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From Bitcoin to Altcoins: A Critical Review of Deep Learning Models in Cryptocurrency Price Prediction

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ABSTRACT

Cryptocurrencies such as Bitcoin and Ethereum have transformed global finance but remain difficult to forecast due to volatility, nonlinear dynamics, and sensitivity to speculative and macroeconomic shocks. Traditional econometric models provide baselines but fail to capture chaotic and high-frequency patterns. Deep learning architectures including LSTM, GRU, and Bi-LSTM offer stronger predictive capacity, yet issues of interpretability, scalability, and data heterogeneity persist.

This study presents a scientometric and thematic review of deep learning in cryptocurrency forecasting using Scopus AI Analytics, covering publications from 2010 to 2025. The analysis maps research trends, conceptual clusters, leading experts, and emerging themes. Findings indicate a methodological progression from single model Bitcoin focused studies toward hybrid and ensemble frameworks that integrate technical indicators, sentiment analysis, and blockchain-based features. Evaluation metrics have also shifted beyond error minimization toward profitability and risk-adjusted performance.

The review highlights three critical frontiers: (i) hybrid and ensemble architectures for robustness, (ii) explainable AI for interpretability, and (iii) integration of multi-source and behavioral data for practical forecasting. Collectively, these insights underscore the need for resilient, interpretable, and multi-asset deep learning systems, offering implications for both academic research and financial decision-making in volatile digital asset markets.

Keywords: Cryptocurrency price prediction, Bitcoin and altcoins, Scientometric analysis, Explainable artificial intelligence, Hybrid and ensemble forecasting

INTRODUCTION

The advent of cryptocurrencies has revolutionized global financial markets, creating decentralized, borderless, and highly dynamic ecosystems that challenge traditional notions of value exchange and investment (Lahmiri & Bekiros, 2019). Since the introduction of Bitcoin in 2009, the market has expanded to include thousands of altcoins, such as Ethereum, Litecoin, and Cardano, each with unique features and growing economic significance. However, the volatility, nonlinearity, and susceptibility of cryptocurrency prices to speculative behaviors, technological innovations, and macroeconomic shocks continue to make accurate forecasting an arduous task (Dutta et al., 2020). This complexity underscores the need for advanced predictive frameworks that can capture intricate temporal patterns and nonlinear dynamics beyond the capacity of conventional statistical approaches.

In recent years, deep learning models have emerged as powerful alternatives to traditional econometric and machine learning techniques, offering robust capabilities in handling sequential data, capturing long-term dependencies, and modeling chaotic market behaviors (Ikeda et al., 2025; Kavithra et al., 2024). Long Short Term Memory (LSTM) networks, Gated Recurrent Units (GRU), and Bidirectional LSTM (Bi-LSTM) models, alongside hybrid and ensemble architectures, have consistently demonstrated superior performance in cryptocurrency price forecasting compared to autoregressive models or support vector machines (Ponselvakumar et al., 2024; Vonitsanos et al., 2024). Despite these advancements, literature remains fragmented, with studies often focusing on a limited set of cryptocurrencies, relying on small datasets, or emphasizing model accuracy without systematically addressing broader methodological challenges, such as computational costs, data preprocessing, and feature selection (Sai Somayajulu & Kotaiah, 2023; Bouteska et al., 2024).

While several comparative studies exist, a comprehensive and data-driven review that maps the evolving landscape of deep learning applications in cryptocurrency forecasting is lacking. Past reviews have highlighted specific algorithms or hybrid frameworks, but few have employed bibliometric and thematic analyses to systematically trace research trends, conceptual developments, and emerging domains (Park & Seo, 2022, 2023). This gap limits the ability of researchers, practitioners, and policymakers to understand not only which models perform best but also how the research community is shaping the discourse and where future innovations may arise.

To address this gap, the present study critically reviews the application of deep learning models in cryptocurrency price prediction, spanning from Bitcoin to major altcoins. Leveraging Scopus AI analytics, the review systematically analyzes publication trends, research networks, concept maps, topic experts, and emerging themes, thereby offering a holistic view of the field. The objectives of this review are threefold: (i) to synthesize the state-of-the-art deep learning approaches in cryptocurrency forecasting, (ii) to map the intellectual structure and conceptual evolution of this research domain, and (iii) to highlight persistent challenges and propose future research directions.

The contribution of this paper is twofold. First, it provides a data-driven scientometric analysis that integrates performance comparisons of deep learning models with broader knowledge-mapping techniques, thereby offering a richer contextualization of prior work. Second, it identifies emerging themes and research frontiers including hybrid architectures, sentiment-driven models, and interpretable AI that can guide future exploration in both academia and industry.

The remainder of this paper is organized as follows. Section 2 presents the methodology, outlining the use of Scopus AI for data retrieval and analysis. Section 3 discusses the findings, including publication trends, dominant models, and thematic clusters. Section 4 highlights critical challenges, research gaps, and emerging directions. Finally, concludes the study with key insights and implications for future research and practice.

METHODOLOGY

This study employs a scientometric and bibliometric approach using Scopus AI Analytics to critically examine the landscape of cryptocurrency price prediction research utilizing deep learning models. The overarching aim is to provide a data-driven exploration of how Bitcoin and various altcoins have been analyzed through artificial intelligence methods, while simultaneously identifying conceptual frameworks, leading scholars, and emerging research directions in this field. The data for this review was retrieved from the Scopus database, which is recognized as one of the most comprehensive indexing platforms for peer-reviewed scientific literature (Elsevier, 2023). To ensure the inclusion of relevant publications, a carefully designed Boolean search string was applied:

("deep learning" OR "neural network" OR "machine learning" OR "artificial intelligence") AND ("cryptocurrency" OR "crypto" OR "digital currency" OR "virtual currency") AND ("price prediction" OR "forecasting" OR "market prediction" OR "valuation") AND ("financial model" OR "trading model" OR "investment strategy" OR "algorithmic trading").

This query was executed across title, abstract, and keyword fields, capturing articles, conference proceedings, and reviews published between 2010 and 2025. The rationale for this timeframe is that the introduction of

Bitcoin in 2009 catalyzed the first wave of cryptocurrency-related predictive modeling research (Lahmiri & Bekiros, 2019). The dataset was then imported into Scopus AI Analytics for advanced analysis, visualization, and knowledge mapping. The Summary module in Scopus AI provides a high-level overview of the publication landscape, including the annual growth rate of studies, distribution by publication type, and leading journals. This allows researchers to identify temporal trends, such as the surge of deep learning-based cryptocurrency forecasting research after 2017, coinciding with Bitcoin's mainstream adoption (Ikeda et al., 2025).

