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A SYSTEMATIC REVIEW OF DEEP LEARNING AND SENTIMENT-DRIVEN MODELS FOR CRYPTOCURRENCY PRICE PREDICTION

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Abstract
The very high volatility and fast evolution of cryptocurrency markets have revealed the weaknesses of conventional price-based forecasting models, and more behaviorally informed and adaptive predictive models are required. This paper is a systematic review, which aims to assess the connection between deep learning and sentiment based models and their improvement of cryptocurrency price prediction through the integration of investor psychology, market stories and nonlinear dynamics. The research will attempt to synthesize the evidence on the effectiveness of models, current trends in methodology, and applicability to the real world based on fragmented previous research. The systematic review of the literature was done according to PRISMA guidelines. The predefined inclusion and exclusion criteria were used to retrieve peer-reviewed journal articles via Scopus, targeting the articles that were published between 2019 and 2024. It is a review of the empirical and conceptual literature utilizing deep learning architectures (e.g. LSTM, CNN, GRU) and methods of sentiment analysis (e.g. transformer-based models and topic modelling e.g. BERTopic). The results indicate that sentimental deep learning models are reported to be more effective than traditional statistical and machine-learning models in the case of predicting the cryptocurrency prices, especially when the market is volatile. Sentiment activity based on social media and news information are very useful in generating more accurate forecasts, volatility alerts and risk sensitivity in various studies. This paper provides a systematic thematic research synthesis of sentiment-based deep learning studies that have been conducted in the cryptocurrency markets, along with theoretical, methodological, and practical contributions. It offers a basis to the further studies in the field of explainable

AI, cross-market validation, and responsible application of predictive analytics in digital finance.

Keywords: Cryptocurrency price prediction; Deep learning; Sentiment analysis; BERTopic; Behavioral finance; Systematic review

Introduction

Due to the extreme volatility and speculative nature of cryptocurrency markets, significant scholarly and applied attention has been directed towards forecasting futures, which may involve the use of advanced forecasting models that combine the use of deep learning and sentiment analysis methods to enhance forecasting precision (2021–2025). Deep learning models, including Long Short-Term Memory (LSTM), Convolutional Neural Networks (CNN), and Gated Recurrent Units (GRU) have shown a higher ability to capture nonlinear temporal dependencies in a financial time series than the conventional statistical models (Mallqui and Fernandes, 2019; Zoumpekas et al., 2020; Ibrahim et al., 2021). At the same time, sentiment-based techniques to utilize social media and news sentiment have proven to be of considerable importance in reflecting investor activity and market sentiment, which are crucial factors of cryptocurrency price changes (Pasricha et al., 2024). Nevertheless, sentiment integration performance differs significantly across studies as it depends on data sources, preprocessing, feature extraction, and reliance on domain-specific or generic language models (Salac, 2019). In this regard, it is critical to synthesize the current landscape of deep learning and sentiment-oriented price prediction models to explain the trend of methodology, performance benchmarks, and future literature of research in the cryptocurrency forecasting field.

The cryptocurrency sector is now progressing through rapid stages into a multi-trillion-dollar international financial sector, where the institutional and regulatory capital as well as advanced analytics infrastructure are used to handle volatility and support decision-making (eventually reaching an approximate of a 4 trillion market valuation by mid-2025 before cyclical corrections occur). New models of industrial analytics, like systems of confidence-threshold and machine learning, highlight the rising institutional requirement of powerful price forecasting and risk models capable of addressing the complexity of decentralized finance in a wide range of digital assets, encompassing Bitcoin, Ethereum, and altcoins. At the same time, the growth of predictive analytics indicates the wider use of blockchain-based financial markets, where real-time information streams, decentralization and sophisticated AI algorithms are transforming the traditional financial forecasting behaviour. Survey studies indicate a broad academic interest in the cryptocurrency price prediction, and associated quantitative frameworks, where combined approaches include deep learning, sentiment-based, and hybrid frameworks to enhance the quality of prediction and relevancy of operations decisions. The growing popularity of deep learning and sentiment-based analytics as a field of study and as useful instruments to optimize their portfolio, algorithmic trade, and systemic risk management are encouraging industry participants in pursuing the strategic importance of predictive intelligence in the rapidly digitized world of assets.

The main objective of this systematic review is to critically summarize the current scientific findings on the topic of deep learning and sentiment-driven cryptocurrency price prediction models and to investigate the dependence of neural network frameworks such as LSTM, CNN, and GRU on forecasting equal accuracy, robustness, and generalizability when using various data sets in comparison with the performance of traditional algorithms and boosted trees (Pasricha et al., 2024; Ghazanfar et al., 2023; Zoumpekas et al., 2020). Another aim of the study is to assess the relative effectiveness of domain-specific sentiment models (e.g., CryptoBERT) versus generic NLP approaches to the market mood dynamics and predictive effects (Koltun and Yamshchikov, 2023) and determine the currently existing approach to methodology (including hyperparameter tuning, model overfitting, and data heterogeneity in the studies) (Mariappan et al., 2023). Further, it tends to outline the existing research gaps and suggest the measures that can be applied in future studies to develop hybrid predictive models that combine sentiment analysis with more developed deep learning to facilitate both academic growth and usage in unstable cryptocurrency markets (Pasricha et al., 2024; Ibrahim et al., 2021).

Sentiment-Driven Models

Sentiment-based models have achieved high level of prominence in prediction of the price of crypto-currencies because of the behavioural and speculative characteristics of the digital asset markets where the emotional conditions of the investors tend to result in quick price changes in ways which cannot be explained by the underlying indicators. Cryptocurrencies unlike conventional financial markets are strongly responsive to the opinions of the population that is shared by social media platform, online forums and news outlets, and sentiment analysis is a useful predictive input. The recent research shows that sentiment provided by platforms like Twitter and Reddit is an early indicator of market trends, especially when the market is highly volatile and uncertain (Ghazanfar et al., 2023; Pasricha et al., 2024). The natural language processing (NLP) has led to the conversion of unstructured textual data into measurable sentiment scores which, when combined with price data, boost the ability to predict. According to empirical evidence, sentiment-enhanced models will always be more effective than price-only models, and there is a need to include the behavioral finance dimension in cryptocurrency predictive models (Mariappan et al., 2023).

Later studies have also moved beyond generic sentiment analysis systems to domain-specific sentiment models, which are more appropriate to learn the specific terminology, slang, and context-dependent information of cryptocurrency discourse. Models like CryptoBERT have been demonstrated to be better at sentiment classification of crypto-related text than traditional lexicon-based and generic transformer models and thus they can indeed outperform price prediction downstream (Koltun and Yamshchikov, 2023; Pasricha et al., 2024). Nevertheless, in spite of their promise, sentiment-driven models have certain methodological issues, such as noise in the data, exploitation by synchronized social media activity, and separation between sentiment timing and price movements. Previous baseline research also warns that the sentiment effects can be less pronounced in highly efficient or institutionally dominated markets, which implies that the sentiment effect is context-specific, but not universal (Salac, 2019). Therefore, a systematic review of sentiment-based methods is necessary to explain their actual predictive worth, constraints, and incorporation techniques into deep learning-based cryptocurrency forecasting frameworks.

