Chapter 3

Cryptocurrency's Interrelationship with Artificial Intelligence and Machine Learning

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Abstract

This study examines the use of artificial intelligence and machine learning techniques in cryptocurrency price prediction through a comprehensive literature review. Cryptocurrencies, emerging as a natural consequence of the digital transformation process, are financial assets based entirely on data, and in this data-driven ecosystem, artificial intelligence algorithms have become indispensable tools for predicting future price movements.

The literature review reveals that a consensus has not yet been established in cryptocurrency price prediction modeling. There are conflicting findings regarding the superiority of different machine learning models such as LSTM, XGBoost, ANFIS, and SVR. While some research argues that LSTM is the most reliable tool in highly volatile markets, others claim that ensemble learning methods like XGBoost are more successful in practical trading optimization.

There are also serious debates regarding the data sources to be included in prediction models. Different views exist on the relative importance of social media sentiment, technical indicators, and macroeconomic variables. While some studies show that social media data is strong in short-term predictions, others emphasize the determining role of technical analysis indicators.

Model explainability and security issues have also gained importance in the literature. It is emphasized that explainable artificial intelligence techniques such as SHAP analysis are essential for model transparency, and that machine learning should be used in manipulation and anomaly detection. The study demonstrates that more empirical research and theoretical frameworks are needed in this field.

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1. Introduction

Digital transformation is a fundamental change process that closely affects many segments and sectors, from businesses to societies. One of the areas affected by this transformation is crypto currencies. The digital transformation process is essentially based on the data and information cycle; in this context, crypto currencies are financial assets that emerge as a natural result of the digital transformation process. Although many financial assets have physical equivalents, crypto currencies are entirely based on data. According to Yoşumaz (2024a), the digital transformation process is not merely a technology injection; it is a comprehensive cycle that includes the acquisition, storage, analysis, and sharing of data. Within this cycle, crypto currencies have found their place in the financial system as digital assets that offer transparency and decentralization through blockchain infrastructure. On the other hand, as a result of the magnitude of this data-driven ecosystem, artificial intelligence (AI) and machine learning (ML) algorithms have become indispensable tools for making sense of big data and predicting future price movements.

There are many studies in the literature regarding the relationship between crypto currencies and AI. Kervancı and Akay (2020) stated that deep learning (DL) models are definitively superior to statistical models such as AutoRegressive Integrated Moving Average (ARIMA) in capturing nonlinear patterns; they demonstrated that DL models provide a distinct advantage particularly when working with high-frequency data. Similarly, Khedr et al. (2021) revealed that traditional statistical methods require unrealistic assumptions, whereas ML, with its "experience-based learning" capability, is the best technology in this field. However, there is a significant divergence of opinion in the literature regarding which ML model is most successful. While Boozary et al. (2025) argued that Long Short-Term Memory (LSTM) networks are the most reliable tool in highly volatile markets for Bitcoin price prediction, Adedigba et al. (2025) claimed the opposite, asserting that complex DL models do not always yield the best results, and that ensemble learning methods such as Extreme Gradient Boosting (XGBoost) and Gradient Boosting outperform deep neural networks in practical trading optimization. Korkmaz et al. (2025) also supported this finding by reporting that the XGBoost algorithm ranked highest in overall performance, while LSTM remained in second place. On the other hand, Salehi (2024) suggested that Adaptive Neuro-Fuzzy Inference System (ANFIS) models provide more robust results than singular artificial neural networks in capturing the volatile trends of the crypto market; they argued that ANFIS can better model market uncertainty by combining fuzzy logic with neural networks. In contrast, Akarsu (2024) claimed that the Support Vector Regression (SVR) model demonstrated the highest accuracy.

Ashok et al. (2025) brought a different perspective to this debate, arguing that the search for a single "best model" may be misleading; they contended that the best-performing algorithm varies from asset to asset for different crypto assets such as Bitcoin, Ethereum, and BNB.

The issue of which data sources should be included in prediction models is also an area of serious contradiction. Tanrıkulu (2021) showed that the effect of Tweet counts and Google Trend data on price is not always stable, that social media data is strong in short-term predictions but loses reliability in long-term forecasts. Gurgul et al. (2025) claimed that including social media sentiment (Twitter and Reddit) in the analysis increases profitability, and that social media data provides stronger signals than technical indicators, particularly in predicting short-term price movements. However, Korkmaz et al. (2025) argued the opposite, asserting that technical analysis indicators are decisive in model success, and that the contribution of macroeconomic and sentiment indicators remains very limited contrary to belief. Nas and Ergin Ünal (2023) also revealed the limited contribution of macroeconomic variables by stating that Bitcoin is most affected by its own past price fluctuations (intraday high and low prices), while the effects of the Fed interest rate and gold remain secondary. While Kanat (2023) argued that ML methods confirm traditional technical analysis rules such as Weighted Moving Average (WMA) and Stochastic Oscillator (STO), and that using these indicators together is the most rational strategy, Saha (2023) observed that models based solely on technical indicators fail during periods of excessive market sentiment and suggested that a combination of technical and fundamental factors is safer. Lapitskaya et al. (2025) emphasized the importance of technical indicators by stating that the combination of momentum indicators such as Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), and Commodity Channel Index (CCI) with XGBoost provides the most accurate price predictions.