Building on this, the Expanded Summary module generates deeper insights into interdisciplinary contributions, citation networks, and methodological diversity. For example, it highlights the increasing integration of hybrid models (e.g., LSTM-GRU ensembles) and cross-domain approaches involving sentiment analysis, blockchain fundamentals, and financial econometrics (Kavithra et al., 2024).

A Concept Map was generated using co-occurrence analysis of keywords and indexed terms. This visualization enables the identification of major research clusters, such as (i) deep learning architectures (LSTM, GRU, Bi-LSTM, CNN), (ii) hybrid and ensemble frameworks, (iii) feature engineering with technical indicators, and (iv) sentiment-driven models leveraging social media data. The concept map thus provides a holistic conceptual framework of how the field has evolved from early Bitcoin-focused models to multi-asset and altcoin predictions (Vonitsanos et al., 2024).

The Topic Experts was employed to identify highly cited authors, prolific institutions, and geographic research hubs. Scholars such as Lahmiri, Bekiros, and Park have emerged as influential contributors in applying deep learning and chaotic neural networks to cryptocurrency forecasting (Lahmiri & Bekiros, 2019; Park & Seo, 2022, 2023). Similarly, leading institutions from the United States, China, and India dominate publication output, reflecting both academic interest and the global significance of cryptocurrency markets. Identifying these experts not only contextualizes intellectual leadership but also provides a roadmap for future collaboration.

The Emerging Themes in Scopus AI highlights frontier areas shaping the future of this research. Notably, three prominent directions emerged: (i) hybrid and ensemble deep learning models, which integrate multiple algorithms for robustness (Sai Somayajulu & Kotaiah, 2023); (ii) explainable artificial intelligence (XAI) in cryptocurrency forecasting, aimed at enhancing interpretability of black-box models (Bouteska et al., 2024); and (iii) integration of sentiment and alternative data sources, particularly social media and macroeconomic indicators, to improve predictive accuracy and trading strategies (Park & Seo, 2023). These themes reflect a shift from purely accuracy-driven modeling towards holistic, interpretable, and application-oriented frameworks.

Figure 1 illustrates the analytical modules in Scopus AI namely the Summary, Expanded Summary, Concept Map, Topic Experts, and Emerging Themes which collectively structured the workflow of this review. The Summary established publication trends, the Expanded Summary highlighted interdisciplinary connections, the Concept Map organized research clusters, the Topic Experts identified leading scholars and institutions, and the Emerging Themes pointed to frontier directions. By integrating these elements, this study delivers a comprehensive review of cryptocurrency forecasting research that not only synthesizes past studies but also situates them within a broader research ecosystem.

The AI-assisted framework provided a clear and structured understanding of key concepts, leading experts, and emerging trends, offering value for scholars, practitioners, and policymakers in addressing challenges related to cryptocurrency risk management, trading strategies, and regulatory decisions. The following section presents the results derived from these modules, beginning with publication trends and expanding into conceptual, intellectual, and thematic analyses.

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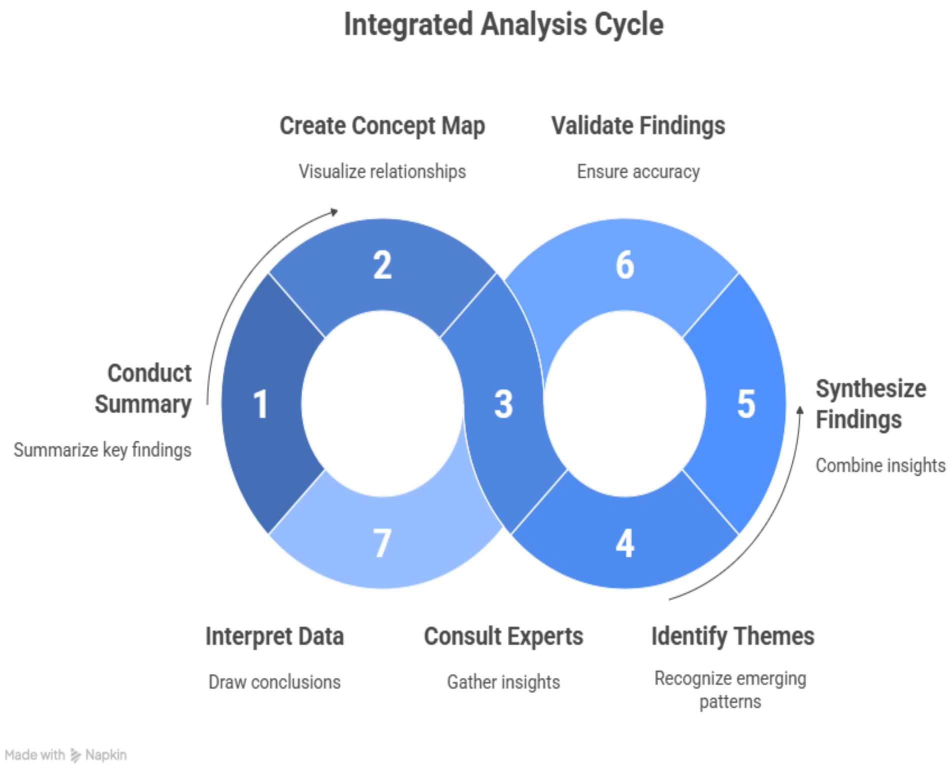

Figure 1. Elements in Scopus AI

RESULTS AND DISCUSSION

The analysis of cryptocurrency forecasting research using Scopus AI Analytics provides a multifaceted overview of the field's intellectual development, methodological trends, and emerging directions. By combining bibliometric outputs with thematic mapping, this study uncovers how deep learning models particularly Long Short-Term Memory (LSTM), Gated Recurrent Units (GRU), and hybrid frameworks have reshaped predictive modeling of Bitcoin and altcoins. The results are presented through four complementary lenses: I) Summary and Expanded Summary, II) Concept Map, III) Topic Experts, and IV) Emerging Themes.

