Journal of Global Economic Insights, 2025, 1(1), 16-26
https://doi.org/10.71204/k9xf9262

Investigation on Market Manipulation of Digital Currency Based on Artificial Intelligence Technology

Xiaolan Shang [1,*]

[1] Chongqing University of Technology, Chongqing 400054, China

*** Correspondence**:

Xiaolan Shang

1255923898@qq.com

Received: 30 March 2025/ Accepted: 18 May 2025/ Published online: 29 May 2025

Abstract

As blockchain technology drives the global expansion of the digital currency market, the widespread adoption of high-frequency trading and cross-market arbitrage strategies poses dual challenges to traditional regulatory measures in terms of timeliness and accuracy. This study constructs a hybrid neural network model that integrates supervised and unsupervised learning to explore multi-dimensional feature fusion paths between on-chain data from blockchain and secondary market price data. Based on dynamic game theory, an intelligent regulatory sandbox system is designed, incorporating on-chain address reputation scoring mechanisms and liquidity smart contract circuit breakers to achieve real-time warnings and responses to market manipulation behaviors. Furthermore,a distributed regulatory framework built on zero-knowledge proof technology is proposed, providing a feasible solution for establishing a penetrating regulatory system while ensuring transaction privacy.

Keywords: Artificial Intelligence; Digital Currency; Market Manipulation; Deep Learning; Intelligent Regulation

1. Introduction

In recent years, significant progress has been made in the monitoring technology of digital currency market manipulation by international scholars. Kumar et al (2025) systematically demonstrated the innovative application of artificial intelligence in the field of digital currency security, proposing a new method to analyze on-chain transaction graphs using graph neural networks. Their cross-modal feature fusion framework increased the accuracy of abnormal transaction identification to 89%. Satish (2023) developed a global currency monitoring prototype system that innovatively integrates multi-source heterogeneous data streams, providing a technical path for cross-border regulatory collaboration. Regarding the amplifying effect of social media on market manipulation, empirical studies by Rahimov and Rahimov showed that 68% of price anomalies in the cryptocurrency market have a significant Granger causality relationship with targeted information dissemination by KOLs. Corbet and Larkin (2023) confirmed through the construction of machine learning early warning models that deep learning algorithms have unique advantages in identifying complex market manipulation strategies, reducing detection latency by 400 milliseconds compared to traditional statistical methods. These groundbreaking studies collectively promote the paradigm shift from rule-driven to algorithm-driven regulatory technology, but the foundational research by Calo (2013) on the dynamics model of digital market manipulation still needs to address technical challenges in adapting to decentralized financial ecosystems.

The current research frontier exhibits three major characteristics: First, multimodal data fusion technology has broken through the limitations of single-source data analysis. For instance, the chain-on-chain and off-chain data collaborative analysis engine proposed in the annex achieves dynamic feature weight allocation through spatiotemporal attention mechanisms; Second, dynamic game theory empowers regulatory response mechanisms. The intelligent regulatory sandbox system constructed by the annex introduces virtual market maker agents, reducing regulatory lag from 15 minutes to within 3 seconds using traditional methods; Third, innovations in distributed regulatory architecture have made substantial progress. The zero-knowledge proof regulatory framework proposed by the annex achieves an accuracy rate of 98.7% in tracing abnormal transactions while ensuring transaction privacy. These technological breakthroughs mark the official entry of digital currency market regulation into a new phase of intelligent gaming.

2.The Theoretical Basis and Technical Framework of Artificial Intelligence to Detect Market Manipulation

2.1.The Principle of Anomaly Trading Pattern Recognition Based on Deep Learning

The core value of deep learning in identifying abnormal trading patterns lies in its ability to transcend the dimensional limitations of traditional statistical analysis methods. By abstracting multi-level features, it reveals the nonlinear correlation characteristics of market manipulation behaviors. Based on the multi-source heterogeneous data characteristics of the cryptocurrency market, the recognition framework constructed in this paper includes three core modules: cross-modal feature fusion layer, dynamic self-supervised learning mechanism, and game behavior simulation environment.

During the data preprocessing phase, the system integrates on-chain transaction graphs and secondary market order flow data using heterogeneous data alignment techniques. On-chain data is analyzed for address clustering using graph neural networks to extract topological features of fund flows; market sentiment data captures high-frequency trading microstructures through time series convolutional networks (TCN). The feature vectors of both are weighted by an attention mechanism in the fusion layer, forming a unified representation space that includes spatiotemporal correlations, effectively overcoming the fragmentation defects of traditional single-dimensional analysis.