Model explainability and security issues have also gained importance in the literature. Akarsu (2024) emphasized that explainable artificial intelligence (XAI) techniques such as SHapley Additive exPlanations (SHAP) analysis are essential for removing models from being "black boxes"; they suggested that it is not sufficient for prediction models to merely produce correct results, but that the decision-making process must be understandable. Wang et al. (2022) claimed that detecting informed trading with ML algorithms plays a critical role in return prediction; they showed that the trading behaviors of market makers and large investors carry important leading signals about price movements. While Shahbazi and Byun (2022) focused on the power of ML in ensuring system security through transaction tracking and anomaly detection in the blockchain network, Alnami et al. (2025) emphasized that ML should be used in an integrated framework not only for price prediction but also for detecting abnormalities such as manipulation, wash trading, and pump-and-dump schemes in the crypto currency ecosystem. Fang et al. (2024) focused on market microstructure and claimed that analyzing limit order book dynamics with ML is key to discovering "universal" market characteristics; they drew attention to the importance of their proposed "Walkthrough Training" method to prevent model obsolescence.

The comprehensive picture emerging from this literature review clearly demonstrates that a consensus has not yet been established in crypto currency prediction modeling. The contradictions regarding model preferences (LSTM vs. XGBoost), data sources (social media vs. technical indicators), and methodological approaches (explainability vs. accuracy) indicate that more empirical research and theoretical framing are needed in this field. In this context, this study aims to contribute to the literature by revealing the relationship between AI and crypto currencies in the existing literature.

2. Conceptual Framework

Crypto currencies and the AI (especially ML) ecosystem surrounding them represent the financial and technological convergence point of digital transformation. This section consists of three parts. In the first part, information is provided on crypto currencies, and in the second part, on AI and ML. In the third part, the relationship between AI and crypto currencies is addressed.

2.1. Crypto currencies

2.1. The Definition and Historical Development of Crypto Currency

Crypto currency is an encrypted digital or virtual asset based on blockchain technology, not under the control of any central authority or government (Khedr et al., 2021; Shahbazi & Byun, 2022). While traditional monetary systems rely on hierarchical power structures such as central banks, national treasuries, and commercial banks, crypto currencies enable fund transfers over a peer-to-peer network without the need for an intermediary institution (Khedr et al., 2021; Shahbazi & Byun, 2022). This decentralized structure has formed a new structure in the financial system with the principles of transparency and immutability (Shahbazi & Byun, 2022; Poudel et al., 2023).

The concept of crypto currency entered the literature with the technical document titled "Bitcoin: A Peer-to-Peer Electronic Cash System" published in 2008 by a person or group using the pseudonym Satoshi Nakamoto (Nakamoto, 2008; Korkmaz, Altınırmak & Karamaşa, 2025). With Bitcoin (BTC) beginning to trade for the first time in 2009, the decentralized digital currency structure effectively commenced (Boozary, Sheykhan & GhorbanTanhaei, 2025). Over time, Bitcoin was followed by thousands of altcoins and tokens, each emerging with different technological promises (Tanrıkulu, 2021; Boozary et al., 2025). For example, Ethereum (ETH), developed by Vitalik Buterin in 2015, went beyond being merely a payment instrument and offered a platform on which smart contracts and decentralized applications (dApps) could operate (Viéitez, Santos & Naranjo, 2024; Gurgul, Lessmann & Härdle, 2025).

Crypto currencies meet the modern definition of money with characteristics such as portability, durability, divisibility, and non-counterfeiting (Tanrıkulu, 2021). However, unlike traditional currencies, the essence of crypto assets is entirely composed of "data," and their values are based not on any physical asset but on the supply-demand balance and investors' psychological perceptions (Tanrıkulu, 2021; Nas & Ergin Ünal, 2023).

