"Early Wallet Behavior and Transparency in Meme Coin Markets"

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Abstract

This thesis aims to analyse behavior in meme coin space by combining on-chain transaction analysis with Reddit sentiment and topic modelling. The research focuses on three Solana tokens built on Solana blockchain: $TRUMP, $MELANIA, and $LIBRA. The study analyzes wallets and identifies patterns of potential manipulation. A suspicion score is developed to flag wallets that show characteristics of manipulative behavior. The results show that profits are highly concentrated among a small group of early entrants or advantaged wallets, while most participants experience financial losses. Reddit data reveals that emotional factors such as hype, FOMO, and social identity contribute to continued investment, even after profitability has passed. The thesis also examines blockchain transparency. The findings show that while data is technically public, the possibility for analysis is limited by poor accessibility and financial barriers. Visual tools created in this project offer an interpretable view to meme coins. The findings suggest that patterns of inequality and manipulation are common in these markets.

Preface

This thesis was completed as the final requirement for our Master's degree in Business Data Science at Aalborg University. It is the result of work carried out from February to June 2025 and reflects several months of research, analysis, and reflection on blockchain and meme coin markets.

We would like to express our sincere gratitude to our supervisor, Primoz Konda, for his guidance, constructive feedback, and support throughout the process. His insights were invaluable in shaping this work.

We are also deeply thankful to our families, especially our parents, for their encouragement, patience, and support during our studies and throughout the writing of this thesis.

We hope that our work contributes to a better understanding of transparency, behavior, and risk in blockchain and cryptocurrency markets.

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1. Introduction

1.1 Background and Context

Since the introduction of Bitcoin in 2008, the cryptocurrency market has transformed from a narrow technological concept for enthusiasts into influential means within global financial markets. Within this system, meme coins, a subset of cryptocurrencies characterized by humor, internet culture, and community, have gained significant popularity. Tokens like Dogecoin, Shiba Inu, and politically branded coins such as $TRUMP show how viral trends and public sentiment can motivate investment activity regardless of technological utility or financial value.

Although often dismissed as pointless jokes or unserious investments, meme coins present new challenges and opportunities for understanding modern investing behavior within decentralized finance (DeFi), for example: increased volatility, emotional crypto trading behavior, and increased exposure to fraudulent schemes. Unlike traditional markets, the launch and promotion of meme coins start quickly and with minimal control. This creates a space for scams such as rug pulls and sniper bot activity, which are tactics that exploit investor enthusiasm.

At the same time, the blockchain's transparency offers a paradox. Although all transactions are publicly available, the amount and complexity of data make meaningful interpretation difficult. This contributes to the presence of fraud and the vulnerability of private investors. As meme coins continue to influence the cryptocurrency market, there is an increasing need for tools that make the early stage of token activity more accessible and interpretable: not only to identify risks but also to better understand why individuals continue to invest in such speculative and volatile environments.

This thesis brings together blockchain analysis and behavioral finance to address this need. It focuses on wallet behavior in the early phases of three meme coin projects: $TRUMP, $MELANIA, and $LIBRA. By identifying and visualizing patterns linked to suspicious activity, we aim to develop a tool that flags risky wallet behaviors. Additionally, we focus on understanding why people continue to invest, even when the profit potential has reduced. The research seeks to make blockchain data more understandable for educational and analytical purposes, and to explore what influences investor decisions in quick and risky markets.

This thesis combines quantitative blockchain analysis and qualitative social media (Reddit) research to examine behavior during meme coin launches and its early stages. We are looking into three meme coins based on Solana blockchain: $TRUMP, $MELANIA, and $LIBRA. The study uses historical blockchain transaction data and Reddit discussions from the date of each coin's launch up to February 28, 2025. The starting dates for each coin are: January 17, 2025 for $TRUMP, January 19, 2025 for $MELANIA, and February 14, 2025 for $LIBRA. Our methodology focuses on two main components: transaction analysis and investor sentiment analysis.

1.2 Problem Statement

While blockchain technology offers full transparency by recording all transactions publicly, the way this data is presented as well as its volume often makes it inaccessible, overwhelming, and difficult to interpret to users. This is especially problematic in the case of meme coins, which attract quick investment using hype and emotional appeal, as early transactional patterns are rarely analyzed in real time by everyday investors. This creates opportunities for attackers, such as snipers and scammers executing rug pulls, to exploit uninformed participants before any meaningful warnings can be identified or communicated.