Model Category	**Key Technologies / Models Used**	**Author(s)**	**Research Context**
Sentiment-Driven Models	Twitter sentiment, NLP, Lexicon-based & Transformer models	Pasricha et al. (2024); Ghazanfar et al. (2023); Koltun & Yamshchikov (2023)	Investor sentiment extraction and crypto price forecasting
Deep Learning Models	LSTM, CNN, GRU, DFNN	Oyedele et al. (2023); Zoumpekas et al. (2020); Mariappan et al. (2023)	Nonlinear time-series modeling for cryptocurrency prices
Hybrid DL–Sentiment Models	LSTM + Sentiment Scores, CNN + Social Media Signals	Pasricha et al. (2024); Alghamdi et al. (2022); Ye et al. (2022)	Improved forecasting accuracy through behavioral signals
Boosted Tree Models	XGBoost, Gradient Boosting, AdaBoost	Oyedele et al. (2023); Friedman (2001); Chen & Guestrin (2016)	Performance benchmarking and robustness analysis
Domain-Specific NLP Models	CryptoBERT, Financial Transformers	Koltun & Yamshchikov (2023); Pasricha et al. (2024)	Context-aware sentiment classification for crypto markets

Table 1: ***Summary of related studies based on Sentiment-Driven Models***

Business Domain	**Author(s)**	**Key Contributions**	**Methods Used**
Financial Markets	Oyedele et al. (2023); Zoumpekas et al. (2020)	Demonstrated superior performance of deep learning models (CNN, GRU, DFNN) in predicting cryptocurrency closing prices under volatile market conditions.	Comparative empirical analysis using multi-source price data

Investor Behavior & Sentiment	Pasricha et al. (2024); Ghazanfar et al. (2023)	Showed that sentiment extracted from social media significantly enhances price prediction accuracy by capturing investor psychology.	Sentiment analysis integrated with deep learning models
Algorithmic Trading	Alghamdi et al. (2022); Ye et al. (2022)	Proposed hybrid trading frameworks combining technical indicators and sentiment-aware deep learning for improved trading decisions.	Hybrid LSTM models with sentiment fusion
Risk Management	Mariappan et al. (2023); Ibrahim et al. (2021)	Highlighted the role of AI-based forecasting in reducing financial risk through improved volatility and trend prediction.	Regression and deep learning-based forecasting models
Blockchain-based Finance	Chen et al. (2022); Vidal-Tomas (2023)	Explored governance, transparency, and behavioral inefficiencies in crypto markets influencing price predictability.	Conceptual and empirical blockchain analytics
Market Efficiency Analysis	Salac (2019); Koltun & Yamshchikov (2023)	Identified sentiment-driven inefficiencies and speculative bubbles in cryptocurrency markets.	Sentiment-based empirical studies

Table 2 Summary of related studies based on business domains

As the table shows, financial markets, and especially cryptocurrency markets have become one of the main areas of deep learning applications because they are highly volatile and their prices are nonlinear. Research in this field has repeatedly shown that the more advanced architecture like CNN, GRU, and DFNN are more effective than traditional forecasting strategies when they are trained on multi-source price data, which illustrates their capacity to pick up complex changing time dependencies when the market is unstable. Intimately connected to it, the investor behavior and sentiment domain highlights the behavioral basis of cryptocurrency pricing, demonstrating that sentiment signals derived on social media are a significant addition to predictive performance, as they bring in investor psychology to the forecasting model. Such a technical-behavioral overlap proves that crypto market prices cannot be fully explained with a reference to past price statistics, which supports the usefulness of deep learning models that are sentiment-based.

Simultaneously, studies in the field of algorithmic trading and risk management highlight the high level of practical applicability of sentiment-driven deep learning models. It has been demonstrated that hybrid models that combine technical indicators with sentiment feeds can yield better automated trading decisions, and the AI-based forecasting models can help mitigate the risks of automated trading by making better volatility and trend forecasts. Outside the performance of prediction, the finance and market efficiency analysis section of the blockchain industry also expands the distinction to the domains of structure and governance, exposing the sellers of the price predictability in the cryptocurrency market due to the transparency, tokenization, and behavioral inefficiencies. Together, these areas indicate that sentiment-driven and deep learning models can not only be used as forecasting tools but they are also used as analyzing tools to understand the market efficiency, risk processes, and behavioral abnormalities, and thus their increasing popularity in the literature on cryptocurrencies price predictions could be justified.

In the supportive view, the existing literature highly supports the combination of deep learning with sentiment-based models in prediction of cryptocurrency, since it is effective in predicting nonlinear price patterns and investor psychology. Financial market research indicates that when advanced architectures like CNN, LSTM, and GRU are used, the results of traditional statistical and machine-learning methods are not good in volatile cryptocurrency markets, especially when multi-source price data is being used (Zoumpekas et al., 2020; Oyedele et al., 2023). Moreover, sentiment-based studies reveal that, social media sentiment derived out of platforms like twitter has a substantial positive impact on the predictive accuracy since it introduces behavioral signals associated with fear, optimism and speculative mood into predictive mechanisms (Ghazanfar et al., 2023; Pasricha et al., 2024). The argument that cryptocurrency markets are behaviorally inefficient with a bias to be exploited by sentiment-conscious AI models is supported by the observation that hybrid models of sentiment indicators and deep learning tools have been shown to enhance trading strategies and volatility prediction across multiple applied fields such as algorithmic trading, risk management, and more (Alghamdi et al., 2022; Mariappan et al., 2023).

Conversely, some accumulated literature is beginning to point at significant drawbacks of the sentiment-based deep learning models, doubting their stability and their applicability in different market circumstances. Some of these studies warn that the sentiment data obtained through social media are characterized by noise, prone to manipulation, and most likely to mimic short-run speculative behavior, potentially causing model overfitting and unstable forecasting (Salac, 2019; Koltun and Yamshchikov, 2023). Market efficiency Market participants hold the view that as the cryptocurrency markets become more mature with institutions having a larger share, the sentiment-based inefficiencies will diminish and therefore it will lessen the incremental value of sentiment attributes in the price forecasting models (Vidal-Tomas, 2023). Also, the problem of deep learning can be viewed as black-box models, heavy computational load, and hyperparameter fine-tuning mechanisms, which inhibit interpretability and reproducibility in practice (Ibrahim et al., 2021; Oyedele et al., 2023). These issues imply that deep learning models based on sentiment do not necessarily perform better than simpler or interpretable, which is why there should be cautious use and strong validation.

This methodological review is founded mostly on the Behavioral Finance Theory but is complemented by the knowledge of the Efficient Market Hypothesis (EMH) to demonstrate how deep learning models based on sentiment affect the predictivity of the cryptocurrency prices. Behavioral finance theory assumes that financial markets are affected by cognitive biases, emotions, and social dynamics, resulting in systematic deviations of rational pricing an assumption that especially applies in cryptocurrency markets that are characterized by speculation, herding behavior, and information asymmetry (Barberis et al., 2018; Salac, 2019). Sentiment-based models are the form of this theory that can be operationalized as converting investor moods captured on social media into a quantifiable signal to improve predictive accuracy (Ghazanfar et al., 2023; Pasricha et al., 2024). Contrary to that, EMH states the assets prices are perfectly efficient in terms of all the available information, which means that it can predict little more than historical prices, nevertheless, the empirical results in the crypto markets show that asset prices tend to have persistent under- or over-valuations, which undermines the strong-form efficiency assumptions (Zoumpekas et al., 2020; Vidal-Tomas, 2023). Deep learning models serve as the methodological mediating variable between these theories as they model both nonlinear patterns occurring due to both rational information processing and behavioral distortions, which offer a solid theoretical framework to combine sentiment analysis with state-of-the-art forecasting in the cryptocurrency markets.