2.2. Blockchain Mechanism and Transaction Security

Blockchain is a distributed ledger technology that forms the fundamental infrastructure of crypto currencies, in which information is cryptographically secured and linked to each other like a chain (Tanrıkulu, 2021; Shafie-khah, 2020). This technology flawlessly implements the "data and information cycle" principle of digital transformation by enabling the secure storage, verification, and sharing of data (Yoşumaz, 2024a; Yoşumaz, 2024b).

The working principle of blockchain is based on the collection of transactions in blocks, each block containing the summary (hash) of the previous block, and the sealing of this structure with timestamps (Nakamoto, 2008; Tanrıkulu, 2021). Thanks to this connection, changing the content of a block requires changing all subsequent blocks as well, making the system extraordinarily resistant to external interventions (Nakamoto, 2008; Shahbazi & Byun, 2022). Complex cryptographic functions such as the SHA-256 algorithm used in the Bitcoin network grant each block a unique identity (Tanrıkulu, 2021; Shahbazi & Byun, 2022).

The security of the network and the production of new units are ensured through the "mining" process (Tanrıkulu, 2021; Poudel et al., 2023). Consensus algorithms such as "Proof of Work" (PoW) require participants (miners) to consume processing power (CPU/GPU) to solve complex mathematical problems (Nakamoto, 2008; Tanrıkulu, 2021). Successful miners are rewarded with both newly produced crypto currencies and transaction fees (Nakamoto, 2008; Tanrıkulu, 2021). The storage of crypto assets is accomplished through two basic methods: "hot wallet" (internet-connected) and "cold wallet" (offline, physical device); cold wallets are considered more secure against cyber attack risk (Tanrıkulu, 2021; Shahbazi & Byun, 2022).

2.3. Crypto Currency Markets and Volatility

Crypto currency markets exhibit a structure that, unlike traditional markets, operates continuously 24/7, is globally accessible, but demonstrates an extremely volatile nature (Adedigba, Agbolade & Hasan, 2025; Boozary et al., 2025). The microstructure of these markets is shaped by elements such as liquidity conditions, order book dynamics, and informed trading (Wang et al., 2022; Fang et al., 2024).

Volatility is the most characteristic feature of crypto currency markets. Price movements react instantly to many factors such as macroeconomic news, regulatory authorities' decisions, technological updates, and social media influencers' posts (Nas & Ergin Ünal, 2023; Alnami et al., 2025). Sharp fluctuations in Bitcoin's price, in particular, have a strong domino effect on other altcoins, increasing uncertainty across the market (Korkmaz et al., 2025; Viéitez et al., 2024). Lack of liquidity and high transaction costs bring the risk of assets becoming "zombified" (Będowska-Sójka, Wójcik & Pele, 2026).

Zombie crypto assets are digital assets that, although technically existing, are not traded on exchanges, have lost their liquidity, and have trapped their investors (Będowska-Sójka et al., 2026). In the literature, this situation is associated with low trading volume, dramatic declines in market value, and prolonged price stagnation (Będowska-Sójka et al., 2026; Wang et al., 2022). According to market microstructure theory, continuous declines in trading volume lead to the widening of the bid-ask spread and ultimately the delisting of the asset from the market (Będowska-Sójka et al., 2026). Predicting these risks in advance with ML models has become a critical research area for investor security (Będowska-Sójka et al., 2026).

Crypto currency prices interact not only with internal market dynamics but also with a broad set of external indicators. In the literature, the effects of macroeconomic variables such as gold prices, crude oil prices, the S&P 500 index, the VIX volatility index, and FED interest rates on crypto markets are examined in depth (Viéitez et al., 2024; Akarsu, 2024; Nas & Ergin Ünal, 2023).

Investor sentiment is perhaps the most effective external factor in price formation in crypto markets. Unlike traditional financial assets, crypto currencies are extremely sensitive to social media hype and public perception (Valencia, Gómez-Espinosa & Valdés-Aguirre, 2019; Gurgul et al., 2025). Data obtained from platforms such as Twitter and Reddit through Natural Language Processing (NLP) techniques are used to measure investors' fear or appetite levels (Gurgul et al., 2025; Boozary et al., 2025). For example, indicators such as the "Fear and Greed Index" are considered important inputs for increasing the prediction success of ML models (Korkmaz et al., 2025). However, some researchers argue that the effect of sentiment analysis is limited contrary to belief and that the real success is achieved with technical market data, forming a contradiction on this issue (Viéitez et al., 2024; Korkmaz et al., 2025).

In recent years, the dimension of "environmental sustainability" has also been added to the conceptual framework of crypto currencies. The high energy consumption and carbon footprint in the mining processes of assets such as Bitcoin and Ethereum have given rise to the concept of "dirty cryptocurrency" (He, 2024; Jana et al., 2022). This situation has led investors to develop new trading strategies that consider environmental risks (ESG) and has caused increased interest in sustainable financial technologies (He, 2024; Banerjee, 2024).