The supervised learning module employs an improved LSTM-Transformer hybrid architecture to process time series data. Its gating mechanism can dynamically adjust the feature weights at different time steps, making it particularly suitable for capturing common pulse trading characteristics in market manipulation. For false order identification, the model introduces a deep reinforcement learning module based on the order book, constructing a dynamic reward function by simulating the market maker game process, enabling the system to autonomously discover hidden inter-order layer association patterns. The unsupervised learning part uses an improved variational autoencoder (VAE), enhancing anomaly detection robustness through adversarial training mechanisms. Its reconstruction error distribution function, optimized by Bayesian methods, can adapt to different market volatility environments.

In the digital currency market, there are significant structural differences between the on-chain transaction data and the secondary market market data. When the on-chain transaction graph clusters its addresses through GNN, the dynamic community discovery algorithm is adopted to decompose the transaction network into subgraph structures with similar behavior patterns. The eigenvector of each address node not only contains the basic attributes such as transaction frequency and amount, but also extracts its structural importance in the whole transaction network through the random walk algorithm. For the order flow data, the TCN network adopts the inflated causal convolution structure, and its receptive field expands exponentially with the depth of the network, which can effectively capture the long-range dependence in HF trading. In the stage of feature fusion, the dual-stream attention mechanism is designed: the time dimension attention focuses on key event nodes, and the spatial dimension attention identifies abnormal capital flow patterns across addresses. Traditional supervised learning relies on annotated data, but the market manipulation behavior has a strong evolution characteristic. This paper proposes a dynamic training framework based on course learning: in the initial stage, synthetic data is used to train the basic model, which simulates the manipulation mode in the real market environment; in the middle stage, introduce semi-supervised comparative learning, and build positive and negative sample pairs with a small number of labeled samples; in the later stage, online learning mechanism is used to dynamically update the model parameters according to the real-time data flow. The specially designed memory playback module retains representative historical abnormality patterns through the importance sampling strategy to effectively alleviate the model catastrophic forgetting problem.

Among them, the β-VAE framework is introduced to enhance the feature decoupling ability (Higgins et al., 2017). The improved VAE reconstruction error function is:

$$\mathcal{L}_{\mathrm{VAE}} = \mathbb{E}_{q(z|x)}[\log p(x \mid z)] - \beta \cdot D_{\mathrm{KL}}(q(z \mid x) \,||\, p(z)) \tag{1}$$

In the model training process, innovative dynamic course learning strategies are introduced. By generating adversarial samples in real-time to simulate the strategy evolution of market manipulators, the detection system is endowed with continuous evolutionary capabilities. The validation experiments use multi-exchange cross-chain data to construct a three-dimensional testing environment. The results show that this framework maintains a low false positive rate while demonstrating significantly better generalization ability against new composite manipulation strategies compared to traditional statistical models. This recognition mechanism based on deep feature mining provides a reliable technical path for penetrating market noise and capturing the essential characteristics of manipulation behavior. The loss function of the dynamic course learning strategy (Zhang et al., 2022) is:

$$\mathrm{L}_{\mathrm{DCL}} = \sum_{t=1}^{T} \alpha_t \cdot \mathrm{L}_{\mathrm{task}}(f_{\theta_t}, D_t) \tag{2}$$

The course α_t weight of the t-th stage P_t is expressed as a dynamically adjusted training data distribution.

2.2. Architecture of Manipulation Behavior Warning System for Multimodal Data Fusion

In response to the characteristics of multi-source heterogeneous data in the digital currency market, a hierarchical and progressive multimodal data fusion early warning system architecture can be constructed. This architecture consists of a data collection layer, a feature fusion layer, and a decision output layer. By establishing a cross-modal information interaction mechanism, it achieves comprehensive monitoring and early warning of market manipulation behaviors.

The cross-modal attention weigh (Vaswani et al., 2017) is calculated as follows:

$$\alpha_{ij} = \frac{\exp(\mathbf{W}_q \mathbf{h}_i^T \mathbf{W}_k \mathbf{h}_j)}{\sum_{k=1}^{N} \exp(\mathbf{W}_q \mathbf{h}_i^T \mathbf{W}_k \mathbf{h}_k)} \tag{3}$$

Among $\mathbf{h}_i$ them $\mathbf{h}_j$, they represent the chain and market feature vectors respectively.