What is more, even after these malicious actions become apparent and most potential profits are gone, investors continue to buy into these tokens. This behavior raises important questions about the psychological and social dynamics of decision-making in uncertain crypto environments.

While some commercial tools exist for tracking blockchain activity, they often focus on real-time alerts or price movements and may not provide insights into the behavioral patterns behind early stages of token investments. This thesis takes a different approach. By developing a visual analysis framework based on historical data from meme coin launches, it aims to highlight suspicious wallet behavior and explore the psychological aspects that lead individuals to continue investing even after potential profits have disappeared. The focus is not on real-time fraud prevention, but on understanding the wallet activity and investor decision-making in speculative crypto environments.

1.3 Research Purpose and Objectives

The main purpose of this thesis is to make early meme coin activity more understandable and transparent for regular investors, especially in high-risk environments where hype often influences decision making. By focusing on real blockchain data from the Solana network, this project aims to develop a visualization framework that highlights suspicious wallet activity and reveals how trading behaviors may be influenced by online trends and community.

A key objective is to build a tool that analyzes and visualizes blockchain transaction data from selected meme coins such as $TRUMP, $MELANIA, and $LIBRA. By calculating “suspicion score” based on on-chain behavior, such as early entry, high profit, frequent trading, and token concentration, the tool identifies wallet patterns that could signal manipulation or bot activity. While the tool is currently applied to historical data for research purposes, the vision is to develop something accessible for broader investor use across different coins and platforms.

This thesis aims to support both research and investor education by showing how blockchain data can be translated into visual and easily interpretable insights that not only reveal profit and loss, but also the human behaviors behind them.

1.4 Research Questions

As mentioned in the previous sections, this thesis aims to explore how blockchain transaction data and visual tools can be used to better understand early meme coin activity, to detect suspicious wallets in early meme coin activity and to analyse why users continue to engage with these tokens even after profits have likely been extracted. Although the analysis is based on historical transaction data, the broader idea is to design a system that could support real-time applications and make token behavior more transparent. The research also connects blockchain patterns to human behavior, showing the role of online hype, emotional decision-making, and social dynamics in speculative crypto environments.

The project is guided by the following main research questions:

- How can early transaction flows be visualized to detect suspicious or manipulative wallet behavior in meme coin launches?
- What kinds of recurring patterns (if any) show up in coins that experience scams like rug pulls or sniper activity?
- How does the narrative of blockchain transparency compare to the reality of analyzing meme coin transactions?
- Why do people keep investing in meme coins, even after it's likely that the main profits have already been extracted?

The answers to these questions will help assess the usefulness of visual tools in crypto fraud awareness and provide insights into behavioral patterns in speculative environments.

2. Literature review

2.1 Overview of Blockchain Technology and Cryptocurrencies

2.1.1 Blockchain Fundamentals

Blockchain is a decentralized and distributed ledger technology that has gained significant attention in recent years due to its potential to transform industries such as finance, healthcare, and e-commerce. Its primary purpose is to ensure transparency, security, and immutability (impossibility to change) in digital transactions (Yuan and Wang, 2018; Ghosh et al., 2020). Blockchain organizes data into blocks with unique digital signatures and links them in chronological order. These blocks are distributed across a network of computers to provide security and trust by eliminating central control (Cahyadi et al., 2021).

The immutability of blockchain is reinforced through cryptographic methods which ensure that once data is recorded, it cannot be altered without the consensus of the network (Pierro, 2017; Gosh et al., 2020). This feature is particularly valuable in industries that prioritize data integrity and traceability.

2.1.2 Core Components of Blockchain

Blockchain technology operates as a decentralized and secure system by integrating critical components such as: blocks, transactions, nodes, and consensus mechanisms.

Blocks are the building components of the blockchain. They act as secure containers for transaction data, timestamps, and cryptographic hashes. Each block links to the previous one via a hash, thus creating a chain resistant to tampering as this design ensures that once a block is added, altering it would require modifying all subsequent blocks. (Beck et al., 2017).

Transactions are the digital records of asset transfers within the network. They must be validated by network participants to prevent fraudulent activity. Once validated, transactions are permanently recorded in the blocks (Beck et al., 2017).