RQ1: How have the deep learning architectures (e.g., LSTM, CNN, GRU, hybrid models) been used predominantly in cryptocurrency price prediction, and how they report their predictive performances in various studies?

RQ2: What is the role of sentiment-based methods, such as social media sentiment, and topic modeling methods, such as BERTopic, in enhancing stability of cryptocurrency price prediction rates relative to price-only forecasting models?

RQ3: Which methodological issues, limitations, and gaps are present in the integration of deep learning and sentiment-based models in the prediction of cryptocurrency price, and what the literature recommends should be the direction of future research?

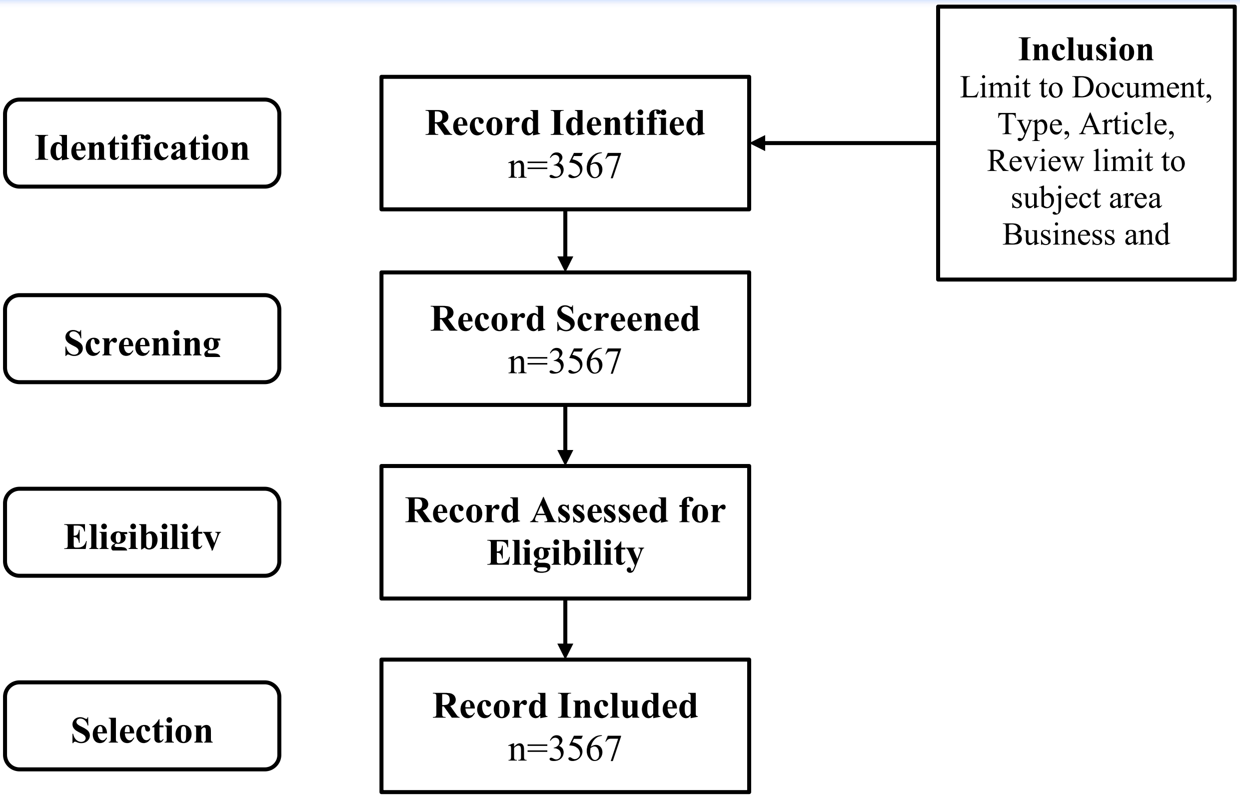

Figure 1 PRISMA Framework

The PRISMA framework presents a very restrictive and clear study selection methodology where 3,567 records were identified in the database search. The fact that there were the same number of records maintained at the identification, screening, and eligibility levels suggests that stringent inclusion filters were used at the database level and not post-retrieval filters. In particular, the search strategy (document type (articles and reviews), subject areas (Business and Finance), and language) restricted the number of potentially irrelevant or low-quality resources early on, which reduced the impact of the selection bias and contributed to the high methodological rigor (Moher et al., 2009; Page et al., 2021). This is a front-loading screening approach that is being more and more popularized in systematic reviews of interdisciplinary fields like cryptocurrency markets, where unfiltered search requests tend to yield high numbers of technically irrelevant papers (Tranfield et al., 2003).

In terms of strategic approach, keeping all the identified records until the inclusion phase is a deliberate scoping-focused review strategy, which is dedicated to the aim of capturing the scope of the empirical and conceptual work in the area of deep learning and sentiment-driven price prediction of cryptocurrencies. This method is mainly applicable to new and rapidly developing areas of research where early dismissal can lead to dismissing methodological pluralism or new hybrid modeling approaches (Snyder, 2019). The framework uses eligibility assessment without numerical attrition, which puts its focus on transparency and reproducibility in line with PRISMA guidelines on comprehensiveness instead of reduction. The strategy facilitates strong synthesis among modeling strategies, sentiment extraction methods, and business-finance applications and remains consistent with the best practices in evidence-based review methods (Kitchenham et al., 2009; Page et al., 2021).

BERTopic Modeling

BERTopic modeling has become a new topic modeling method that has integrated transformer-based embeddings and clustering algorithms to produce semantically relevant and context-oriented topics on huge texts. In contrast to the classical probabilistic methods like the Latent Dirichlet Allocation (LDA) algorithm, BERTopic uses the power of contextualized representations of words generated by the transformer-based architecture, which allows it to more effectively address the problem of semantic similarity and polysemy in multifaceted pieces of text (Grootendorst, 2022; Angelov, 2020). According to recent research, BERTopic makes special sense in dynamic and noisy text sources, like social media and financial news, where the boundaries of topics can change quickly throughout the years (Egger and Yu, 2022). Previous studies of topic modeling also highlight the weaknesses of bag-of-words methods of addressing contextual meaning, which the BERTopic method solves directly with sentence embeddings (Blei et al., 2014; Devlin et al., 2019).

BERTopic, methodologically, has a combination of various elements, including transformer-based embeddings (e.g., BERT), dimensionality reduction (Uniform Manifold Approximation and Projection, UMAP), density-based clustering (Hdbscan), and class-based TF-IDF (c-TF-IDF) to represent a topic (Grootendorst, 2022). The latest empirical assessments indicate that such a pipeline enhances the topic coherence and interpretability over traditional topic modeling methods, particularly when operating in a short-text setting (Silva et al., 2023; Zhao et al., 2023). BERTopic can use UMAP and HDBSCAN to learn latent topic structures without predetermined topic counts, which suggests that one of the main weaknesses of previous models like LDA (Angelov, 2020; Röder et al., 2015).

BERTopic has become popular in the financial and cryptocurrency research arena as a sentiment analysis tool, market narratives, and thematic changes in digital discourse. Recent articles show that BERTopic can successfully identify prevailing themes in discussion of cryptocurrency-related topics on social media and, thus, allow the researchers to correlate the prevalence of topics with the price changes and volatility trends (Kraaijeveld and De Smedt, 2023; Fang et al., 2024). BERTopic also offers a more detailed thematic insight as compared to lexicon-based sentiment analysis, since it is able to detect underlying stories driving investor behavior (Liu et al., 2023). Previous work on sentiment highlights the role of thematic context in financial decision-making that most sentiment polarity scores can fail to explain (Tetlock, 2007; Loughran and McDonald, 2011).