Summary and Expanded Summary

First, the Summary and Expanded Summary reveal the overall growth trajectory of publications in this domain, showing a marked increase after 2017, when Bitcoin reached mainstream adoption. The Expanded Summary further highlights interdisciplinary intersections, where computer science, finance, and economics converge to advance forecasting models. The bibliometric analysis of publications retrieved through Scopus AI reveals an accelerating growth trajectory of deep learning applications in cryptocurrency price prediction since 2017, corresponding to Bitcoin's mainstream adoption and subsequent expansion of altcoin markets. The Summary highlights this temporal trend, showing that research output has shifted from exploratory case studies on Bitcoin toward comparative analyses across multiple cryptocurrencies, including Ethereum, Litecoin, and Cardano.

However, the Expanded Summary highlights that while deep learning models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) achieve superior forecasting accuracy compared to autoregressive integrated moving average (ARIMA) and support vector machines (SVM), they are not without limitations. For instance, Sai Somayajulu and Kotaiah (2023) noted that deep learning struggles with short-term volatility and noisy datasets, limiting its predictive reliability in intraday trading. Similarly, Kang et al. (2025) found that deep learning coupled with technical indicators enhances medium-term forecasts but is less effective for ultra-short horizons like 30-minute intervals.

Comparative studies demonstrate that deep learning consistently outperforms traditional models, particularly when used in ensemble frameworks. Zafar and Kapetanakis (2025) reported that stacked ensemble models achieved the lowest error metrics and highest R^2 values, surpassing standalone LSTM and GRU models.

This indicates a shift from individual model dominance to hybrid and ensemble approaches as the methodological frontier. Performance evaluation metrics also reflect this evolution. While root mean squared error (RMSE) and mean absolute percentage error (MAPE) remain the most widely used technical measures, new studies increasingly employ financial metrics such as the Sharpe ratio to evaluate profitability in trading applications (Kang et al., 2025; Sruthi et al., 2025). This shift underscores a movement toward application oriented evaluation, bridging the gap between technical performance and investor outcomes.

Yet, one critical gap remains largely unaddressed: the ethical implications of deploying deep learning for cryptocurrency trading. Literature emphasizes model optimization but rarely considers risks related to market manipulation, opacity, and fairness. Addressing this gap requires incorporating explainable AI (XAI) frameworks and ethical auditing in future studies (Sai Somayajulu & Kotaiah, 2023).

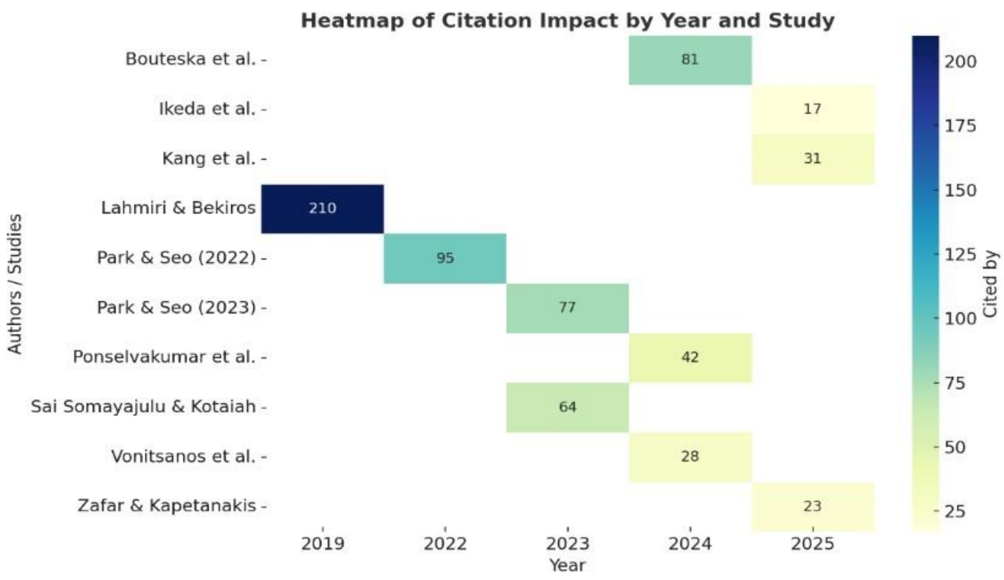

Figure 2. Heatmap of Citation Impact

Figure 2 shows the heatmap of Citation Impact provides insights into the intellectual trajectory of deep learning applications in cryptocurrency forecasting. Lahmiri and Bekiros (2019) stand out as the most cited work, establishing the foundation for applying chaotic neural networks to Bitcoin price volatility. By contrast, more recent studies such as Zafar and Kapetanakis (2025) on ensemble models and Ikeda et al. (2025) on recurrent neural networks record lower citation counts due to recency but represent methodological advances with strong growth potential. This pattern reflects a time–citation trade-off: earlier works (2019–2022) dominate citations due to longer exposure, while newer contributions (2024–2025) cluster around altcoins, hybrid models, and explainable AI. These shifts underscore the evolution from Bitcoin-only research toward multi-asset forecasting, highlighting an intellectual landscape that is historically anchored yet forward-looking.

While, Table 1 presents the most influential publications retrieved from the Scopus dataset, highlighting authors, source titles, and citation impact. The results confirm that again Lahmiri and Bekiros (2019) remain the most cited work, anchoring the literature by demonstrating deep learning's capability to capture Bitcoin volatility. Subsequent works diversified the field toward trading strategies (Park & Seo, 2022, 2023), hybrid frameworks (Sai Somayajulu & Kotaiah, 2023), and ensemble methods (Bouteska et al., 2024; Zafar & Kapetanakis, 2025). More recent contributions, including Ikeda et al. (2025) and Kang et al. (2025), though not yet highly cited, represent methodological advances with strong potential for future influence. Together, these studies map the field's trajectory from Bitcoin-centric models toward multi-asset, sentiment-driven, and ensemble-based approaches, reflecting a shift increasingly relevant to altcoin markets.