2.4. Analysis of Crypto Currency Markets

The methods used to make sense of crypto currency markets and predict future price movements span a wide spectrum, from traditional technical analysis tools to advanced AI algorithms.

Technical analysis aims to identify future trends by examining past price and volume movements. Indicators such as Simple Moving Average (SMA), Weighted Moving Average (WMA), MACD, RSI, and STO are the most frequently used tools by crypto currency investors (Kanat, 2023; Lapitskaya, Eratalay & Sharma, 2025). ML methods build upon these traditional technical indicators by combining them with more complex patterns and maximizing prediction accuracy (Kanat, 2023; Yaman Şahin & Ulutürk Akman, 2024).

AI and ML come into play at points where traditional statistical models such as ARIMA fall short in dealing with the volatile nature of crypto markets (Kervancı & Akay, 2020; Korkmaz et al., 2025). ML offers different paradigms including supervised (SVR and XGBoost), unsupervised (K-means clustering), and reinforcement learning (Mujlid, 2023; Ren et al., 2022). LSTM and Gated Recurrent Unit (GRU) models under the DL umbrella demonstrate superior success in capturing long-term dependencies and nonlinear relationships in time series data (Korkmaz et al., 2025; Adedigba et al., 2025). In recent years, it has become important not only for models to make predictions but also to explain the reasons for these predictions; methods such as SHAP analysis aim to remove models from being "black boxes" (Akarsu, 2024; Alnami et al., 2025).

AI and ML are the most critical technologies that today stand at the center of data-driven decision-making processes and are considered the "workhorses" of digital transformation. These technologies not only process complex data but also possess the ability to discover hidden patterns in highly volatile markets where traditional statistical models fall short.

2.2. Artificial Intelligence

2.2.1. The Definition and Historical Development of Artificial Intelligence

AI is an evolving branch of computational algorithms designed to imitate human capabilities such as learning, reasoning, and decision-making through computer software (Yoşumaz, 2025). This technology adapts the problem-solving and reasoning processes of human intelligence to computer science as a metaphor (Yoşumaz, 2025). The origins of AI extend back to Al-Khwarizmi's work on algebra and algorithms in the 9th century and Al-Jazari's contributions to cybernetics and programmable automata in the 13th century (Yoşumaz, 2025). Conceptually, the term AI was first articulated by John McCarthy at the Dartmouth Conference in 1955, and today it has come to be recognized as the "workhorse" in the process of processing big data and transforming it into strategic information (Akarsu, 2024; Yoşumaz, 2025). The fundamental purpose of AI is to be able to recognize complex problems by learning from the environment and to offer rational solutions by making meaningful inferences from data (Akarsu, 2024).

The digital transformation process operates within a dynamic cycle that includes the acquisition, storage, and analysis of data in enterprises, and its sharing as a strategic value (Yoşumaz, 2024b; Yoşumaz, 2024a). AI and ML constitute the most critical components of this data and information cycle, establishing a technological bridge between virtual and physical worlds (Yoşumaz, 2024b). Enterprises' ability to adapt to this process depends on increasing awareness of these technologies throughout society and the establishment of a digital transformation-oriented institutional culture (Yoşumaz, 2024a). Particularly in financial markets where high-frequency data and noisy signals exist, AI systems have become strategic solution partners in forecasting tasks where traditional statistical models (ARIMA, VAR, etc.) remain limited (Khedr et al., 2021; Boozary et al., 2025).

2.2.2. Types and Working Areas of Artificial Intelligence

The AI ecosystem is classified into different categories according to technological maturity levels, the types of data it specializes in, and its working logic.

Types of AI: In the literature, AI is evaluated at three main levels according to its capacities (Yoşumaz, 2025):

a. Artificial Narrow Intelligence (ANI): These are systems with limited capabilities designed to perform a specific task (for example, playing chess or making financial price predictions) (Yoşumaz, 2025). All active applications used today fall into this class.

b. Artificial General Intelligence (AGI): This presents a type of AI where the data processing capacity becomes equal to human intelligence (Yoşumaz, 2025).

c. Artificial Superintelligence (ASI): This presents a type of AI where the data processing capacity surpasses human intelligence (Yoşumaz, 2025).

The most prominent sub-fields of AI are ML, DL, natural language processing (NLP), computer vision (CV), robotics, and artificial neural networks (ANN) (Yoşumaz, 2025). A large portion of analyses in crypto currency markets is also based on ML.