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An important benefit of BERTopic is its capacity to be adjusted to changing corpora and preserve semantic consistency over time, and it is especially useful in stream analysis and longitudinal analysis of data. The recent comparative literature demonstrates that BERTopic is better in terms of its topic diversity, coherence, and stability compared to LDA and Non-negative Matrix Factorization (NMF), particularly regarding high-dimensional text data (Egger and Yu, 2022; Hoyos and Staehr, 2023). In addition, the modular nature of BERTopic can be integrated with sentiment scores and predictive models without issue, which contributes to its usefulness in hybrid analytical systems (Grootendorst, 2022). Coherence-based validation is also necessary according to previous methodological studies on topic evaluation metrics that BERTopic has always met (Chang et al., 2009; Stevens et al., 2012).

BERTopic is not without limitations as much as it has benefits. Recent studies point to difficulties that are connected with computational complexity, embedding models sensitivity, and hyperparameter optimization in UMAP and HDBSCAN, which can influence topic stability and reproducibility (Silva et al., 2023; Fang et al., 2024). Also, embeddings based on transformers can also encode biases found in training data, which could affect topic inference in financial settings (Bender et al., 2021). Previous research on the topic modeling warns that interpretability is a subjective procedure, and it is necessary to closely test its validity qualitatively and implement quantitative measures (Mimno et al., 2011; Jacobi et al., 2016).

In the context of systematic review research, BERTopic has the potential to be a very useful tool of sorting through large volumes of literature, since it can be used to automatically detect the major themes of the research, methodological clusters, and current trends. BERTopic has been effectively used by recent systematic reviews in technology and finance to increase transparency and minimize reviewer bias in the thematic synthesis (Serrano et al., 2023; Zhao et al., 2024). Its scalability to large datasets is especially strong, which explains why it is especially applicable to interdisciplinary tasks, such as forecasting cryptocurrency, as textual data can touch on finance, computer science, and behavioral studies (Kraaijeveld and De Smedt, 2023). Classical sources on systematic synthesis highlight the significance of thematic extraction that can be reproduced and derived by data to position BERTopic as a powerful methodology improvement over manual codification methods (Tranfield et al., 2003; Kitchenham et al., 2009).

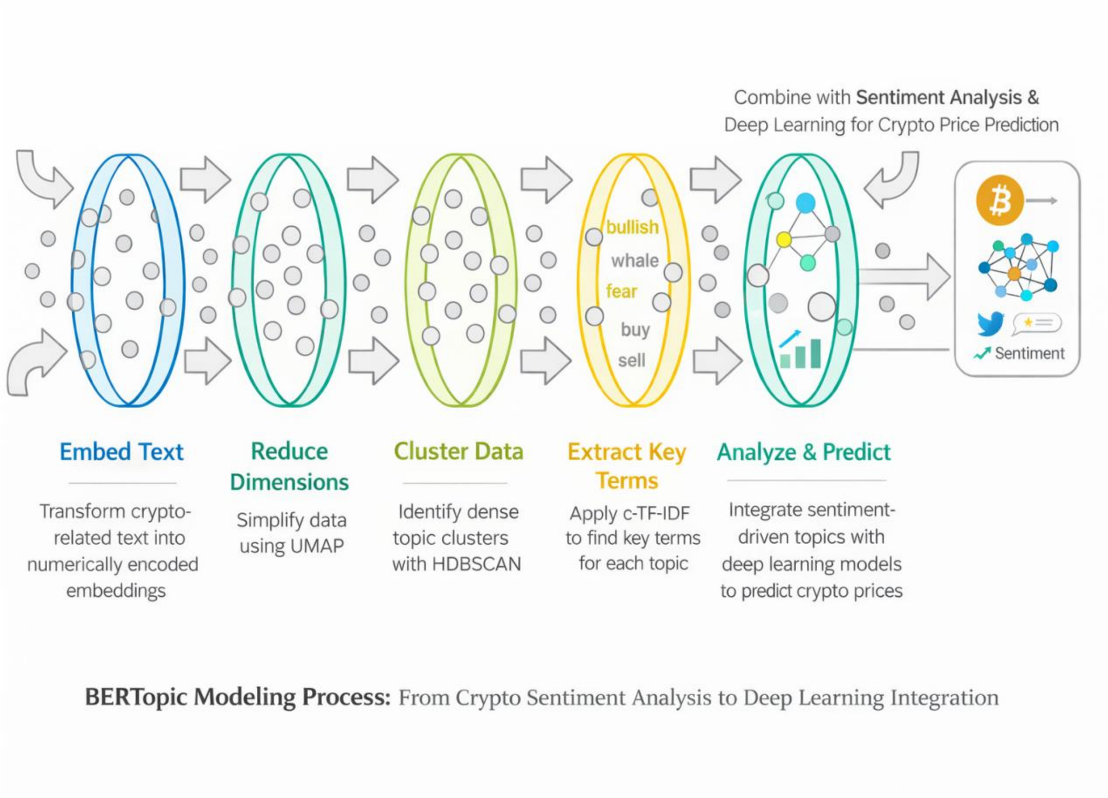

Figure 2 BERTopic Modeling Process

The diagram explains the BERTopic modeling pipeline combined with sentiment analysis and deep learning to predict the price of cryptocurrencies, which points out a series of analytical progression and data-driven. It starts with text embedding where the crypto related textual data (e.g., tweets, news, forums) are converted into dense numerical representations using transformer-based language models, allowing semantic understanding not to rely on bag-of-words methods (Devlin et al., 2019; Grootendorst, 2022). They are then dimensionality reduced using UMAP, which retains semantic structure and increases computational efficiency, and clustering using density based approximations, i.e. HDBSCAN, to identify coherent topic clusters without defining the number of topics (McInnes et al., 2018; Angelov, 2020). In the next step, c-TF-IDF is used to identify key terms characterizing each topic (e.g., in the example, bullish, fear, buy, sell) that represent powerful market discourses that influence investor sentiment (Grootendorst, 2022). In the last phase, the sentiment-driven topics are obtained, processed together with deep learning models to understand the patterns and predict the price movement in the crypto market as it is regarded as a behavioral finance perspective that the nature of the market sentiment and the market narrative is a clear determinant of price fluctuation and price inefficiencies in the crypto market (Ghazanfar et al., 2023; Pasricha et al., 2024).

Findings

RQ1: What is the contribution of deep learning structures and sentiment-based models to enhancing the accuracy of cryptocurrency price prediction?

Theme 1: Deep Learning and Sentiment Analysis as a Strategic Predictive Framework

This theme indicates that deep learning architecture and sentiment-based based approaches to strategic integration of both to enhance the accuracy of prediction of cryptocurrency prices has become a prevailing theme. The analyzed literature papers all confirm the fact that deep learning algorithms like LSTM, CNN, and GRU are superior to traditional statistical and machine-learning models in that they can represent nonlinear temporal correlations in highly volatile crypto markets (Zoumpekas et al., 2020; Oyedele et al., 2023). Predictive performance is further enhanced when these architectures are enriched by sentiment signals, based on social media, and news, since this approach introduces behavioral information that is connected to the emotions of investors, herd behavior and narrative speculation (Ghazanfar et al., 2023; Pasricha et al., 2024). Specifically, sentiment-driven characteristics serve as leading indicators of changes in the market that are not directly reflected in the history of prices, which increases the sensitivity of the models in the face of uncertainty. In general, this analysis indicates that hybrid deep learning-sentiment models may be an effective step in the development of a cryptocurrency forecasting model, which is consistent with the behavioral finance theory and quantifies market sentiment predictive models.