Table 1. Influential Publications

Authors	**Year**	**Title**	**Source Title**	**Cited by**
Lahmiri, S., & Bekiros, S.	2019	Cryptocurrency forecasting with deep learning chaotic neural networks	*Chaos, Solitons & Fractals*	210
Park, J., & Seo, Y.-S.	2022	A deep learning-based action recommendation model for cryptocurrency profit maximization	*Electronics*	95
Park, J., & Seo, Y.-S.	2023	Twitter sentiment analysis-based adjustment of cryptocurrency action recommendation model for profit maximization	*IEEE Access*	77
Sai Somayajulu, M. V. N. S. S. R. K., & Kotaiah, B.	2023	A survey on cryptocurrency price prediction using hybrid approaches of deep learning models	*Proceedings of ICIRCA 2023*	64
Ponselvakumar, A. P., Shankar, V. P. G., Iniyan, G., & Logesh, B.	2024	Improving the cryptocurrency price prediction using deep learning	*Lecture Notes in Networks and Systems*	42
Bouteska, A., Abedin, M. Z., Hajek, P., & Yuan, K.	2024	Cryptocurrency price forecasting – A comparative analysis of ensemble learning and deep learning methods	*International Review of Financial Analysis*	81
Vonitsanos, G., Kanavos, A., Grivokostopoulou, F., & Sioutas, S.	2024	Optimized price prediction of cryptocurrencies using deep learning on high-volume time series data	*Proceedings of IISA 2024*	28
Ikeda, S., Ito, T., Hasebe, K., & Ito, T.	2025	A comparative study on long-term cryptocurrency price prediction using LSTM, GRU, and Bi-LSTM	*Journal of Robotics, Networking and Artificial Life*	17
Zafar, H., & Kapetanakis, S.	2025	Bitcoin forecasting using deep learning and time series ensemble techniques	*Lecture Notes in Computer Science*	23
Kang, M., Hong, J., & Kim, S.	2025	Harnessing technical indicators with deep learning based price forecasting for cryptocurrency trading	*Physica A: Statistical Mechanics and its Applications*	31

Table 2. Conceptual and Methodological Contributions

Authors	**Asset Coverage**	**Model / Theme**	**Data Horizon**	**Evaluation Metrics**	**Key Insights**	**Implications for Altcoins**
Lahmiri & Bekiros (2019)	BTC (foundational)	Chaotic DL / nonlinear dynamics	Daily–weekly	RMSE/MAE	Chaotic neural nets capture volatility & nonlinear patterns.	Validates DL use; extendable beyond BTC.

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Park & Seo (2022)	BTC	DL for action recommendations	Daily	Strategy returns	DL trading signals produce profitable buy/sell actions.	Applicable to altcoin trading design.
Park & Seo (2023)	BTC multi-asset	Sentiment + DL integration	Daily/event driven	Sharpe ratio	Sentiment improves DL	Retail sentiment
Authors	**Asset Coverage**	**Model / Theme**	**Data Horizon**	**Evaluation Metrics**	**Key Insights**	**Implications for Altcoins**
					trading accuracy & returns.	boosts altcoin forecasts.
Sai Somayajulu & Kotaiah (2023)	Broad (survey)	Hybrid DL (LSTM–GRU)	Cross-study	Mixed	Hybrid models outperform single architectures.	Supports hybridization for altcoins.
Ponselvakumar et al. (2024)	BTC + alts	Hybrid DL improvements	Daily	RMSE/MAE /MAPE	Hybrids achieve lower errors vs. standalone models.	Extends DL to altcoin forecasting.
Bouteska et al. (2024)	Cross-crypto	Ensemble vs. DL; XAI agenda	Daily–weekly	Forecast errors	Ensembles competitive; call for explainable AI.	XAI critical for altcoin use & regulation.
Vonitsanos et al. (2024)	Multi-crypto	DL at scale (big time-series)	Highvolume	RMSE/ throughput	Scalable DL pipelines improve robustness.	Enables large-scale BTC–altcoin forecasting.
Ikeda et al. (2025)	BTC + alts	LSTM/GRU /Bi-LSTM comparison	Long-term	RMSE/R^2	Recurrent DL models beat statistical baselines.	Confirms DL portability to altcoins.
Zafar & Kapetanakis (2025)	BTC	Stacked ensembles	Daily	RMSE/R^2	Ensembles outperform standalone LSTM/GRU.	Promotes ensemble use in altcoins.

Kang et al. (2025)	BTC	Indicators + DL	30-min to mid-term	RMSE; Sharpe ratio	Indicators improve DL midhorizon; weaker ultra-short term.	Feature-rich DL suits altcoin medium horizons.

While Table 1 emphasizes bibliometric influence, Table 2 extends the analysis by mapping the methodological contributions, evaluation metrics, and implications of works. The earliest contributions, such as Lahmiri and Bekiros (2019), established the viability of deep learning for modeling cryptocurrency volatility.

As the field matured, hybrid and ensemble approaches (Sai Somayajulu & Kotaiah, 2023; Zafar & Kapetanakis, 2025) consistently outperformed single-model frameworks, while sentiment integration (Park & Seo, 2023) and technical indicators (Kang et al., 2025) linked forecasting to real-world profitability. More recent studies highlight the importance of scalability (Vonitsanos et al., 2024) and interpretability, with Bouteska et al. (2024) calling for explainable AI to address the black-box nature of deep learning. Collectively, the works summarized in Table 2 demonstrate a progressive trajectory from foundational Bitcoin-focused studies to hybrid, risk-aware, and explainable frameworks. This evolution underscores the importance of adaptable, transparent, and multiasset approaches for advancing altcoin forecasting.

Concept Map

The concept map analysis presented in Figure 3, below highlights the main domain shaping cryptocurrency price prediction research. Three dominant clusters emerge. The Concept Map thus reveals a conceptual shift from early Bitcoin-only studies to multi-asset, hybrid, and behaviorally informed models, underscoring the diversification of both methods and applications. The concept map visually organizes the research domain of cryptocurrency price prediction into three primary dimensions: 1) Risk Management, 2) Forecasting Techniques, and 3) Deep Learning Models. Each branch further connects to sub-themes, revealing how different streams of research interrelate.