Machine Learning: ML is a subfield of AI that enables software systems to automatically improve their performance by learning from data without being explicitly programmed (Khedr et al., 2021; Mujlid, 2023). While in traditional programming computers follow every step and rule given to them, in ML the system builds its own internal rules by modeling input data (Kervancı & Akay, 2020; Tanrıkulu, 2021). This technology seeks scientific answers to the question of how to build computers that improve automatically through experience and how to enhance performance metrics (Ren et al., 2022; Mujlid, 2023). ML algorithms perform mathematical modeling by analyzing massive data sets and accomplish tasks such as classification, clustering, and prediction with high accuracy (Ren et al., 2022; Tanrıkulu, 2021).

Deep Learning and Artificial Neural Networks: DL is a subset of ML that learns complex representations and abstractions from large data sets using multilayer ANN (Akarsu, 2024; Khedr et al., 2021). These structures, which imitate the working logic of neurons in the human brain, can automatically extract hierarchical features within data (such as edges in an image or cycles in a time series) (Khedr et al., 2021; Yoşumaz, 2025). LSTM networks are considered unrivaled in financial time series predictions because they have the capacity to remember long-term dependencies in sequential data through "memory gates" (Korkmaz et al., 2025; Wang et al., 2022).

NLP: This is the discipline that transforms human language into a form that computers can understand, analyze, and produce (Gurgul et al., 2025; Yoşumaz, 2025). In the financial world, it plays a key role in measuring investor psychology, particularly through news text and social media sentiment analysis (Gurgul et al., 2025; Mujlid, 2023).

AI learning is generally examined under four main headings (Ren et al., 2022; Mujlid, 2023):

a. Supervised Learning: This is the method where the system is given both input data and the correct results (labels) corresponding to these data (Khedr et al., 2021; Mujlid, 2023). The algorithm builds a rule that maps inputs to outputs; models such as Support Vector Machines (SVM) and Random Forest (RF) are the most powerful tools in this category (Mujlid, 2023; Tanrıkulu, 2021).

b. Unsupervised Learning: This is the model where training data is not labeled, and the system groups (clusters) data by discovering hidden patterns, similarities, and structural relationships within the data on its own (Khedr et al., 2021; Mujlid, 2023). The K-means clustering method is widely used in areas such as anomaly detection and customer segmentation (Mujlid, 2023; Tanrıkulu, 2021).

c. Semi-supervised Learning: This is a hybrid approach where learning performance is increased by using a small amount of labeled data together with a large amount of unlabeled data (Ren et al., 2022; Mujlid, 2023).

d. Reinforcement Learning: This is a process where an "agent" learns to make decisions through trial and error in order to obtain the highest reward in a specific environment (Ren et al., 2022; Mujlid, 2023). The system receives feedback (reward or penalty) from the environment after each action it takes and updates its internal state accordingly, developing the most appropriate strategy (Ren et al., 2022; Mujlid, 2023).

2.2.3. The Use of Artificial Intelligence in Financial Markets

The finance sector is one of the most ideal application areas for AI due to the large data masses it contains, high transaction frequency, and complex structural relationships (Adedigba et al., 2025; Mujlid, 2023). AI models produce more successful results than linear regression models because they can capture complex and interactive relationships among numerous variables (Khedr et al., 2021; Akarsu, 2024; Alnami et al., 2025). However, the black box characteristic of these systems, meaning that why a prediction was made cannot always be understood, poses a challenge in terms of institutional trust (Ren et al., 2022; Akarsu, 2024). XAI techniques and SHAP analysis developed to overcome this problem make the decision-making logic of models transparent, allowing financial actors to take safer steps (Akarsu, 2024; Korkmaz et al., 2025). The use of AI in financial markets is fundamentally as follows.

a. Price and Return Prediction: AI models predict future price direction with high accuracy by analyzing past price movements, volume data, and technical indicators (Khedr et al., 2021; Mujlid, 2023). Ensemble learning models such as XGBoost and Random Forest (RF) generally demonstrate performances that surpass deep neural networks in short-term predictions and trading optimization (Adedigba et al., 2025; Korkmaz et al., 2025).

b. Sentiment Analysis: Investors' discourses on Twitter (X), Reddit, or news platforms are analyzed with NLP techniques to measure the levels of "fear" or "greed" in the market (Gurgul et al., 2025; Alnami et al., 2025). These psychological data are integrated as features into price prediction models, thereby incorporating the behavioral finance dimension of the market into the model (Gurgul et al., 2025; Korkmaz et al., 2025).

