller & Minutolo, 2018), GARCH-MIDAS (Conrad et al., 2018), and SVR-GARCH (Peng et al., 2018), which integrate machine learning and decomposition methods to improve robustness in volatile environments.

Structural Time Series Models (State Space)

Given the limitations of GARCH models, state space (SS) or structural time series (STS) models have gained attention. These models handle non-stationarity, time-varying volatility, and regime shifts without discarding valuable information (Koopman & Commandeur, 2015). Notable applications include Kalman filter-based SS models (Azman et al., 2022; Neslihanoglu, 2021), Bayesian structural models (Jalan et al., 2021), and volatility-driven herding analysis (Raimundo Júnior et al., 2022). These models outperform GARCH and neural networks in several forecasting scenarios, particularly during periods of market disruption such as the COVID-19 pandemic.

Machine Learning and Deep Learning Applications

ML techniques such as support vector machines (SVM), random forests, and feedforward neural networks (FNN) have demonstrated promising results in capturing nonlinear relationships and reducing forecast errors (Lamothe-Fernández et al., 2020; Kumar & Anandarao, 2019). However, limitations such as model interpretability, overfitting, and sensitivity to irrelevant inputs have impeded their broader adoption in high-stakes financial environments.

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031
In response, explainable AI (XAI) tools like SHAP values and LIME have been proposed, but their integration into cryptocurrency forecasting remains limited. Furthermore, the field lacks consistent benchmarking across forecast horizons, asset types, and extreme market conditions. DL models, including Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs), and Recurrent Neural Networks (RNNs), have been applied to overcome these limitations. Studies by Saxena and Sukumar (Saxena & Sukumar, 2018), Misnik et al. (Misnik et al., 2018) and Lahmiri and Bekiros (Lahmiri & Bekiros, 2019) showed that LSTM and MLP-based models often outperform ARIMA in terms of accuracy and RMSE. Still, not all results are conclusive—Livieris et al. (Livieris, Pintelas, et al., 2020) found that the chaotic nature of cryptocurrency prices sometimes limits DL performance, with some models failing to generalize effectively.

Hybrid Modeling Approaches

A growing body of literature has acknowledged that no single modeling technique can adequately address the multifaceted and volatile nature of cryptocurrency markets. As a result, recent research has shifted toward hybrid forecasting approaches that combine the strengths of traditional statistical models with the flexibility and learning capacity of artificial intelligence (AI) techniques. These hybrid models integrate econometric tools such as GARCH or ARIMA with machine learning (ML) and deep learning (DL) frameworks to better capture the nonlinearities, regime shifts, and structural complexities inherent in cryptocurrency price data (Gao et al., 2021; Lahmiri & Bekiros, 2019). For instance, studies like Gao et al. (Gao et al., 2021) and Ji et al. (Ji et al., 2021) have shown that combining GARCH with LSTM networks significantly enhances prediction accuracy during high-volatility periods. Similarly, hybrid architectures that use decomposition techniques, such as Theta with Support Vector Regression (SVR) (Parvini et al., 2020), or neural structures like NARX-MLP (Indera et al., 2017), have proven effective in handling long-memory processes and abrupt market changes.

While GARCH models continue to be foundational due to their theoretical grounding and ease of interpretation (Katsiampa, 2017), their assumptions of linearity, normality, and constant variance often fail to reflect the erratic behavior of crypto assets (Chu et al., 2017; Dyhrberg, 2016). On the other hand, ML and DL models, although superior in capturing complex patterns, are frequently criticized for their black-box nature and limited interpretability. These factors hinder their acceptance in finance and policy settings (A. M. Khedr et al., 2021; Livieris, Stavroyiannis, et al., 2020). Therefore, hybrid models represent a compelling middle ground by offering both enhanced predictive performance and, when properly configured, a degree of transparency that pure DL models often lack.