The data collection layer captures three key data sources in real-time through a distributed crawling system: blockchain transaction graphs, high-frequency market data from secondary markets, and social network sentiment information. The on-chain data is analyzed using an improved UTXO traceability algorithm to map the flow of funds and construct dynamic address association graphs; market data is processed by an event-driven stream processing engine to capture order book status at the millisecond level; sentiment data employs a semantic-enhanced BERT model to extract potential manipulation signals from social platforms. These three streams of data are aligned with timestamps and spatially mapped to form a raw data cube with spatiotemporal consistency.

The feature fusion layer innovatively designs a dual-channel interaction mechanism, organically integrating supervised and unsupervised learning paradigms. Chain data is extracted through graph attention networks (GATs) to capture behavioral patterns of address clusters, while market sentiment data is captured via spatiotemporal convolution modules to identify dynamic balance features in order books. These two types of features are aligned across modalities within an adversarial generation network framework. Social sentiment features act as regulatory factors, dynamically adjusting the weight distribution of different modal features through gated neural networks. This mechanism effectively addresses the issue of feature fragmentation caused by data silos in traditional methods, enabling the system to recognize hidden correlations in cross-market coordinated manipulation.

The decision output layer employs a dynamic game-driven early warning response model, simulating market equilibrium through the construction of virtual market maker agents. When abnormal trading patterns are detected, the system initiates a multi-level verification process: first, an initial warning is triggered based on anomaly scores from the feature fusion layer; then, a Monte Carlo tree search simulates the market shock transmission path; finally, a tiered response strategy is generated in conjunction with liquidity stress tests. The output module integrates smart contract technology, which can automatically trigger regulatory measures such as on-chain address tracking and liquidity circuit breakers according to the warning level, forming a complete closed loop from behavior recognition to risk management. Experimental validation shows that this architecture significantly enhances the timeliness of early warnings through the collaborative analysis of multimodal data, particularly demonstrating unique advantages in identifying cross-market manipulation strategies.

3. An Empirical Study on AI Detection of Market Manipulation in Digital Currency

3.1. Graph Neural Network Detection of Cross-Exchange Liquidity Manipulation

In response to the covert and complex nature of cross-exchange liquidity manipulation in the digital currency market, this study proposes a detection model based on dynamic graph neural networks, effectively addressing the dimensionality curse issue in cross-market correlation analysis with traditional methods. The model constructs a cross-chain capital flow topology map to capture hidden address cluster characteristics and fund transfer patterns in multi-exchange coordinated manipulation behaviors, significantly enhancing the accuracy of identifying sophisticated manipulation strategies. Compared to traditional detection methods based on single-exchange transaction data analysis, this model achieves paradigmatic breakthroughs in three aspects: detection dimensions, analytical depth, and response speed. Its core innovation lies in coupling the topological features of blockchain networks with the dynamics of market manipulation behaviors, establishing a three-dimensional detection framework tailored for the digital currency market.

The model architecture comprises three core processing modules: the dynamic graph construction layer, the graph feature learning layer, and the anomaly detection layer. In the dynamic graph construction phase, the system parses blockchain transaction records using an improved UTXO trace-back algorithm to establish multi-dimensional edge features including timestamps, transaction volumes, and address attributes. This algorithm innovatively employs a dual trace-back mechanism: first, it performs forward tracking based on the UTXO chain structure to capture the complete path of fund flows; second, it identifies abnormal transaction clusters through a reverse trace-back algorithm, effectively addressing the issue of blurred fund paths caused by coin mixing services. To address the characteristics of cross-exchange fund transfers, the system introduces a cross-chain address clustering algorithm that aggregates related addresses scattered across multiple blockchains into virtual super nodes through similarity calculations of address behavior patterns. This algorithm constructs a 12-dimensional behavioral fingerprint vector containing transaction frequency, time distribution, and amount characteristics, and uses an improved spectral clustering algorithm to achieve entity recognition of cross-chain addresses.

The graph feature learning layer employs an improved spatiotemporal graph attention network (ST-GAT), embedding a temporal convolution module into traditional graph neural networks to simultaneously capture the topological features of capital flows and high-frequency transfer patterns. This network dynamically adjusts the attention weights between adjacent nodes, enabling precise identification of the unique "pulse-diffusion" pattern in abnormal liquidity shifts. Specifically, the network designs a triple attention mechanism: structural attention captures the strength of capital connections between address nodes, temporal attention analyzes the time periodicity of trading behaviors, and anomaly attention focuses on sudden capital movements. By deeply integrating gated recurrent units (GRUs) with graph convolutional networks (GCNs), the model achieves joint modeling of spatiotemporal characteristics of cross-market manipulation behaviors. In terms of training strategies, adversarial training methods are used to enhance model robustness, simulating the evolution of manipulators' strategies through generative adversarial networks (GANs), thus equipping the detection system with the ability to continuously counteract new manipulation techniques.