Nodes are participants that maintain the blockchain. They can be categorized into full nodes, miners, and validators. Full nodes store the entire blockchain and validate data, miners create blocks through computation (solving complex cryptographic problems), and validators confirm transactions in Proof of Stake systems (Zhang et al., 2021; Khamar & Patel, 2020).

Consensus mechanisms are protocols that ensure agreement on the validity of transactions across the network. They are crucial for maintaining the security and performance of the blockchain (Zhou et al., 2023).

Smart contracts are self-executing code deployed on the blockchain to further improve automation and decentralization. Smart contracts are not a fundamental part of all blockchain architectures but have become a key feature of modern blockchain ecosystems that support decentralized applications (Wang et al., 2019).

2.1.3 Consensus Mechanisms

Consensus protocols are important as they are responsible for ensuring that all nodes in the blockchain network agree on the validity of transactions. Each node in a blockchain network functions together as a host and a validator that exchange data continuously with other nodes (Zhang & Lee, 2020). However, consensus can be challenged when nodes go offline or act maliciously. To reduce this risk, they should develop strong protocols to keep the network safe. This challenge is often explained using the Byzantine Generals Problem, which shows how hard it is to reach agreement when there are dishonest participants (nodes).

Table 1. Categorization of consensus protocols and its use cases

Type	**Protocol**	**Abbr.**	**Use Case**
Probabilistic-finality	Proof of Work	PoW	Bitcoin
	Proof of Stake	PoS	Ethereum
Absolute-finality	Delegated Proof of Stake	DPoS	EOS
	Practical Byzantine Fault Tolerance	PBFT	Hyperledger Fabric

Type	Protocol	Abbr.	Use Case
New Approach	Proof of History	PoH	Solana

Zhang and Lee (2020) categorize consensus protocols into two main types: probabilistic-finality and absolute-finality protocols. Probabilistic-finality protocols do not give instant validation, but the chances of a transaction being reversed decreases over time. However, absolute-finality protocols guarantee that once a transaction is confirmed and added to the blockchain, it is permanently recorded and cannot be changed.

Under the probabilistic-finality category, the two used mechanisms are Proof of Work (PoW) and Proof of Stake (PoS). Proof of Work is usually used among the early cryptocurrencies such as Bitcoin. PoW needs miners to use their computational powers to solve difficult mathematical problems to create and validate new blocks. The first miner who is able to finish solving the puzzle can add the new block to the chain. This process ensures security and decentralization but is criticized for its energy inefficiency (Zhang & Lee, 2020; Yusoff, Mohamad & Anuar, 2022). For that reason, Proof of Stake was introduced as a more energy efficient alternative. In the PoS system, users can join in by either lending their coins to a pool or becoming part of a pool themselves. In these pools, the profits are shared based on how much each user has staked, or put in. Who gets to create the next block on the blockchain is chosen randomly from those who have staked coins. It’s not possible to guess who will be chosen next but the more coins a user stakes, the better their chances of being selected to create a block. This encourages users to hold onto their coins and stake more, which helps make the blockchain more secure because it becomes harder and more expensive for anyone to attempt a hack. Although Proof of Stake uses less energy, it can lead to centralization as only a few actors hold most of the tokens (Zhang & Lee, 2020; Yusoff, Mohamad & Anuar, 2022).

In the category of absolute-finality protocols, examples include Delegated Proof of Stake (DPoS) and Practical Byzantine Fault Tolerance (PBFT). DPoS improves PoS by using a voting system where stakeholders elect a limited number of delegates to create and validate blocks. If a delegate misbehaves or underperforms, they can be voted out. This model makes transactions slower and can reduce decentralization by giving power to a few chosen participants (Zhang &

Lee, 2020; Yusoff, Mohamad & Anuar, 2022). PBFT addresses the Byzantine Generals Problem as it allows consensus even if a subset of nodes is unreliable. One node acts as the leader and proposes a block. Other nodes vote on the block proposal through multiple rounds. If over two third of the nodes agree, the block is finalized. It works well in systems where access is controlled (Zhang & Lee, 2020; Yusoff, Mohamad & Anuar, 2022).