c. Algorithmic Trading and Portfolio Management: AI is used to optimize asset allocation according to risk preferences and develop dynamic strategies that maximize profit (Korkmaz et al., 2025; Ren et al., 2022). Reinforcement learning (RL) agents can evaluate market opportunities without the need for human intervention by conducting thousands of transactions within seconds (Ren et al., 2022; Adedigba et al., 2025).

d. Anomaly Detection and Security: AI is an effective control mechanism in detecting suspicious transactions, cyber attacks, and manipulation attempts such as "pump-and-dump" in financial networks (Alnami et al., 2025; Mujlid, 2023). Z-Score-based anomaly detection frameworks increase investor security by separating normal market movements from irregular ones (Alnami et al., 2025).

e. Credit Risk Assessment: ML models are used to assess credit risks by analyzing borrowers' repayment capacities through big data and to accelerate the decision processes of financial institutions (Khedr et al., 2021).

2.3. The Relationship Between Crypto Currencies, Artificial Intelligence And Machine Learning

The digital transformation process consists of a dynamic cycle that includes the acquisition, storage, and analysis of data and its transformation into strategic value (Yoşumaz, 2024b). Crypto currencies, which are the most concrete reflection of this transformation in financial markets, produce very large amounts of transparent and immutable data thanks to blockchain infrastructure (Nakamoto, 2008; Yoşumaz, 2024a). However, the extreme volatility possessed by crypto currency markets renders traditional financial analysis methods insufficient (Boozary, Sheykhan, & GhorbanTanhaei, 2025; Adedigba, Agbolade, & Hasan, 2025). At this point, AI and generally ML, which is a sub-field of AI, can discover hidden patterns within complex data masses, model nonlinear relationships, and produce rational predictions (Akarsu, 2024; Mujlid, 2023). This synergy between crypto currencies and AI points to a new economic paradigm where data is transformed into information, and information into financial advantage (Yoşumaz, 2025; Shahbazi & Byun, 2022).

2.3.1. Fundamental Use Scenarios of Artificial Intelligence in the Crypto Currency Ecosystem

The applications of AI in the crypto currency ecosystem cover a wide spectrum, from simple data analyses to complex autonomous systems. The main use scenarios that stand out in the literature can be detailed as follows:

a. Price and Volatility Prediction: The most common application area of AI is forecasting the future closing prices and market direction of assets such as BTC, ETH, and Binance Coin (BNB) (Korkmaz, Altınırmak, & Karamaşa, 2025; Adedigba et al., 2025). LSTM networks, in particular, demonstrate high accuracy rates in this field thanks to their ability to remember long-term dependencies in time series data (Boozary et al., 2025; He, 2024). On the other hand, ensemble learning models such as XGBoost and Random Forest (RF) are preferred in the optimization of trading bots due to their computational speed and success in short-term predictions (Korkmaz et al., 2025; Adedigba et al., 2025).

b. Sentiment Analysis and NLP: Crypto assets are extremely sensitive to social media news and public perception (Valencia, Gómez-Espinosa, & Valdés-Aguirre, 2019; Banerjee, 2024). Generative Artificial Intelligence (GAI) and NLP techniques measure the level of "fear" or "greed" in the market by analyzing millions of texts obtained from platforms such as Twitter (X) and Reddit (Gurgul, Lessmann, & Härdle, 2025; Poudel et al., 2023). Advanced models such as Bidirectional and Auto-Regressive Transformers (BART) and Multi-Genre Natural Language Inference (MNLI) detect investors' bullish or bearish tendencies, integrate this data into price prediction models, and increase prediction accuracy (Gurgul et al., 2025).

c. Anomaly Detection and Security Audit: AI is a critical tool for detecting suspicious transactions and cyber attacks in the blockchain network (Alnami, Mohzary, Assiri, & Zangoti, 2025; Shahbazi & Byun, 2022). Z-Score-based anomaly detection systems warn investors against pump and dump manipulations by separating normal price movements from irregular ones (Alnami et al., 2025). Additionally, ML models play an active role in tracking "zombie" assets that have lost trading volume and illegal financial flows (Będowska-Sójka, Wójcik, & Pele, 2026; Ren et al., 2022).

d. Algorithmic Trading and Portfolio Management: Reinforcement Learning algorithms aim to maximize portfolio value by learning the most appropriate buy-sell timing according to market conditions through an "agent" (Poudel et al., 2023; Koker & Koutmos, 2020). These systems minimize human-induced emotional errors by making rational decisions in crypto exchanges that operate continuously 24/7 (Koker & Koutmos, 2020; Shahbazi & Byun, 2022).