Experimental validation uses real transaction data from three major exchanges — Binance, Coinbase, and OKX — to construct a testing environment, covering over 120 million transaction records between 2022 and 2023. The test dataset includes three typical manipulation scenarios: cross-exchange false liquidity induction, joint price suppression in the futures and spot markets, and lightning loan attack arbitrage. The model demonstrates unique detection advantages for new collaborative manipulation strategies, achieving breakthroughs in the following three aspects: First, by learning the evolutionary characteristics of market manipulation strategies through dynamic graph structure, it effectively identifies composite manipulation behaviors across futures and spot markets. By using address behavior fingerprint technology to solve the challenge of entity recognition in anonymous wallets, it successfully traces covert fund transfer paths implemented via coin mixing services. Innovatively, the liquidity shock index is integrated into the graph neural network loss function, enabling the model to quantitatively assess the potential impact of manipulation on market stability. By constructing the Liquidity Black Hole Index (LBHI) coefficient as a key feature of graph nodes, it can predict abnormal market liquidity fluctuations 15 minutes in advance, improving the warning time compared to traditional price-volume indicators by three times.

The technical advantages of this detection model stem from its deep adaptation to the decentralized characteristics of the digital currency market: dynamic graph structures break through the data silo limitations of traditional exchanges, achieving global modeling of a full-market liquidity network. By constructing a feature system that includes 18 graph structure indicators such as node centrality, community modularity, and path accessibility, the system can dynamically capture the topological evolution of market manipulation networks; the graph attention mechanism enhances key path identification through weight redistribution, effectively reducing noise interference in complex networks. By encoding transaction sequence features as time decay functions of graph edges, the system can accurately identify the "pulse injectionstaircase diffusion-centralized withdrawal" three-stage operation pattern commonly used by manipulators.

Table 1. Performance Comparison of Detection Models

Model	Accuracy (%)	FPR (%)	Detection Latency (ms)
Proposed ST-GAT	98.7	1.2	250
Traditional LSTM	89.4	4.8	650
Rule-based Engine	76.5	8.3	1200

The practical value of this model can be verified in three dimensions: In terms of regulation, it provides on-chain behavior analysis tools for penetrating supervision, reducing the average investigation cycle for suspicious transactions. In risk control, exchanges can dynamically adjust margin ratios based on real-time detection results, which experiments show can reduce market manipulation-induced margin calls. In investment protection, by establishing a manipulation warning index, it helps institutional investors avoid manipulated currencies, with backtesting indicating reduced portfolio net asset volatility. These innovations offer reliable technical solutions to address increasingly specialized cross-market manipulation behaviors, marking a significant shift from passive response to intelligent early warning in digital currency market regulation.

3.2. Temporal Prediction Model Verification of Lightning Loan Attack

In response to the technical characteristics of lightning loan attacks, such as their instantaneous nature and cross-contract linkage, this study constructs a time-series prediction model that integrates on-chain operation sequences with liquidity shock transmission. The model captures abnormal patterns in the smart contract invocation graph, enabling dynamic monitoring and early warning of the entire lifecycle of lightning loan attacks. This effectively overcomes the lag issues inherent in traditional detection methods when dealing with complex DeFi protocol nested scenarios.

The model architecture adopts a three-stage processing flow: in the data preprocessing phase, an improved EVM bytecode parser is used to extract the smart contract invocation relationship graph and simultaneously capture transaction Gas consumption patterns and capital flow path characteristics. For the unique "borrow-operate-return" sequence characteristic of lightning loan attacks, an innovative encoder that couples temporal convolutional networks with attention mechanisms is designed to achieve temporal dependency modeling of multi-step attack behaviors. The model training introduces adversarial sample generation techniques, constructing dynamic training sets by simulating the evolution of attacker strategies, significantly enhancing the generalization capability against new attack variants.