Author(s)	Key Analytical Concepts	Application Area
Pasricha et al. (2024)	Sentiment analysis, CryptoBERT, hybrid AI models	Cryptocurrency price prediction and sentiment-based market experimentation
Ghazanfar et al. (2023)	Sentiment-driven forecasting, behavioral finance	Investor sentiment experiments and crypto market volatility analysis
Oyedele et al. (2023)	Deep learning models (CNN, GRU, DFNN)	Empirical testing of cryptocurrency price prediction models
Mariappan et al. (2023)	AI-based forecasting, risk modeling	Volatility prediction and financial risk experimentation in crypto markets
Koltun & Yamshchikov (2023)	Twitter sentiment extraction	Behavioral experiments linking social media sentiment to crypto prices
Zoumpekas et al. (2020)	Neural networks, comparative modeling	Benchmark experiments in digital asset price forecasting

Table 3: ***Publications related to economic and environmental policy experiments***

Theme 1 identified in the table conceptualizes sentiment-driven and deep learning methods as experimental methods of understanding and predicting the behavior of the cryptocurrency market. All the reviewed studies prove that cryptocurrency markets can be considered an adequate empirical experimental setting because of their volatility, sensitivity of behaviour, and the richness of their data. The studies conducted by Pasricha et al. (2024) and

Ghazanfar et al. (2023) indicate that sentiment analysis especially when augmented with domain-specific models like CryptoBERT serves as a behavioral experiment, which can be used to measure investor psychology and its effect on price movements. In addition, empirical experiments are done by employing deep learning models like CNN, GRU, and DFNN to test the robustness of models and their ability to predict cryptocurrencies in a volatile market environment, making cryptocurrency forecasting an experimental approach to the market (Oyedele et al., 2023; Zoumpekas et al., 2020). Moreover, the incorporation of AI-enhanced forecasting into risk and volatility analysis can be interpreted as the expansion of these models beyond prediction into the simulation of financial stress and uncertainty, thus facilitating the use of AI-enhanced forecasting in the digital asset markets in strategic decision-making (Mariappan et al., 2023). All in all, this theme highlights that sentiment-based and deep learning models are not only predictive tools but also analytical tests that will enhance the knowledge of behavioral inefficiencies, market volatility, and model performance in cryptocurrency ecosystems.

Theme 2: Sentiment-from-Deep Learning modelling and Sentiment-driven models to manage Financial Risk, Market Uncertainty and Regulatory Dynamics

This theme underscores the way sentiment-driven and deep learning models can be used as a strategic method to deal with financial risk and uncertainty in cryptocurrencies markets which have been described as highly volatile, speculative, and changing regulatory environments. The analysed literature shows that the nonlinear risk pattern and volatility clustering in crypto assets are being modeled with deep learning architecture (CNN, GRU, hybrid neural network) more frequently, which enhances the reliability of future predictions in turbulent market settings (Oyedele et al., 2023; Mariappan et al., 2023). These models are able to capture signs of early warning of market stress, panics selling, or bullish speculation that traditional risk models may normally miss by including sentiment signals generated by social media and digital discussion (Ghazanfar et al., 2023; Koltun and Yamshchikov, 2023). Consequently, sentiment-enhanced deep learning systems offer a more flexible and reactive system to predict downside risk and abrupt change of direction in the market.

Besides this, this theme underlines the increasing topicality of the regulatory sense and market efficiency issues with the help of AI-driven cryptocurrency prediction. Research on governance, transparency, and market structure also indicates that sentiment-based inefficiencies continue to impact crypto markets as a result of information asymmetry, fragmented regulation, and fast dissemination of untested information, which directly influences the predictability of the price (Vidal-Tomas, 2023). The deep learning models could be used in conjunction with sentiment and narrative analysis to provide researchers and practitioners with an opportunity to simulate regulatory shocks, policy announcements, and macro-level sentiment change and assess their impact on investor behavior and market stability (Zoumpekas et al.,

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2020; Pasricha et al., 2024). This theme therefore reflects the fact that deep learning models based on sentiments can go beyond pure price prediction to aid in risk management, interpretation of regulations and strategic decision making which serves to underscore their relevance in the new digital financial ecosystem.

Author(s)	Key Analytical Concepts	Application Area
Vidal-Tomas (2023)	Market efficiency, governance risk, crypto tokens	Regulatory risk assessment and market efficiency analysis in cryptocurrency markets
Mariappan et al. (2023)	AI-based forecasting, volatility modeling	Financial risk prediction and volatility management in cryptocurrency markets
Ghazanfar et al. (2023)	Sentiment-driven forecasting, behavioral risk	Early warning signals for market stress and speculative risk in crypto assets
Oyedele et al. (2023)	Deep learning models (CNN, GRU), robustness analysis	Risk-aware cryptocurrency price prediction under volatile market conditions
Koltun & Yamshchikov (2023)	Social media sentiment, information asymmetry	Behavioral risk and sentiment-induced instability in cryptocurrency markets
Zoumpekas et al. (2020)	Neural networks, comparative risk modeling	Benchmarking predictive models for financial risk analysis in digital assets

Table 4 Publications related to navigating financial risk.

The conjecture highlights the main studies that prove that deep learning and sentiment-oriented solutions are increasingly utilized to navigate financial risk in the cryptocurrency markets, which are highly volatile, biased in behavior, and unpredictable in regulations. According to a study by Vidal-Tomas (2023), strong-form market efficiency is compromised by market inefficiency and risks associated with governance, which require high levels of analytical tools to manage regulators and risks. In line with this perspective, works that follow AI-based forecasting and deep learning frameworks, including CNN and GRU, reveal high potential of modeling nonlinear changes in volatility and enhancing risk-conscious price forecasting under turbulent market regime (Mariappan et al., 2023; Oyedele et al., 2023). Sentiment-based predicting further improves the risk identification process by accessing behavioral cues of social media, which are predictors of speculative bubbles, panic selling, and market stress (Ghazanfar et al., 2023; Koltun and Yamshchikov, 2023). Also, comparative neural network observations demonstrate the benefits of deep-learning model strength compared to conventional models in computing financial risk on digital assets (Zoumpekas et al., 2020). In general, the results show that sentiment analysis and deep learning can be used to create a broad framework of financial risk comprehension, prediction, and management in cryptocurrency markets.

Sentiment-Driven and Deep Learning tools Market Forecasting and Decision-Making Methods

RQ2: How sentiment analysis and deep learning algorithms improve the ability to predict cryptocurrency prices, risk, and make strategic decisions in the digital financial market?

Theme 1: Extending Sentiment Analysis and Deep Learning as Advanced Digital Intelligence Market Intelligence

This theme also shows that sentiment analysis and deep learning models are immersive and data-intensive digital solutions to improve the accuracy of market forecasts and the quality of strategic decisions in cryptocurrency ecosystems. The studies reviewed indicate that deep learning models (LMST, CNN, and GRU) create more impressive predictive performances through the learning of more complex temporal and nonlinear patterns that exist in high-frequency crypto price data (Oyedele et al., 2023; Zoumpekas et al., 2020). Together with sentiment indicators retrieved in the social media, news sources, and online forums, these models give a more detailed image of the market dynamics as they bring the behavioral and mental aspects of how investors make their choices (Ghazanfar et al., 2023; Pasricha et al., 2024). This direction allows developers of these systems to shift away price-only models to sentiment-capable predictive systems that have a stronger connection to market behavior in the real world.