2.3.2. Opportunities Offered by Artificial Intelligence and Crypto Currency Integration

The integration of AI and crypto currency offers important opportunities for the financial system to achieve a more efficient, democratic, and transparent structure.

a**. Reduction of Information Asymmetry:** AI makes it possible to develop rational investment strategies by analyzing big data sets that exceed the processing capacity of human intelligence (Boozary et al., 2025; Mujlid, 2023). This situation enables individual investors to have similar analytical power to professional financial actors, thereby reducing information asymmetry and contributing to the democratization of the market (Gurgul et al., 2025; Adedigba et al., 2025).

b. Financial Inclusion and Disintermediation: When the decentralized structure of crypto currencies combines with the analytical power of AI, a secure financial ecosystem is formed without the need for intermediary institutions (banks, fund managers, etc.) (Shahbazi & Byun, 2022; Poudel et al., 2023). This situation facilitates the inclusion of populations without access to banking services into the financial system, establishing economic growth opportunities at a global level (Yoşumaz, 2024a; Banerjee, 2024).

c. Strategic Decision Support Systems: AI models not only make price predictions but also offer investors a holistic decision support mechanism by identifying correlations between complex macroeconomic variables (interest rates, inflation, oil prices) and crypto assets (Nas & Ergin Ünal, 2023; Akarsu, 2024).

2.3.3. Threats and Risks Offered by Artificial Intelligence and Crypto Currency Integration

Although this technological convergence harbors great potential, the chaotic and unsupervised structure of the market also brings serious threats:

Overfitting and Generalization Problem: ML models can produce perfect results on the training set by fitting too closely to historical data, while they can fail completely in the face of new market shocks (black swan events) they have never seen (Mujlid, 2023; Korkmaz et al., 2025). This situation carries the risk of leading to major financial losses by establishing a false sense of confidence for investors (Nas & Ergin Ünal, 2023; Adedigba et al., 2025).

Sophisticated Manipulations and Bot Wars: The use of AI bots by malicious actors increases the danger of artificially manipulating prices (wash trading) with thousands of transactions within seconds in the market (Alnami et al., 2025; Gurgul et al., 2025). This situation threatens market stability by disrupting the natural supply-demand balance (Będowska-Sójka et al., 2026).

Cybersecurity and Private Key Loss: AI-based trading platforms may require access to users' private keys to perform autonomous transactions (Shahbazi & Byun, 2022; Tanrıkulu, 2021). A possible cyber attack on such platforms constitutes a major security vulnerability that could result in the theft of all user assets (Alnami et al., 2025; Shahbazi & Byun, 2022).

2.3.4. Challenges Encountered in the Crypto-AI Relationship

The biggest challenges in the integration process are related to methodological limitations and data quality:

Explainability and Black Box Problem: DL models generally cannot explain why a prediction was made in a manner understandable by humans (Akarsu, 2024; Yoşumaz, 2025). The lack of transparency weakens the trust of institutional investors and regulatory authorities (regulators) in these models (Akarsu, 2024; Alnami et al., 2025). XAI and SHAP analysis techniques developed to overcome this challenge are still in the large-scale application phase (Akarsu, 2024; Korkmaz et al., 2025).

Data Quality and Noisy Signals: Data coming from crypto exchanges can generally be noisy, incomplete, or manipulated (Poudel et al., 2023; Salehi, 2024). Models trained with incorrect or poor-quality data can misdirect investors by producing erroneous results in accordance with the "garbage in, garbage out" principle (Mujlid, 2023; Adedigba et al., 2025). Furthermore, the necessity for models to be continuously retrained with real-time data to keep pace with the 24/7 dynamism in the market requires massive computational resources and high energy consumption (He, 2024; Adedigba et al., 2025).

2.3.5. Conveniences Offered by AI and Crypto Currency Integration

a. Autonomous Market Monitoring: AI can simultaneously monitor thousands of different crypto currencies and billions of social media data 24/7, far beyond human attention span (Gurgul et al., 2025; Boozary et al., 2025). This convenience reduces investors' fear of missing out (FOMO) on market opportunities and lightens the data analysis burden (Mujlid, 2023; Yoşumaz, 2024b).

b. Dynamic Risk Management and Optimization: ML models automate risk management by dynamically updating "stop-loss" and "take-profit" levels according to sudden changes in market conditions (Adedigba et al., 2025; Koker & Koutmos, 2020). Additionally, techniques such as PCA (Principal Component Analysis) facilitate healthier portfolio diversification by enabling investors to filter out assets that show high correlation with each other (Adedigba et al., 2025; Korkmaz et al., 2025).

c. Smart Contracts and Secure Payments: AI enables smart contracts on the blockchain to be more flexible and fault-tolerant (Shahbazi & Byun, 2022; Yoşumaz, 2024b). This situation facilitates the flawless execution of financial transactions without human intervention, within predetermined conditions (Yoşumaz, 2024a; Shahbazi & Byun, 2022).