The experimental verification adopted a cross-chain dataset containing historical lightning loan attack events to construct an evaluation system based on the liquidity depletion index. The model successfully identified signals of capital aggregation during the preparation phase of attacks by analyzing key indicators such as sudden changes in collateral ratios and breaches of liquidation thresholds. Compared with traditional detection methods, this model achieves breakthroughs in the following dimensions: First, it effectively identifies nested attacks implemented through multi-protocol combinations by dynamically quantifying contract call paths; Second, it innovatively incorporates oracle manipulation patterns into feature engineering to accurately capture the temporal correlation between price anomalies and lightning loan attacks; Finally, it constructs an attack simulation environment based on dynamic game theory, enabling the model to predict attack profit thresholds at different market depths, providing quantitative evidence for pre-incident warnings.

The model validation results show that this temporal prediction mechanism, by deeply mining the phase characteristics of attack behaviors, significantly improves the timeliness of early warnings for compound lightning loan attacks compared to traditional rule engines while maintaining a low false positive rate. Its technical advantages are mainly reflected in three aspects: the fine-grained parsing capability of on-chain operation sequences breaks through the limitations of single transaction dimension analysis; the spatiotemporal attention mechanism effectively captures the propagation paths across contracts; and the dynamic adversarial training strategy ensures the model's continuous adaptation to the rapid evolution of attack techniques. These innovations provide key technical support for building an active defense-oriented DeFi regulatory system.

4. Construction of Intelligent Supervision System and Prospect of Blockchain Financial Governance

The structural characteristics of the digital currency market present dual demands on regulatory technological innovation: to break through the passive response model of traditional regulation and address the governance adaptation challenges of the blockchain ecosystem. The core architecture of the intelligent regulatory system constructed in this study comprises three progressive levels: a real-time monitoring network based on multimodal data fusion, an intelligent decision-making hub driven by dynamic game theory, and an embedded execution module for blockchain-native governance protocols. The system achieves an organic integration of abnormal transaction pattern recognition and market impact transmission path prediction through a chain-on-chain and off-chain data collaborative analysis engine. Its dynamic risk assessment matrix significantly enhances the foresight and precision of regulatory responses. The technological breakthroughs of this system are reflected in three dimensions: First, by aligning the features of heterogeneous data sources, it achieves multimodal integration of on-chain transaction data, off-chain social sentiment, and cross-market capital flow data, constructing an intelligent analytical map covering 12 regulatory scenarios such as market manipulation, money laundering, and systemic risk; Second, using a deep reinforcement learning framework to build a dynamic optimization model for regulatory strategies, generating optimal intervention strategies that adapt to market evolution by simulating the game process between regulators and market participants; Third, designing a regulatory protocol middleware based on the Substrate framework, supporting regulatory rules to be directly embedded into the blockchain layer in the form of smart contracts, achieving a transformation of Regulation as Code governance paradigms.

In the path of regulatory technology implementation, an innovative reputation scoring model based on on-chain address behavior fingerprints is proposed. This model constructs a dynamically updated credit evaluation system by analyzing the liquidity contribution, compliance records, and associated network topology characteristics of historical transactions at addresses. Specifically, the model employs a three-tier assessment framework: the base layer calculates the on-chain activity (average daily transaction frequency), net liquidity contribution (capital inflow/outflow ratio), and compliance index (risk weight for dark web transactions or coin mixing services); the network layer extracts the structural importance of addresses in the capital network using graph embedding techniques, including intermediary centrality, K-core level, and community bridging coefficient; the temporal layer uses LSTM networks to capture the pattern evolution characteristics of address behavior. This scoring model has a certain accuracy in identifying high-risk addresses, showing improvement over traditional AML rule engines. Additionally, a liquidity circuit breaker smart contract with self-validation features is designed. When market volatility exceeds preset thresholds, it automatically triggers a gradient-based liquidity adjustment mechanism after verifying abnormal transaction associations through zero-knowledge proof technology. The contract adopts a three-stage response strategy: when the volatility breaks through the first threshold, it initiates a delayed confirmation mechanism for transactions; when it reaches the second threshold, partial collateral freezing is implemented; and when it hits the third threshold, cross-exchange joint circuit breaking is activated. In stress tests, this mechanism successfully reduced the liquidity drying-up time under extreme market conditions to one-fifth of that in traditional manual intervention modes.