Proof of History (PoH) is a new approach proposed in the "Solana Whitepaper" by Yakovenko (2018) for validating the order and timing between events on a blockchain without relying on external timekeeping. This method doesn't require all the computers in the network to agree on the time, which often slows things down. PoH records each event in order by using a process that involves hashing. PoH takes data from one event, runs it through a hash function, and creates a hash. This hash then gets used as the input for the next event's hash. This chain of hashes shows the order of events and the time between them. This built-in timing helps speed things as each computer on the network can see the order of events and verify them without needing to communicate back and forth to decide what happened first. This makes the blockchain quicker and more secure as it's harder for anyone to tamper with the history of transactions (Yakovenko, 2018).

There is no single consensus protocol that could be superior in all scenarios. The most appropriate mechanism is determined by the goals, constraints, and environment of the blockchain application (Zhou et al., 2023).

2.1.4 Types of Blockchain

There are different blockchain types: public, private, and consortium-. Each supports various use cases by regulating access and validation rights. Public blockchains like Bitcoin and Ethereum are decentralized and open to anyone. They use consensus mechanisms such as Proof of Work and Proof of Stake. Private blockchains are permissioned and controlled by a central authority that determines participation. They utilize consensus algorithms such as Practical Byzantine Fault Tolerance or Proof of Authority and are suitable for enterprise use cases, for example blockchain-based payroll. Consortium blockchains are managed by a group of organizations. They can be found for example in healthcare where hospitals are able to exchange patient data between hospitals, insurance companies, and labs. They apply consensus protocols like PBFT, Proof of Vote, or Proof of Trust (Yusoff, Mohamad & Anuar, 2022).

2.1.5 Cryptocurrencies and their Classification

Cryptocurrencies are digital assets that operate on blockchain networks. They eliminate the need for central banks and instead they rely on trust in cryptographic algorithms and consensus mechanisms (Härdle, Harvey & Reule, 2020; Patel et al., 2020). Transactions are verified by network participants (miners or validators) who are incentivized through rewards (Härdle, Harvey & Reule, 2020).

Each user manages their holdings through digital wallets with public and private keys. Public keys enable receiving funds, while private keys authorize transactions (Yetmar, 2023). When a transaction happens, it is broadcast to the network and added to a public ledger. While the transaction data is transparent, user identities remain pseudonymous.

Cryptocurrencies might be categorized by functionality as by Härdle, Harvey and Reule (2020), by consensus mechanism as per Zhang and Lee (2020), or economic role as by Grasselli & Lipton (2021). Table 2 shows the types and examples that are present in each category.

Table 2. Categorization of cryptocurrencies

Category	Type	Examples	Key Features
Functionality	Transaction Mechanisms	Bitcoin (BTC), Litecoin (LTC)	Used for transactions, decentralized and often deflationary
	Distributed Computation Tokens	Ethereum (ETH), Texos, EOS, DFinity	Enable execution of smart contracts
	Utility Tokens	Golem, Storj, Sia, FileCoin	Used to access or pay for product or service (like computing/storage) inside a specific platform
	Security Tokens	Security Token Offerings (STOs)	Digital representation of traditional investments like stock and bonds

Category	Type	Examples	Key Features
	Fungible Tokens	USDT, ETH, BTC	All tokens are equal and interchangeable
	Non-Fungible Tokens (NFTs)	CryptoPunks, Bored Apes Yacht Club (BAYC)	Unique tokens representing assets with unique identities- digital art
	Stablecoins	Tether (USDT), USDC, Tiberius Coin (TCX)	Aimed for price stability and tied to stable assets (fiat, crypto or none)
Economic Role	Pure-Asset Coins	BTC, ETH, Ripple (XRP)	Not backed by any entity, value depends on supply and demand, highly volatile, similar to gold
	Central Bank Digital Currencies (CBDC)	e-CNY (China), Sand Dollar (Bahamas)	Issued by central banks, similar to physical cash
	Fiat-Backed Stablecoins (FBSC)	USDCoin (USDC), TrueUSD (TUSD)	Issued by private institutions, backed by fiat reserves, stable value
	Custodial Stablecoins (CSC)	USDT, SilaToken	Backed by bank deposits, credit risk from custodian that might fail or not have enough funds
	Digital Trade Coins (DTC)	TCX	Backed by basket of assets (currencies, gold, government bonds), designed for global trade, low volatility
	Over Collateralized Stablecoins (OSC)	DAI	Backed by crypto collateral, created via smart contracts, decentralized stability mechanism (smart contracts and community manage its supply and demand)
Consensus Mechanism	As per Table 1 in chapter 2.1.4		

2.1.6 Summary

Blockchain is known and praised for being decentralized, secure, and transparent, which makes it a great tool for digital transactions. It's the technology behind cryptocurrencies and decentralized finance. However, the same features that make it secure can also be misused for fraud. This mix of benefits and risks is what the next parts will focus on: looking at common scams, potential dangers, and how to spot them.