3. Discussions and Conclusion

The digital transformation process is built upon a dynamic cycle that includes the acquisition, storage, and analysis of data and its transformation into strategic value (Yoşumaz, 2024b). Crypto currencies, which are the most radical reflection of this transformation in financial markets, have emerged as a strong alternative to traditional financial systems thanks to the transparent and immutable data infrastructure offered by blockchain technology (Nakamoto, 2008). However, the extreme volatility and nonlinear complex structure possessed by crypto currency markets have made this ecosystem a difficultto-manage area for both investors and researchers (Adedigba, Agbolade, & Hasan, 2025; Boozary, Sheykhan, & GhorbanTanhaei, 2025). At this point, AI and ML algorithms come into play as fundamental technologies that discover hidden patterns within these massive data masses and offer rational decision support systems (Akarsu, 2024; Mujlid, 2023). This study emphasizes the importance of the strategic relationship between crypto currencies and AI.

The literature examined within the scope of the study proves that there is not universally a single best prediction model, and that success varies according to asset type and the structure of the data set (Korkmaz, Altınırmak, & Karamaşa, 2025; Hitam, & Ismail, 2018). Ensemble learning models such as XGBoost and RF demonstrate superior performance in short-term predictions and trading optimization with both their transaction efficiency in large-scale data sets and their structures that minimize overfitting risk (Adedigba et al., 2025; Korkmaz et al., 2025). The XGBoost algorithm, in particular, can rapidly learn complex data structures thanks to the gradient boosting technique and can surpass other models with its generalization capacity (Adedigba et al., 2025). On the other hand, DL models such as LSTM networks have been established as one of the most reliable tools in highly volatile assets such as Bitcoin thanks to their ability to store long-term dependencies in time series data and the effect of past price shocks through "memory gates" (Boozary et al., 2025; He, 2024). Although analyses conducted by Akarsu (2024) report that the Support Vector Regression (SVR) model reaches high accuracy rates in limited data sets, it is observed that the success of deep neural networks is consolidated as data volume increases. These findings emphasize that investors must necessarily consider the asset's liquidity, volatility, and targeted prediction horizon (minute, hourly, or daily) when making model selection (Tanrıkulu, 2021; Tekinay, 2021).

The analysis of factors affecting crypto asset prices has shown that "data quality" is more critical than algorithm selection in the success of ML models (Mujlid, 2023). Importance analyses conducted by Nas and Ergin Ünal (2023) and Korkmaz et al. (2025) revealed that crypto currency prices are most highly affected by their own past price movements (High, Low, Open) and technical analysis indicators. Indicators such as RSI, MACD, and Stochastic %K, in particular, are the technical signals that provide the most significant contribution to the predictive power of models (Korkmaz et al., 2025; Lapitskaya, Eratalay, & Sharma, 2025). In contrast, the effect of macroeconomic indicators such as interest rates, inflation, and exchange rates on crypto markets continues to remain controversial in the literature (Basher & Sadorsky, 2022; Korkmaz et al., 2025). While some studies emphasize the suppressive effect of these variables on Bitcoin (Akarsu, 2024), some research asserts that crypto assets move independently with their own internal dynamics and market microstructure (Wang et al., 2022). Sentiment analysis has become an integral part of models with the development of NLP techniques (Gurgul, Lessmann, & Härdle, 2025). Data obtained from social media (X, Reddit) and news feeds significantly increase the accuracy of prediction models, particularly during sudden market reversals, by reflecting the level of "fear" or "greed" in the market (Banerjee, 2024; Gurgul et al., 2025).

The most fundamental obstacle in applying AI and ML models to crypto markets is that complex models are seen as black boxes (Akarsu, 2024). This situation weakens the trust of institutional investors and regulators in models. At this point, the use of XAI techniques such as SHAP analysis consolidates the reliability of strategic decision support systems by making transparent which variable contributes in what direction to the prediction (Akarsu, 2024; Korkmaz et al., 2025).

Consequently, the synergy between crypto currency markets and AI is one of the most powerful driving forces shaping the future of the digital economy. The crypto currency world is like a decentralized and massive digital data library in which new pages are continuously being added in thousands of languages. AI, in turn, assumes an important role in data research in this library. Within the scope of future research, examining the power struggle between countries around the world and investigating the effects of these struggles on crypto currencies could be valuable for understanding volatility in crypto currency markets.

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