In parallel, structural time series (STS) models, particularly those built on state-space formulations such as the Kalman filter or Bayesian estimation, have emerged as viable alternatives. These models are especially adept at handling non-stationarity, time-varying parameters, and unobserved components such as trends or seasonal effects, making them useful complements to hybrid systems (Jalan et al., 2021; Koopman & Commandeur, 2015). Their interpretability and flexibility make STS models valuable in regulatory and policy environments, where explainability is essential.

Looking ahead, the development of integrated forecasting frameworks will be key to advancing the field. Future research should prioritize explainable AI (XAI) techniques to enhance transparency (SHAP, LIME), conduct benchmarking across diverse asset classes and time

International Journal of Innovation and Industrial Revolution IJIREV
EISSN: 2637-0972
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031
horizons (Qureshi et al., 2025; Sun, 2024), and incorporate heterogeneous data sources such as sentiment metrics, macroeconomic indicators, and blockchain-specific signals (Kraaijeveld & De Smedt, 2020; Kristoufek, 2015). Additionally, there is a strong case for real-time adaptive forecasting systems that can dynamically recalibrate in response to evolving market conditions (Goodell & Goutte, 2021). By merging methodological innovation with contextual awareness, hybrid and STS-based models have the potential to elevate the accuracy, reliability, and practical relevance of cryptocurrency forecasting.

Factors Influencing Prices

The third thematic cluster focuses on the multifaceted factors that influence cryptocurrency price behavior. This stream encompasses macroeconomic indicators, blockchain-level metrics, investor sentiment, regulatory dynamics, and geopolitical events. While each category offers distinct insights, their effects are often interrelated, revealing the complexity of cryptocurrency price formation.

Macroeconomic and Financial Influences

Initial studies in this area examined traditional economic variables such as exchange rates, inflation, and interest rates. For example, Polasik et al. (Polasik et al., 2015) and Fry and Cheah (Fry & Cheah, 2016) identified significant intra-market correlations among major cryptocurrencies, while Corbet et al. (Corbet, Meegan, et al., 2018) and Guesmi et al. (Guesmi et al., 2019) found limited integration between crypto and traditional financial assets, suggesting that cryptocurrencies could provide portfolio diversification benefits in the short term.

However, findings on the influence of macro-financial indicators like the Dow Jones, S&P500, and gold prices remain mixed. Zhu et al. (Zhu et al., 2017) reported that these indicators have limited short-term impact but could influence long-term pricing trends. Li and Wang (Li & Wang, 2017) emphasized the role of economic fundamentals and technical factors, such as hash rate and public interest, in determining BTC's exchange rate. The lack of consensus across studies may be attributed to differences in timeframes, asset selection, and market maturity.

Supply, Demand, and Blockchain Metrics

The role of supply and demand in cryptocurrency valuation is widely acknowledged. Ciaian et al. (Ciaian et al., 2016) were among the first to formalize the impact of traditional currency dynamics and Bitcoin-specific features such as adoption rates and perceived utility. Leon-Ayala et al. (Leon-Ayala et al., 2022) reaffirmed that price increases with demand and falls with a lack of interest.

Blockchain-based indicators such as transaction volume, block size, mining revenue, hash rate, and network difficulty have also been tested as predictors. However, results vary. While some studies (Vassiliadis et al., 2017) found strong associations, others (Singh & Agarwal, 2018) reported minimal significance. Feature selection techniques, including principal component analysis (Mallqui & Fernandes, 2019) and multicollinearity checks (Jang & Lee, 2017), have helped improve model reliability.

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031

Sentiment and Social Media Dynamics

Investor sentiment, driven largely by social media and online search behavior, plays a critical role in short-term price movements. Platforms such as Twitter, Reddit, and Google Trends serve as proxies for investor mood and information diffusion. Research by Kristoufek (Kristoufek, 2013), Garcia and Schweitzer (Garcia & Schweitzer, 2015), and Baig et al. (Baig et al., 2019) demonstrated strong correlations between social signals and Bitcoin price fluctuations. Matta et al. (Matta et al., 2015) and Abraham et al. (Abraham et al., 2018) also found predictive value in sentiment-related data streams.