2.2 Understanding Meme Coins

Internet memes have become a significant component of modern digital communication. They are multimodal creations as they combine images and text to express humor, irony, sarcasm, opinion, or even misinformation (Dancygier & Vandelanotte, 2017). Typically inspired by popular culture, memes engage online audiences by offering a comedic or relatable commentary on current issues (Way, 2019). Beyond mirroring societal trends, memes also influence public discourse and play an active role in shaping online debates (Syzonov, 2023). Memes have evolved into means of social and political commentary. During events such as Brexit and the Trump presidency, they were used to criticise and inform on political figures and policy decisions (Way, 2019; Zhou & Jin, 2021). A meme's ability to go viral is influenced by factors such as cultural relevance and context (Wong & Holyoak, 2021). Therefore, memes are now considered to be an influential form of participation in digital (social) media.

Since 2013, the influence of memes has extended into the financial market through the creation of meme coins. Meme coins are the cryptocurrencies inspired by internet culture, memes, jokes, or viral content. The first examples of these were Bellscoin and Dogecoin (both released in 2013). Meme coins are defined by their humorous origins, strong community involvement, and high price volatility (CoinAPI, n.d.). Unlike cryptocurrencies developed for technical functionality or financial infrastructure, meme coins depend on viral appeal and user engagement for growth (CoinAPI, n.d.).

Examples such as Dogecoin, Shiba Inu, and Pepe demonstrate how branding, community enthusiasm, and celebrity endorsements on platforms like Twitter, Reddit or TikTok can drive sharp price fluctuations (Bitpanda Academy, n.d.; Nevil, 2025). Despite their comedic appearance, some meme coins have reached noticeable trading volumes. In early 2025, a number of these coins recorded daily trading volumes exceeding $6 billion (Nevil, 2025).

Despite their growing market presence, meme coins still remain underexplored in academic literature. There's still limited understanding of their market behavior, investor motivations, and potential risks.

2.3 Types of Frauds in Cryptocurrencies

Despite the technological innovations that blockchain and cryptocurrencies offer, the decentralized and pseudonymous nature of these systems also creates vulnerabilities. Features such as the lack of centralized control, irreversible transactions, and anonymity make cryptocurrencies exposed to various forms of fraud. This is especially true in the decentralized finance system. Decentralized Finance (DeFi) refers to financial services based on blockchain that operate without intermediaries like banks or traditional institutions. DeFi platforms allow users to lend, borrow, trade, and earn interest on digital assets without requiring centralized control. However, the absence of regulatory protections and reliance on open-source, smart contracts present additional risks (Zetzsche, Arner & Buckley, 2020).

Fraudulent activities in the cryptocurrency market take many forms. These are phishing, Ponzi schemes, fake initial coin offerings (ICOs), pump-and-dump schemes, rug pulls, wash trading, flash loan attacks, and sniper bot manipulation.

Phishing is a common attack where scammers impersonate legitimate platforms or individuals to trick users into revealing private keys or login credentials. Once they obtain relevant information, attackers can access and empty users' wallets (Astrakhantseva et al., 2021).

Ponzi schemes promise high returns to investors from supposedly profitable business opportunities. However, the returns are paid from the incoming funds contributed by new investors, not from profit earned by the organization. The use of cryptocurrencies as Ponzi schemes is troubling due to the ease with which operators can remain anonymous, making it harder for investors to verify the legitimacy of the operation and for authorities to track down the fraudsters (Saha et al., 2024).

Fake ICOs (Initial Coin Offerings) involve creating fake tokens or projects with no real value. Scammers publish whitepapers and marketing material to attract investors, then disappear with the funds once enough capital has been raised or when the fraudulent nature of the ICO is revealed (Baum, 2018).