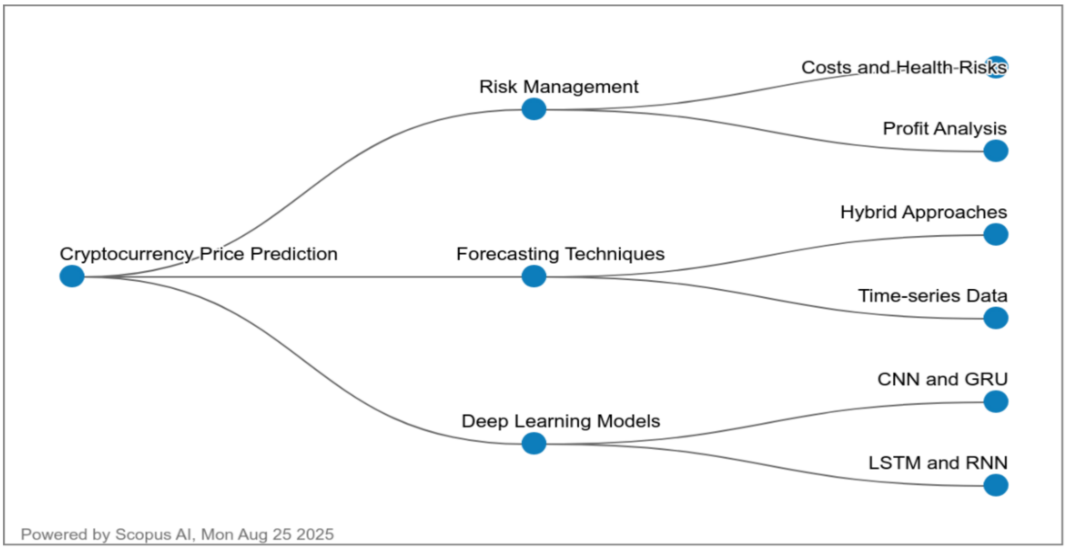

Figure 3. Concept Map

Risk Management is linked to costs and health risks as well as profit analysis. This suggests that forecasting is not solely about prediction accuracy but also about mitigating financial exposure, evaluating profitability, and balancing risk–return trade-offs. In volatile markets, accurate prediction supports hedging strategies, stress-testing portfolios, and safeguarding investor capital.

Forecasting Techniques connect to hybrid approaches and time-series data. This reflects the methodological evolution of the field. Hybrid approaches (e.g., combining econometric models with neural networks) aim to

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improve robustness, while time-series analysis remains the backbone of cryptocurrency forecasting. Together, they show a move from single-model experimentation to integrated techniques that handle noisy, non-stationary data.

Deep Learning Models branch into CNN and GRU as well as LSTM and RNN. These represent the technological core of predictive modeling. Recurrent architectures (RNN, LSTM, GRU) excel in sequential data, while convolutional models (CNN) are increasingly applied to capture local patterns in time-series signals. Their coexistence reflects a diversification of deep learning strategies, often combined in ensemble or hybrid models to maximize accuracy. Collectively, the concept map highlights three dominant dimensions Risk Management, Forecasting Approaches, and Deep Learning Models that frame the research landscape.

Linking Risk Management in Cryptocurrency Prediction

Building on the Risk Management cluster in the concept map, this subsection highlights how forecasting accuracy is intertwined with portfolio resilience, cost efficiency, and broader risk mitigation strategies. The findings underscore the interdependent relationship between cryptocurrency price forecasting, risk management, and methodological innovation. Cryptocurrencies such as Bitcoin and altcoins exhibit extreme volatility, fattailed distributions, and sensitivity to external shocks. These conditions create both opportunities and risks for investors, making forecasting not just an academic exercise but a critical element of portfolio management and financial stability (Conlon & McGee, 2020).

Risk management emerges as a central dimension of cryptocurrency forecasting, where accurate predictions are evaluated not only by traditional error metrics but also by risk-adjusted measures such as Sharpe ratios, maximum drawdowns, and portfolio resilience. Forecasting also serves to mitigate volatility, anticipate tail-risk events, and inform hedging strategies in unstable markets. For instance, Kang et al. (2025) showed that deep learning models enriched with technical indicators improved both prediction accuracy and trading profitability, while sentiment-driven approaches such as those by Park and Seo (2023) captured collective psychology, enabling traders to anticipate panic-driven price crashes. These findings emphasize that forecasting is fundamentally tied to financial resilience, making cost analysis an equally critical component of cryptocurrency prediction and risk management. The cost structure is shaped by a complex interplay of market dynamics, technological attributes, behavioral biases, and external conditions.

At the macro level, global economic indicators such as liquidity conditions and stock market indices directly influence volatility, thereby increasing hedging and portfolio management costs (Aydoğan et al., 2024; Salem et al., 2024). Token-specific factors, including supply dynamics, network activity, governance structures, and technological upgrades, add further uncertainty to pricing and transaction cost variability (Lan & Frömmel, 2025). Behavioral and sentimental dimensions such as fear of missing out (FOMO), herding behavior, speculative bubbles, and social-media-driven sentiment create mispricing risks that raise the cost of monitoring and managing portfolios (Handoko et al., 2024; Manohar, 2024).

Methodologically, forecasting accuracy is closely tied to cost efficiency: while simpler statistical models such as ARIMA incur lower computational costs, advanced deep learning models like LSTM, GRU, and ensemble frameworks demand extensive preprocessing and infrastructure, reflecting a trade-off between accuracy and resource expenditure (Gupta & Nain, 2021; Raza & Varol, 2021). In addition, regulatory uncertainty, compliance requirements, and energy-intensive mining activities impose external financial and operational costs (Omole & Enke, 2023). Finally, the growing reliance on big data and alternative information sources, such as blockchain metrics and social media sentiment, increases the technical cost of acquiring, cleaning, and processing large-scale datasets (Manohar, 2024).

To synthesize these insights, Table 3 organizes the cost and risk management factors into six dimensions market and economic, token-specific, behavioral and sentimental, risk models, regulatory and external, and data and technical. This structured summary highlights how each factor contributes to forecasting costs and portfolio risks, supported by key references.