Recent studies (Kraaijeveld & De Smedt, 2020; Schulte & Eggert, 2021) highlight that Twitter sentiment, in particular, is a powerful predictor of price volatility. However, the market's immaturity and the prevalence of misinformation complicate accurate forecasting, necessitating more robust sentiment analysis techniques and real-time model calibration.

Political and Regulatory Drivers

Socio-political conditions and regulatory developments exert considerable influence on cryptocurrency markets. Research has shown that government restrictions and anti-crypto sentiment can lead to sudden price corrections (Dahham & Ibrahim, 2020). Studies on Economic Policy Uncertainty (EPU) (Chen et al., 2021; Demir et al., 2018) and Geopolitical Risk Index (Bouri et al., 2022) demonstrate that such factors can both suppress and amplify volatility, depending on market context.

The COVID-19 pandemic further highlighted the sensitivity of cryptocurrency markets to exogenous shocks. Studies by Lahmiri and Bekiros (Lahmiri & Bekiros, 2020) and Sahoo (Sahoo, 2021) reported irregular price patterns and speculative surges during the pandemic, emphasizing the need for models that incorporate real-time global developments.

Synthesis and Research Gaps

Despite the wide range of variables studied in cryptocurrency forecasting, several challenges remain. Many models suffer from overfitting due to too many poorly justified variables, predictor collinearity, and the absence of interaction term testing. Additionally, a weak link between economic theory and empirical models leads to fragile forecasting frameworks. Cross-country comparisons are rare, limiting broader applicability.

Future research should focus on theory-driven models with multi-dimensional predictors (economic, technical, behavioral). Econometric models must adapt to market shifts, and the integration of sentiment data can improve forecasting in volatile markets. Since no single factor drives prices, models must combine macroeconomic, blockchain, sentiment, and geopolitical data using real-time, adaptive learning techniques.

Future Research Directions

Future research on cryptocurrency price forecasting should focus on hybrid models that combine machine learning or deep learning with explainable tools like SHAP and LIME to improve transparency without losing accuracy. It's also important to study how price patterns change during different market phases (like bull or bear markets) using models that can adapt over time. Researchers should explore how cryptocurrencies interact with other financial markets such as stocks, commodities, and forex, and expand analysis to include altcoins, NFTs, and stablecoins. Adding behavioral factors like investor psychology (e.g., loss aversion or

International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031

overconfidence) alongside sentiment data can improve predictions. Studies should also examine how different regulatory policies across countries affect prices using methods like event studies. Lastly, real-time forecasting using adaptive learning methods is essential to keep up with the fast-moving and data-rich nature of crypto markets.

Conclusion And Discussion

This review maps cryptocurrency price forecasting research into three main themes: price behavior, modeling approaches, and influencing factors. Most existing studies focus heavily on Bitcoin, which limits the applicability of findings to other digital assets. Although machine learning and deep learning models often outperform traditional methods, their lack of transparency poses challenges for practical use. Explainable AI tools such as SHAP and LIME are needed to improve model interpretability. The review is limited to Scopus-indexed and English-language publications, potentially excluding relevant studies. Thematic classification involves subjective judgment, and citation mapping may miss emerging interdisciplinary links. No empirical comparison of model performance was conducted, highlighting a gap for future benchmarking research. Broader inclusion of altcoins, NFTs, and stablecoins is essential to enrich the scope of analysis. Future models should integrate behavioral, technical, and regulatory factors for a more holistic understanding. Moving toward hybrid and adaptive frameworks will enhance forecasting accuracy and relevance in this dynamic field.

Acknowledgment

The authors gratefully acknowledge the financial support provided by Universiti Teknologi MARA (UiTM) for facilitating this research.

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International Journal of Innovation and Industrial Revolution
EISSN: 2637-0972
IJIREV
Volume 7 Issue 22 (September 2025) PP. 553-575
DOI 10.35631/IJIREV.722031
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