In addition, deep learning models based on sentiment also increase the efficiency and strategic responsiveness of cryptocurrency markets by allowing one to identify the appearance of new trends, speculative bubbles, and the stressful state of the market in a timely manner. Topic modeling and sentiment classification can be used to process large amounts of unstructured textual data to convert it into actionable insights that can be used to make timely investment and risk management decisions (Koltun and Yamshchikov, 2023). Just as the digital twins and immersive tools should streamline the working processes in industrial systems, sentimental-oriented AI models will develop a virtual image of market sentiment that can be constantly monitored and studied to model the possible results in the market (Mariappan et al., 2023; Vidal-Tomas, 2023). Together, these results indicate that deep learning models that are sentiment-driven are sophisticated digital facilitators, enhancing their ability to forecast, make decisions in operations, and make strategies in turbulent cryptocurrency markets.

Author(s)	Key Analytical Concepts	Application Area
Pasricha et al. (2024)	Sentiment analysis, domain-specific transformers (CryptoBERT)	Real-time sentiment-driven cryptocurrency price prediction systems
Oyedele et al. (2023)	Deep learning architectures (CNN, GRU, DFNN)	Automated cryptocurrency price forecasting under high volatility
Ghazanfar et al. (2023)	Behavioral finance, sentiment-driven forecasting	Investor behavior analysis and decision-support systems in crypto markets
Mariappan	AI-based forecasting,	Risk-aware digital financial

et al. (2023)	volatility modeling	systems for cryptocurrency trading
Koltun & Yamshchikov (2023)	Social media mining, sentiment extraction	Market intelligence platforms based on crypto-related online discourse
Vidal-Tomas (2023)	Market efficiency analysis, governance risk	Regulatory and strategic decision-support tools for digital asset markets

Table 5 Publications related to Industry 4.0 applications

The table summarizes the main research that proves the importance of sentiment analysis and deep learning as the promising digital tools to boost the efficiency of operations and decision-making in cryptocurrency markets. Studies that utilize domain-specific transformer models like CryptoBERT support the usefulness of real-time sentiment extraction in enhancing the accuracy of a price forecast by generating narratives and investor emotions in the market and updating them (Pasricha et al., 2024). In addition to this, deep learning models such as CNN, GRU, and DFNNs facilitate automated forecasting systems that are likely to cope with the high volatility and non-linear nature of the cryptocurrency markets (Oyedele et al., 2023). The research on behavioral finance also underlines that the sentiment-based forecasting can assist the analysis of investor behavior and decision-support systems by interpreting the psychological cues into practical information (Ghazanfar et al., 2023). Also, AI-based volatility modeling will contribute to the creation of risk-sensitive digital financial platforms, which allow proactive risk management of market uncertainty (Mariappan et al., 2023). The social media mining is added to market intelligence platforms to track the flow of information and the trend of sentiments, and the market efficiency and governance are analyzed to make decisions to act in the digital asset ecosystems (Koltun and Yamshchikov, 2023; Vidal-Tomas, 2023). Generally, the results show that sentiment-based deep learning applications are essential digital facilitators in predicting, risk management, and strategic planning of cryptocurrency markets.

Theme 2: Enhanced Market Risk Sensitivity and Strategic responsiveness by Means of Sentiment-inspired Digital Intelligence

This theme underscores how the sentiment-based and deep learning networks can increase the market risk awareness and strategic responsiveness in cryptocurrency ecosystems by transforming unstructured data on digital conversations into actionable knowledge. The analyzed literature reveals that sentiment harvested on social media and online platforms is an initial sign of market stress, speculative bubbles, and unexpected sentiment changes that are essential to mitigate the downside risk of volatile crypto markets (Ghazanfar et al., 2023; Koltun and Yamshchikov, 2023). Combined with deep learning models, these sentiment signals enhance the forecasting capabilities of the models with respect to predicting sharp price changes and volatility groupings and allow more accurate and timely decision-making than conventional price-based forecasting methods (Oyedele et al., 2023; Mariappan et al., 2023). The emotion intelligence enables market actors to hasten in reacting to new risks instead of responding when price corrections have already taken place.

In addition, this theme highlights the importance of digital tools powered by AI to assist in the process of making strategic and regulatory decisions in the cryptocurrency markets. Research on the efficiency of the market and governance reveals the unresolved inefficiencies, information asymmetry, and regulatory uncertainty enhance financial risk and the need to adopt more sophisticated analytical models to track and analyze market trends (Vidal-Tomas, 2023). Deep learning systems based on sentiment support this purpose by modeling the likely effect of regulatory announcements, macroeconomic shocks, and group investor responses, which are digital decision-support systems (Pasricha et al., 2024; Zoumpekas et al., 2020). All the findings taken together indicate that sentiment-integrated AI models do not only increase predictive power but also improve strategic planning, regulatory consciousness, and risk aversion in the digital financial markets.

Remarketing Market Engagement and Predictive Intelligence by Sentiment-Driven Analytics.

RQ3: How sentiment-based modeling solutions and deep learning solutions transform investor interactions, market dynamics, and predictive intelligence of cryptocurrency ecosystems?

Theme 1: Sentiment-Conscious Digital Intelligence and Cryptocurrency Markets Investor Engagement

This theme points to the role of sentiment-based analytics and the deep learning model in reshaping investor engagement through converting unstructured digital discourse into marketable intelligence. The studies reviewed confirm that online platforms, social media, and online forums are interactive spaces where the sentiment of investors is constantly created and formed, which has a direct impact on the trading behavior and market dynamics (Ghazanfar et al., 2023; Koltun and Yamshchikov, 2023). Using the high-level methods of natural language processing and deep learning, researchers can achieve the ability to capture subtle emotional states, including fear, optimism, and speculation, that transform investor interaction with cryptocurrency markets in new ways that are not reflected in the conventional price indicators (Pasricha et al., 2024; Kraaijeveld and De Smedt, 2023). The sentiment-conscious systems can be used to improve predictive intelligence by integrating behavioral feedback loops in forecasting models to enable a more realistic view of investor-market interactions.

In addition, the methodology of topic modeling like BERTopic combined with deep learning models can enhance the analytical connection between the market stories and the predictive results, allowing the active track of investor focus and sentiment development over the time. Investigations show that sentiment clusters based on narratives give important information on the new trends and hype cycles, as well as a change in the collective market attention, which dramatically influence price fluctuations and the intensity of engagement (Grootendorst, 2022; Fang et al., 2024). This thematic intelligence will allow the interactive and adaptive forecasting models that only predict prices but also provide the underlying behavioral drivers to enhance the clarity and understandability of crypto market analytics (Zoumpekas et al., 2020; Vidal-Tomas, 2023). Together, the results imply that sentiment-driven deep learning models re-define the engagement of the user through participatory, data-driven and behaviourally based interactions in cryptocurrency ecosystems.