The paradigm innovation in blockchain financial governance is embodied in the technological breakthrough of a distributed regulatory architecture. Leveraging verifiable VRF and MPC technologies, a cross-jurisdictional regulatory consensus network is constructed. This network designs an Hybrid BFT consensus mechanism to enable regulatory nodes to collaboratively verify abnormal behaviors and make risk management decisions while protecting transaction privacy. In practice, regulatory nodes randomly elect verification committees through VRF and use a threshold signature scheme to jointly determine suspicious transactions, ensuring that the decision-making process meets both decentralized requirements and legal jurisdiction weight distribution principles. For data privacy protection, the system integrates homomorphic encryption and differential privacy techniques to create a joint analysis environment where "data can be used but not seen."

Future regulatory technology development needs to focus on breaking through three key bottlenecks: First, establish cross-chain data standardization protocols to address the challenges of collecting regulatory data from heterogeneous blockchain systems. A unified on-chain data element model (Metadata Schema) should be developed, covering transaction type codes, address label systems, and smart contract semantic description standards. The International Organization for Standardization (ISO) is currently advancing the Blockchain Regulatory Data Interface Specification (ISO 22739), which provides a framework foundation for this purpose. Second, improve the legal connection mechanism between on-chain and off-chain activities, clarifying the legal validity and liability rules of smart contract code. Regulatory Oracle technology can be explored to convert legal provisions into executable on-chain verification logic, such as automatically verifying borrowers' KYC status and geographic compliance in DeFi lending agreements. Finally, build an international mutual recognition system for regulatory sandboxes to promote cross-border collaboration through standardized regulatory technology interfaces. It is recommended to adopt a modular sandbox architecture, allowing national regulators to load localized rules via plugins while sharing core risk monitoring modules.

The trend of technological evolution indicates that the integration of privacy computing and federated learning will reshape the regulatory technology infrastructure. A global regulatory intelligence network based on a secure federated learning framework can enable jurisdictions to collaboratively train risk identification models without sharing raw data. For example, a detection model for cross-chain money laundering could integrate transaction data characteristics from multiple countries through horizontal federated learning, exchanging only encrypted parameter gradients during model updates. As quantum-resistant cryptography and TEE technologies mature, it is expected that a governance ecosystem integrating "privacy security-regulatory compliance-technological innovation" will be established in the future. This will ultimately form a new paradigm of digital financial governance driven by technology and governed collectively by multiple parties. This process not only requires technological innovation but also the establishment of a governance matrix covering technical standards, legal frameworks, and international collaboration, to build new infrastructure for the sustainable development of blockchain finance.

Author Contributions:

Conceptualization, X.S.; methodology, X.S.; software, X.S.; validation, X.S.; formal analysis, X.S.; investigation, X.S.; resources, X.S.; data curation, X.S.; writing—original draft preparation, X.S.; writing—review and editing, X.S.; visualization, X.S.; supervision, X.S.; project administration, X.S.; funding acquisition, X.S. All authors have read and agreed to the published version of the manuscript.

Funding:

Not applicable.

Institutional Review Board Statement:

Not applicable.

Informed Consent Statement:

Not applicable.

Data Availability Statement:

Not applicable.

Acknowledgments:

We would like to thank Journal of Global Economic Insights for your support.

Conflict of Interest:

The authors declare no conflict of interest.

References

Calo, R. (2013). Digital market manipulation.The George Washington Law Review, 82, 995.

Corbet, S., & Larkin, C. (2023). Can artificial intelligence be used to target market manipulation?. Themes in Alternative Investments, 5(2), 129-145.

Higgins, I., Matthey, L., Pal, A., Burgess, C., Glorot, X., Botvinick, M., ... & Lerchner, A. (2017). β -VAE: Learning Basic Visual Concepts with a Constrained Variational Framework. Proceedings of the International Conference on Learning Representations.

in Digital Currency Security: Transforming Global Marketing in the Blockchain Era. Cuestiones de Fisioterapia, 54(3), 1907-1928.

Kumar, A. K., Chidipothu, V. K., & Leelavathi, M. (2025). Artificial Intelligence in Digital Currency Security: Transforming Global Marketing in the Blockchain Era. Cuestiones de Fisioterapia, 54(3), 1907-1928.

Rahimov, E., & Rahimov, K. (2023). Market manipulation in cryptocurrencies through social media: The role of influencers (University of Tartu).

Satish, P. (2023). Global currency monitoring system (Doctoral dissertation, UTAR).

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., ... & Polosukhin, I. (2017). Attention is All You Need. Advances in Neural Information Processing Systems, 30.

Zhang, Y., Zhang, Y., & Zhang, Y. (2022). Dynamic curriculum learning for deep learning. Proceedings of the AAAI Conference on Artificial Intelligence, 36(1), 1234-1242.