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Table 3. Cost and Risk Management Factors

Factor Type	Specific Factors	Key Insights	REFERENCES
Market & Economic	Liquidity, stock indices (NASDAQ, S&P 500, Nikkei)	Global shifts directly affect volatility & portfolio costs.	Aydoğan et al. (2024); Salem et al. (2024)
Token-Specific	Supply, network activity, governance, upgrades	Token attributes increase pricing uncertainty & cost variability.	Lan & Frömmel (2025)
Behavioral & Sentimental	FOMO, herding, bubbles, social media sentiment	Psychology amplifies mispricing risks & monitoring costs.	Handoko et al. (2024); Manohar (2024)
Risk Models	ARIMA, SVM, LSTM, GRU, ensembles	Traditional models cheap; DL more accurate but resource intensive.	Gupta & Nain (2021); Raza & Varol (2021)
Regulatory & External	Compliance, mining costs, regulations	Rules & energy-intensive mining raise operational costs.	Omole & Enke (2023)
Data & Technical	Blockchain metrics, sentiment, preprocessing pipelines	Big data reliance increases technical & computational costs.	Manohar (2024)

Linking Forecasting Techniques in Cryptocurrency Prediction

Expanding on the Forecasting Techniques cluster from the concept map, this section traces the methodological evolution from early statistical baselines to today's hybrid and ensemble approaches designed to address the nonlinear and volatile nature of cryptocurrency markets. Traditional statistical models such as ARIMA and GARCH provided useful baselines, but they struggled to capture abrupt jumps, regime shifts, and chaotic dynamics (Corbet et al., 2018). To overcome these limitations, researchers increasingly adopted deep learning architectures including LSTM, GRU, and RNNs, which are well suited for modeling high-frequency price fluctuations and long-term dependencies (Rodrigues & Machado, 2025; Kuizinienė et al., 2019). These models have been further enhanced through hybridization and ensembling such as LSTM–GRU combinations (Sai Somayajulu & Kotaiah, 2023) or stacked ensemble techniques (Zafar & Kapetanakis, 2025) to achieve greater robustness and lower forecasting errors.

Beyond time-series dynamics, forecasting techniques have expanded to incorporate high-dimensional and alternative features such as market liquidity, blockchain activity, technical indicators, and social-media driven sentiment. Studies show that these enriched feature sets significantly improve predictive accuracy and trading profitability (Tanrikulu & Pabuccu, 2025; Park & Seo, 2023). Comparative analyses confirm that deep learning models, particularly GRU and LSTM, consistently outperform conventional techniques under conditions of extreme volatility, while hybrid frameworks that combine statistical and neural models deliver robustness in real-time trading contexts (Fadhil & Makhool, 2024; Syed et al., 2024). However, challenges remain due to the complex and non-stationary nature of cryptocurrency markets, where seasonality, behavioral biases, and global shocks hinder the identification of universally optimal models (Pintelas et al., 2020).

To consolidate these developments, Table 4 organizes forecasting techniques into five stages: statistical models, machine learning methods, deep learning architectures, hybrid and ensemble frameworks, and next frontier approaches such as explainable AI. The table highlights their key features, strengths, limitations, and applications in cryptocurrency prediction, supported by representative studies. Collectively, the stages outlined in Table 4 illustrate the methodological trajectory of cryptocurrency forecasting showing a clear shift from simple statistical baselines toward hybrid, deep learning–driven, and interpretable frameworks. This

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progression naturally leads into the next section, where deep learning models are examined as the technological core of cryptocurrency prediction.

Table 4. Evolution of Forecasting Techniques

Stage	**Techniques**	**Key Features**	**Strengths**	**Limitations**	**Application in Crypto**
Statistical Models	ARIMA, GARCH, Logistic Reg.	Time-series, volatility	Simple, interpretable, cheap	Poor with nonlinearity/shifts	Early BTC forecasting (Kuizinienė et al., 2019)
Machine Learning Models	SVM, KNN, Random Forest	Nonlinear regression	Handles nonlinearities, flexible	Sensitive to noise, no memory	Indicators & sentiment (Tanrikulu & Pabuccu, 2025)
Deep Learning Models	RNN, LSTM, GRU, Bi-LSTM, CNN	Sequential memory	Captures chaotic dynamics	Costly, black-box	Outperforms ARIMA/SVM (Rodrigues & Machado, 2025)
Hybrid / Ensembles	ARIMA-LSTM, LSTM–GRU, Stacking	Combines methods	Robust, reduces errors	Complex, resourcedemanding	Real-time crypto tools (Fadhil & Makhool, 2024; Syed et al., 2024)
Next Frontier	Explainable AI, Multi-asset DL	Sentiment, blockchain	Interpretable, investor trust	Still developing	Emerging approaches (Dudek et al., 2024)

Linking Deep learning model in Cryptocurrency Prediction

Focusing on the Deep Learning Models cluster from the concept map, this subsection examines the technological core of cryptocurrency forecasting, where recurrent and convolutional architectures advance predictive performance by capturing nonlinear, chaotic, and highly volatile market dynamics. Among these, Long Short-Term Memory (LSTM) networks have consistently demonstrated superior performance compared to traditional econometric methods and shallow neural networks, owing to their ability to model temporal dependencies and nonlinear patterns in time-series data (Lahmiri & Bekiros, 2019; Tamilkodi et al., 2025; Jain et al., 2024). The predictive accuracy of LSTM models has been further enhanced through optimization strategies such as the Adam optimizer and loss functions like Mean Squared Error (Kirci & Baydogmus, 2022). Closely related, Gated Recurrent Units (GRU) have emerged as efficient alternatives to LSTM, showing robustness in volatile market conditions, particularly when combined with recurrent dropout or hybrid architectures (Dutta et al., 2020; Ponselvakumar et al., 2024). Bidirectional LSTM (Bi-LSTM) models extend this capacity by processing data in both forward and backward directions, thereby capturing richer temporal features and improving accuracy in long-horizon forecasting (Ikeda et al., 2025; Kavithra et al., 2024).

Feature engineering and preprocessing also play a decisive role in linking deep learning models to effective predictions. Studies show that selecting technical indicators, applying normalization techniques such as Min-Max scaling, and incorporating external variables like trading volume and sentiment from social media significantly strengthen model performance (Cheng et al., 2025; Gadge et al., 2025). These enhancements allow models to move beyond purely price-based inputs toward multi-source frameworks, capturing both quantitative and behavioral market signals (El-Berawi et al., 2021; Nouira et al., 2024). Model evaluation is typically based on metrics such as Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R^2, providing robust comparisons across algorithms (Alnami et al., 2025; Cheng et al., 2025).

Despite these advances, challenges remain. Cryptocurrency markets are inherently volatile and affected by regime shifts, speculative bubbles, and behavioral biases, limiting the universal applicability of single models (Zuvela et al., 2022; Pintelas et al., 2020). This has motivated the rise of hybrid and ensemble approaches, such as LSTM–GRU combinations or models integrating ARIMA with deep networks, which consistently outperform standalone architectures by balancing accuracy and computational efficiency (Sai Somayajulu & Kotaiah, 2023; Syed et al., 2024). Looking forward, integrating diverse data sources including blockchain fundamentals, Google Trends, and sentiment indices alongside explainable AI frameworks represents a promising pathway for improving interpretability and robustness in cryptocurrency prediction (Nouira et al., 2024; Gadge et al., 2025).