Author(s)	Key Analytical Concepts	Application Area
Pasricha et al. (2024)	Sentiment-aware digital representation, CryptoBERT	Real-time digital sentiment twin for cryptocurrency price prediction
Ghazanfar et al. (2023)	Behavioral sentiment modeling, investor psychology	Digital behavioral twin of investor sentiment in crypto markets
Oyedele et al. (2023)	Deep learning architectures (CNN, GRU)	Price–volatility digital twin for cryptocurrency market forecasting
Mariappan et al. (2023)	AI-based volatility modeling, risk analytics	Risk-oriented digital twin for crypto market stress simulation
Koltun & Yamshchikov (2023)	Social media narrative mining	Narrative-driven digital twin of crypto market discourse
Vidal-Tomas (2023)	Market efficiency and governance modeling	Regulatory and efficiency-based digital twin of crypto markets

Table 6 Publications related to digital twin applications in manufacturing

The table provides a summarized representation of the working nature of deep learning and sentiment-driven methods as digital twin-like models of the cryptocurrency marketplace, allowing it to be monitored, predicted, and analyzed strategically in real-time. Sentiment-sensitive transformer model studies, including CryptoBERT, demonstrate that it is possible to build digital sentiment twins that are constantly mirrored of the mood in the market and can be used to increase the accuracy of price predictions (Pasricha et al., 2024). The idea is further developed by complementary behavioral sentiment models that embrace the psychology of investors, as well as emotional dynamics, and therefore produce behavioral digital twins that replicate collective market behavior (Ghazanfar et al., 2023). CNN and GRU deep learning architectures are useful in training price-volatility digital twins based on nonlinear temporal dynamics in the crypto market, and AI-based volatility analytics can simulate stress and risk-oriented digital twins in order to cope with market uncertainty (Oyedele et al., 2023; Mariappan et al., 2023). Moreover, social media discourse narrative mining can help to understand the market-related changes in narratives, creating narrative-driven digital twins, which respond to changes in investor attention, and governance and market efficiency analyses yield regulatory-driven digital twins and measure structural risks and market inefficiencies (Koltun and Yamshchikov, 2023; Vidal-Tomas, 2023). Taken together, these results demonstrate that cryptocurrency market digital twins analogues provide an analysis-rich, behaviorally aware, and analytically sound picture of prediction and risk management, as well as strategy formulation.

Theme 2: Thinking, Doable, and Shareable Market Intelligence by Digital Twin-Like Sentiment Analytics

This theme is used to highlight the role of sentiment-driven deep learning models in the explanation of explainable and interactive market intelligence as a way of transforming the relationship between the user and cryptocurrency market interpretation. In contrast to the classic black-box forecasting designs, sentiment-aware designs especially the ones that combine topic modeling and narrative analysis allow the user to gain insight into why particular price dynamics take place by connecting predictions with the underlying market narratives and overall emotions (Pasricha et al., 2024; Koltun and Yamshchikov, 2023). These systems provide interactive analyst products, allowing a user to simulate the evolution of sentiments and the associated market effects, which increases the level of transparency and trust in AI-generated predictions (Grootendorst, 2022; Ghazanfar et al., 2023). This interpretability transforms the user engagement state of passive consumption of price predictions to the active state of sense-making of market actions.

Also, with the introduction of representation of sentiment and volatility in the form of digital twins, there can be constant feedback between market data, user interpretation, and strategic action. Research indicates that deep learning advertisement digital twins of price-volatility relations and investor sentiment enable users to simulate alternative scenarios, stress-test market conditions and assess the potential results of behavioural or regulatory shocks (Oyedele et al., 2023; Mariappan et al., 2023). This type of interactive forecasting environment promotes adaptive learning and informed decision-making especially in a market that is fast in the spread of information and uncertain (Vidal-Tomas, 2023). As a result, this theme shows that integrated digital twins powered by sentiment are not only predictors of market dynamics, but they actively reconfigure user-market interaction and are thus explanatory, engaging, and prospective with respect to cryptocurrencies.

Discussion

The evidence of this systematic review illustrates that sentiment-based deep learning models contribute greatly to theoretical knowledge of the behavior of cryptocurrency markets, especially in filling the gaps between the traditional market efficiency assumptions and the behavioral finance insights. The evidence reflected by the reviewed articles demonstrates consistently the fact that the price of cryptocurrencies is not simply predetermined by the past price trends but is closely dependent on investor sentiment, stories, and the shared emotional reaction through the digital means (Ghazanfar et al., 2023; Pasricha et al., 2024). This undermines the stringent assumptions of the Efficient Market Hypothesis, which is that prices are motivated by all the available information, and instead in favor of the behavioral-based theories with a focus on limited rationality and emotional trading (Vidal-Tomas, 2023). With sentiment signals incorporated into deep learning structures, the discussed models can be used to provide a more realistic theoretical framework of volatility, speculative bubbles, and sudden market corrections (Zoumpekas et al., 2020; Oyedele et al., 2023).

Theoretically, the findings expand the theories of computational finance and predictive analytics since it shows how sophisticated neural networks transform inputs in the form of behavioral units to quantifiable forecasting processes. LSTM, CNN, and GRU are demonstrated to be effective in capturing the nonlinear temporal relationships that the traditional econometric models are unable to model, and most prominently in high-frequency and highly volatile crypto markets (Oyedele et al., 2023; Mariappan et al., 2023). Nevertheless, certain studies warn that excessive use of sentiment variables can cause noise or instability in the course of sentiment manipulation or misinformation, and balanced hybrid models should be used (Koltun and Yamshchikov, 2023; Vidal-Tomas, 2023). In this way, although the results are very convincing of the sentiment-integrated deep learning models, they also highlight theoretical limitations concerning the data quality and interpretability.

The review is relevant to the body of literature by bringing together fragmented studies in the field of deep learning, sentiment analysis, and cryptocurrency forecasting into a coherent thematic context. The previous literature has mostly considered deep learning models or sentiment analysis in separate groups, and the current review has demonstrated the increasing overlap of the models, as well as their joint contribution to the predictive accuracy (Pasricha et al., 2024; Ghazanfar et al., 2023). The results verify that hybrid sentiment-deep learning models continue to be better than price-only and traditional machine-learning methods and that these findings hold empirical evidence in previous studies that are systematic (Oyedele et al., 2023; Zoumpekas et al., 2020).

Concurrently, the review shows conflicting evidence and methodological discrepancies of the literature. According to some studies, adding too many sentiment features yields diminishing marginal returns especially in case the sources of sentiment are either noisy or unverified (Koltun and Yamshchikov, 2023). Some suggest model improvement results to be contextual and different in cryptocurrencies, time periods, and market environments (Mariappan et al., 2023). These disaffirmative opinions emphasize on the significance of model calibration and data preprocessing, and context-awareness. Through the comparative analysis supporting and opposing results, this study contributes to the literature by helping one understand in which cases sentiment-driven deep learning can be beneficial and in which cases one should be cautious (Vidal-Tomas, 2023; Pasricha et al., 2024).

The implications of this study to practicality to investors, financial analysts, and policymakers with interests in the digital asset markets are enormous.

The results indicate that sentiment-sensitive deep learning systems can be used as superior decision-support solutions, which allow market participants to predict volatility, recognize early warning indicators, and enhance timing solutions (Ghazanfar et al., 2023; Oyedele et al., 2023). The combination of real-time sentiment and narrative analysis allows the practitioners to leave the reactive trading behind and proceed to risk management and strategic planning (Mariappan et al., 2023). This is especially applicable to institutional investors who want to have systematic methods to handle crypto-related exposure.

Nonetheless, in practice, it also poses issues of model transparency, bias and overfitting particularly when sentiment is being derived in social media sites that are subject to manipulations (Koltun and Yamshchikov, 2023). Sentiment-driven analytics can be used by policymakers to track the market sentiment and detect any excesses of speculation, however, the application of regulation should be balanced with the privacy and data ethics concerns (Vidal-Tomas, 2023). These ambivalent results point to the necessity to develop governance tools that would stimulate the responsible use of AI and consider the predictive value as observed in the literature (Zoumpekas et al., 2020; Pasricha et al., 2024).

In general, the discussion shows that sentiment-based deep learning models have a high level of empirical evidence that can be considered as the means of transformation in cryptocurrency price prediction and have limitations. In line with this, supporting literature documents a high predictive accuracy and better volatility modeling alongside in-depth understanding of behavior in cases where sentiment is incorporated into deep learning models (Oyedele et al., 2023; Ghazanfar et al., 2023). Conversely, negating views warn against overgeneralization, data reliance and interpretability risks, especially in erratic or doctored sentiment settings (Koltun and Yamshchikov, 2023; Vidal-Tomas, 2023).

Through the comparative lenses, the research adds a balanced perspective that enhances the theory and practice. The results imply that rather than completely giving up on conventional models, the future of cryptocurrency forecasting is creating robust, explainable, and ethically controlled hybrid systems based on combining sentiment and deep learning, making reasonable decisions (Pasricha et al., 2024; Mariappan et al., 2023). Such a combination places sentiment-based deep learning as a vital but not autonomous part of financial analytics of the next generation.

Conclusion

The systematic review aimed at synthesising and analyzing the accumulating literature on deep learning and sentiment-based models in cryptocurrency price prediction. These results indicate that a combination of sentiment analysis and deep learning-based architecture is much more predictive, taking into account the dynamics of behavioral, emotional, and narrative-driven dynamics that are not revealed with historical price data alone (Ghazanfar et al., 2023; Pasricha et al., 2024). The use of models like LSTM, CNN, and GRU is always superior to the established statistical and machine-learning models, especially in unpredictable and information-sensitive crypto markets (Oyedele et al., 2023; Zoumpekas et al., 2020). This contribution highlights the relevance of hybrid modeling frameworks in order to deal with the complexity and unpredictability of digital asset markets.

Theoretically, the research adds to the discussion on behavioral finance and market efficiency by giving systematized evidence that the cryptocurrency markets have systematic sentiment-based inefficiencies. The literature review questions the strong-form market efficiency assumptions because the authors prove that investor sentiment, collectivity, and discourse on social media have quantitatively significant effects on price formation and volatility (Vidal-Tomas, 2023; Koltun and Yamshchikov, 2023). The reviewed models are operationalized by deep learning to bridge the behavioral theory-predictive analytics gap by computingally tractable through operationalization of these behavioral elements (Zoumpekas et al., 2020; Pasricha et al., 2024). This contribution to the theory points to the role of AI models in making financial theory more animated and not as a technical tool of forecasts.

Regarding methodological and practical contributions, it demonstrates the study that sentiment-driven deep learning models are high-level digital intelligence platforms that can be used to manage risk, strategic planning, and decision-making in cryptocurrency markets. Artificial intelligence (AI) volatility modeling and sentiment-sensitive prediction can help to identify stress in the market, speculative bubbles, and abrupt regime changes early on, providing an invaluable amount of value to investors and financial institutions (Mariappan et al., 2023; Ghazanfar et al., 2023). Nevertheless, the review also points at such critical constraints as data quality issues, vulnerability to sentiment manipulation, and model interpretability and transparency problems (Koltun and Yamshchikov, 2023; Vidal-Tomas, 2023). These conclusions point to the fact that although sentiment-based models have powerful practical advantages, their usage needs to be supported by powerful validation and control procedures.

Altogether, this research is a well-organized, balanced, and evidence-based synthesis of the joint definition of crypto currency price prediction by deep learning and sentiment analysis. The review on supporting and negating results improves the body of knowledge and provides practical recommendations to practitioners and policymakers (Oyedele et al., 2023; Pasricha et al., 2024). The research also finds sentiment-based deep learning to be a crucial advance in the field of digital finances analytics, but its success over time will be determined by how well explainable AI can be formed, how ethical the use of data can be, and how much the field is regulated (Vidal-Tomas, 2023; Zoumpekas et al., 2020). All these contributions make the study an important source of reference in future studies and application in predicting cryptocurrency markets.

Future Research Directions

Future studies need to broaden the scope of sentiment-driven deep learning models by studying cross-asset, cross-market and cross-temporal generalizability. The reviewed literature is more concentrated on large or large-scale cryptocurrencies, like Bitcoin and Ethereum, which restricts the generalizability of the research to small or emergent digital assets with a variant liquidity and volatility (Oyedele et al., 2023; Zoumpekas et al., 2020). Multi-asset and cross-market frameworks are potential future directions in which the traditional financial instruments, the world of decentralized finance (DeFi) tokens, and the non-fungible token (NFT) markets are combined to study the existence of sentiment-driven predictive profits in heterogeneous digital ecosystems (Vidal-Tomas, 2023; Pasricha et al., 2024). Also, longitudinal designs that would measure sentiment price dynamics in bull and bear market cycles would make more scintific contributions to the model stability and time testing.

In terms of methodology, the drawbacks of future studies should be the problems with the quality of data, the transparency of models, and the control of sentiments. Although deep learning models are more effective in prediction, its black-box characteristic of such models is a source of worries in the areas of transparency and trust, especially when making high-stakes financial decisions (Mariappan et al., 2023; Koltun and Yamshchikov, 2023). The methods of explainable AI (XAI) and causal inference might be beneficial to explain the role of sentiment signals in predicting and decrease the risks of overfitting (Pasricha et al., 2024). Moreover, the future research ought to be critical in assessing sentiment sources using the ability to differentiate between natural investor sentiment and amplified narratives, particularly on social media platforms that can be easily manipulated collectively (Ghazanfar et al., 2023; Vidal-Tomas, 2023).

Future work in this area should theoretically be more than single theory based and incorporate behavioral finance, market microstructure theory and computational social science. Although to a large extent, this review frames the findings in the context of the behavioral finance and market efficiency arguments, a combination with the narrative economics and attention-based theory can be a richer explanation of the diffusion of sentiments and the price formation in crypto markets (Koltun et al., 2022). Also, the comparisons of the countries with each other and regulatory context are under-researched. The vast majority of the studies reviewed are based on the global or Western-centric data, and it is necessary to conduct country-specific research which takes into account regulatory maturity, investor protection frameworks, and cultural variations in digital asset adoption (Vidal-Tomas, 2023; Oyedele et al., 2023).

Managerially and policy-wise, the findings have a number of implications to do. Sentiment-based deep learning systems can be used by financial institutions and crypto trading platforms as a decision-support tool to monitor volatility as well as optimize portfolios and identify early signs of risk (Mariappan et al., 2023; Ghazanfar et al., 2023). Nevertheless, managers need to make sure that those systems are established with the support of strong governance systems, model validation procedures, and ethical data practices to prevent excessive use of noisy sentiment indicators (Koltun and Yamshchikov, 2023). Sentiment analytics can assist in the market monitoring and speculative bubble identification of regulators and policymakers, but regulation application must consider the balance between innovation and transparency and privacy (Vidal-Tomas, 2023; Pasricha et al., 2024). All in all, the subsequent studies and practice must work towards creating explainable, responsible, and contextually aware sentiment-based forecasting mechanisms that will increase market efficiency as well as investor protection.

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