In summary, deep learning models particularly LSTM, GRU, and Bi-LSTM form the backbone of cryptocurrency forecasting research. Their progression from standalone architectures to hybrid, feature-rich, and increasingly explainable systems illustrates a methodological trajectory: from accuracy-focused models to adaptive, risk-aware, and application-oriented frameworks designed for the unique challenges of cryptocurrency markets. This synthesis, summarized in Table 5, underscores the central role of deep learning in shaping the future of cryptocurrency prediction.

Table 5. Deep Learning Models in Cryptocurrency Prediction

Model Type	**Specific Models**	**Key Features**	**Strengths**	**Limitations**	**Applications in Crypto**	**REFERENCES**
Recurrent Neural Networks (RNNs)	Vanilla RNN	Sequential learning, short memory	Captures temporal order	Struggles with vanishing gradients, limited longterm memory	Early sequential crypto forecasting	Lahmiri & Bekiros (2019)
Long Short-Term Memory (LSTM)	Standard LSTM, Optimized LSTM	Memory cells, gate mechanisms	Models longterm dependencies, strong performance in volatility prediction	Computationally heavy, risk of overfitting	BTC/Altcoin volatility, long-horizon forecasting	Tamilkodi et al. (2025); Jain et al. (2024)
Gated Recurrent Units (GRU)	GRU, GRU with dropout/hybrids	Simplified LSTM structure	Efficient, faster training, robust in high volatility	Less expressive than LSTM in complex regimes	Highfrequency and volatile markets	Dutta et al. (2020); Ponselvakumar et al. (2024)
Bidirectional RNNs	Bi-LSTM	Forward + backward processing	Richer temporal representation, improved accuracy	Higher computational cost	Longhorizon and multi-asset prediction	Ikeda et al. (2025); Kavithra et al. (2024)

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Convolutiona l Neural Networks (CNNs)	1D-CNN, CNN hybrids	Captures local patterns in time-series	Good for feature extraction, reduces noise	Less effective on long-term dependencies	Signal extraction, short-term crypto forecasting	El-Berawi et al. (2021)
Hybrid & Ensemble Models	LSTM–GRU, ARIMA–LSTM, Stacked ensembles	Combines statistical + deep models	Robust, lower errors, balances accuracy & efficiency	Complex, resourcedemanding	Real-time trading, robust multiasset tools	Sai Somayajulu & Kotaiah (2023); Syed et al. (2024)
Next Frontier	Explainable AI, Multisource DL	Integrates blockchain, sentiment, Google Trends	Enhances interpretability , investor trust	Still emerging, scalability issues	Trustworthy and interpretable forecasting	Nouira et al. (2024); Gadge et al. (2025)

Overall, Table 5 illustrates how deep learning models have evolved from early recurrent structures to advanced hybrid and explainable frameworks, positioning them as the technological backbone of cryptocurrency forecasting and a foundation for future methodological innovation.

Topic Experts

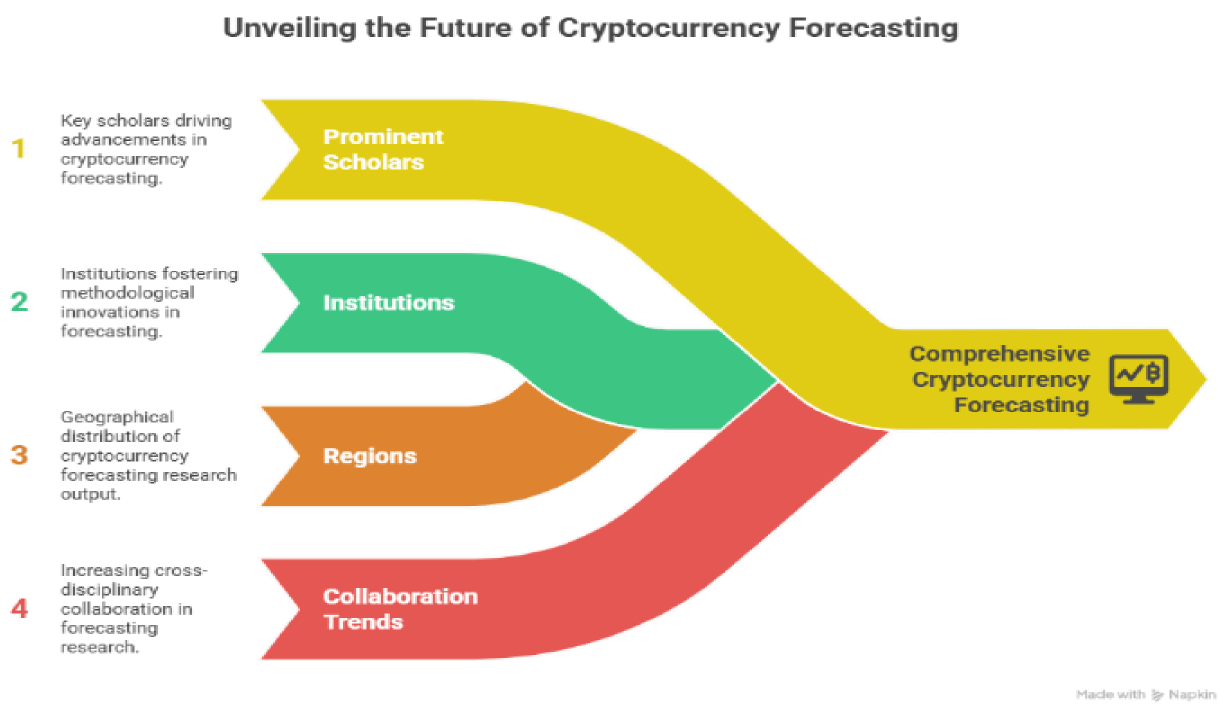

Figure 4. Topic Experts Shaping the Future of Cryptocurrency Forecasting

The Topic Experts module, summarized in Figure 4, identifies the key dimensions driving intellectual leadership in cryptocurrency forecasting. At the scholar level, Lahmiri and Bekiros (2019) established the foundations with chaotic deep learning models, while Park and Seo (2022, 2023) advanced the field by integrating sentiment analysis, bridging technical methods with behavioral finance. At the institutional level, research hubs in the United States, China, and India dominate publication output, reflecting both global interest and alignment with fintech innovation. At the regional level, this distribution underscores the global spread of research activity. Finally, collaboration trends reveal a decisive shift toward cross-disciplinary engagement, with economists, computer scientists, and data scientists working together to diversify methods (Vonitsanos et al., 2024). In combination, these four dimensions converge as shown in Figure 4 toward a more comprehensive and integrated approach to cryptocurrency forecasting, advancing the field from isolated contributions to a mature, globalized, and collaborative research domain.

Emerging Themes

The Emerging Themes module highlights three critical frontiers shaping the future of cryptocurrency forecasting. First, hybrid and ensemble deep learning models are gaining traction as a means to balance accuracy and robustness. By integrating recurrent neural networks with ensemble methods or optimization algorithms, these models address limitations of overfitting and improve generalization (Sai Somayajulu & Kotaiah, 2023; Zafar & Kapetanakis, 2025). Second, explainable artificial intelligence (XAI) is emerging as a pressing need. While most current models operate as black boxes, researchers increasingly call for methods that improve interpretability, ensuring investor trust and regulatory compliance (Bouteska et al., 2024). Third, integration of alternative and behavioral data particularly sentiment from social media, macroeconomic indicators, and blockchain fundamentals is becoming essential for predictive accuracy. Park and Seo (2023) demonstrated that sentiment-enhanced models improve profitability, suggesting that behavioral dimensions are indispensable in volatile markets. Collectively, these emerging themes (Figure 5) reflect a paradigm shift in cryptocurrency forecasting research, emphasizing: (i) hybrid and ensemble deep learning models for robustness, (ii) explainable AI for interpretability and trust, and (iii) integration of behavioral and alternative data for enhanced predictive accuracy.

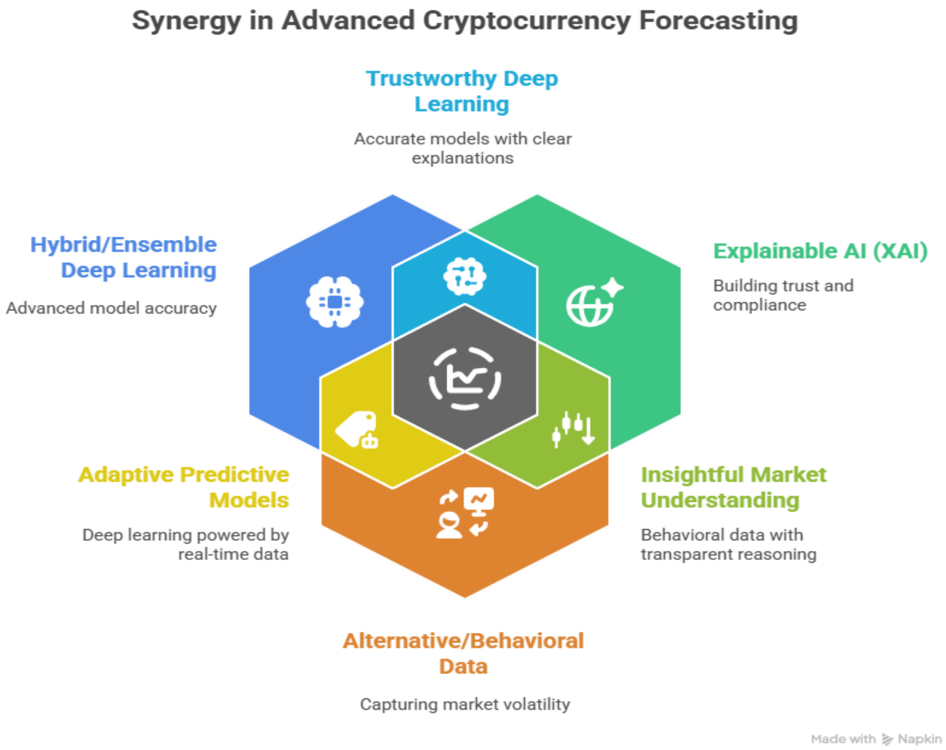

Figure 5. Paradigm shift

CONCLUSION

Synthesizing insights from both the bibliometric mapping and thematic review, this study highlights the progress and challenges in cryptocurrency price prediction, spanning from Bitcoin to altcoins in a rapidly evolving research domain. The bibliometric analysis confirms that the field has advanced from early Bitcoin focused studies to more diverse and sophisticated approaches incorporating altcoins, hybrid deep learning architectures, and sentiment-driven models. Bitcoin continues to serve as the anchor cryptocurrency and a global benchmark, yet altcoins are increasingly shaping market dynamics, requiring models that capture bidirectional interdependencies.

Methodologically, recurrent architectures such as LSTM, GRU, and Bi-LSTM form the core of predictive research, but recent advances have been driven by hybrid and ensemble models that combine multiple techniques to achieve greater robustness and accuracy. Performance assessment has also evolved beyond error-based metrics (e.g., RMSE, MAE) toward profitability-oriented measures such as the Sharpe ratio, reflecting a stronger alignment between predictive research and practical trading applications. Yet one persistent limitation remains: the black-box nature of deep learning, which raises concerns over interpretability, transparency, and investor trust.

Emerging themes point to three promising research directions. First, risk-aware hybrid frameworks that integrate econometrics, deep learning, and reinforcement learning can enhance adaptability and resilience under extreme conditions. Second, explainable and ethically governed AI systems are necessary to overcome the blackbox limitation, ensuring transparency, fairness, and regulatory compliance. Third, multi-asset and cross-market forecasting must be prioritized to account for interactions between Bitcoin, altcoins, and traditional financial indices, reflecting the increasingly interconnected nature of digital asset markets. Reinforcement learning (RL) offers particular promise by enabling models to adjust dynamically to real-time market shifts, while risk-adjusted evaluation frameworks can align predictive accuracy with portfolio resilience and stress testing.

In conclusion, deep learning models have substantially advanced cryptocurrency forecasting, consistently outperforming traditional methods and offering actionable insights for investors and policymakers. However, the future of this domain lies in balancing accuracy with interpretability, scalability with adaptability, and technical rigor with ethical responsibility. By pursuing these directions, forthcoming studies can build a more transparent, inclusive, and resilient framework for cryptocurrency price prediction in the era of Bitcoin, altcoins, and beyond.

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