Pump and dump schemes involve outside traders inflating the price of a cryptocurrency by releasing exaggerated, false and/or misleading positive statements in order to sell the cheaply purchased cryptocurrency at a higher price. Once the operators dump their overvalued cryptocurrency, the price typically falls and leaves other investors at a loss (Baum, 2018).

Rug pulls occur when developers launch a token, promote it to attract investment, and then suddenly withdraw all funds thus making the token worthless (Zhou et al., 2024). Both rug pulls and pump and dump schemes are common cryptocurrency scams that might seem similar. However, a rug pull is executed by the project's developers who withdraw all assets or abandon the project, whereas a pump and dump is typically done by external groups who artificially increase a token's price before quickly selling off their holdings for profit (Baum, 2018; Zhou et al., 2024).

Wash trading is a type of market manipulation where a trader buys and sells the same token at the same time to make it look like there's more trading activity than there really is. This practice is often used by exchanges to make their platform seem more popular and active than it actually is (Cong et al., 2019).

Flash loan attacks take advantage of uncollateralized loans that must be borrowed and fully repaid within one blockchain transaction. Because everything happens instantly and within the same block, attackers can borrow large amounts of crypto and carry out actions like manipulating prices or exploiting smart contracts without putting up any of their own money. These attacks can cause major losses in just one hit. Since they happen so quickly and cost very little to pull off, they're hard to spot and stop (Wang et al., 2021).

Sniper bots are automated programs designed to detect new tokens listed on decentralized exchanges and purchase large portions before human traders can react. These bots monitor blockchain activity to detect newly created liquidity pools and execute buy transactions in the same or following block. These bots often support rug pulls and pump and dump schemes by inflating prices early and exiting before the scam is revealed (Cernera et al., 2023).

Table 3 summarizes key fraud types, mechanisms, their primary targets, and risk level assessed by us. The risk factor takes into consideration the potential financial harm, impact that it has on the victims and how likely it is to succeed.

Table 3. Summary of fraud types

Fraud Type	**Mechanism**	**Target**	**Risk Level**
Phishing	Impersonation to steal credentials	Individual users	High
Ponzi Scheme	Returns paid with new investor funds	General investors	High
Fake ICO	Selling non-existent tokens through false marketing	Crypto investors	High
Pump-and-Dump	Artificial price inflation followed by rapid selling	Retail traders	Medium–High
Rug Pull	Liquidity pulled by project creators	DeFi investors	High
Wash Trading	Repeated small amount trading to fake demand	General market participants	Medium
Flash Loan Attack	Manipulating smart contracts using uncollateralized loans	DeFi protocols	High

Fraud Type	Mechanism	Target	Risk Level
Sniper Bot Manipulation	Automated early token buys and exits	Manual traders	Medium–High

DeFi is especially vulnerable to these types of fraud. Its dependence on automated smart contracts, lack of central authority, and no entry restrictions allow attackers to act quickly and anonymously. Recognizing the mechanisms of these fraudulent activities is necessary for developing detection strategies and implementing protective measures. In the following sections, we will explore how such frauds can be identified and how technologies like machine learning can support real-time fraud detection.

2.4 Transaction Tracking in Blockchain networks

One of the most important features of blockchain technology is its transparency. Every transaction recorded on a public blockchain is stored in a decentralized ledger that is visible to anyone. This allows for the tracking of digital asset transfers across addresses and makes it possible to trace suspicious activities. However, while blockchains are transparent, they are also pseudonymous. Wallet addresses are not directly tied to users' real-world identities, which creates challenges in connecting activity to individuals (Bhutta et al., 2021).

Transaction tracking involves following how cryptocurrencies move between wallets and how different addresses interact with each other. Tools like Etherscan[1] and BSCScan[2] offer insights into wallet activity, smart contract calls, and historical data. These tools are commonly used for manual inspection, but advanced analysis relies on more practical methods. For example, blockchain forensics firms such as Chainalysis[3], CipherTrace[4], and Elliptic [5]apply clustering algorithms to associate addresses, which are likely controlled by the same entity, based on patterns like shared inputs or transaction timing. This enables the identification of broader

[1] http://etherscan.io/
[2] https://bscscan.com/
[3] https://www.chainalysis.com/
[4] https://cryptoslate.com/companies/ciphertrace/
[5] https://www.elliptic.co/

networks behind suspicious activity, even when actors attempt to stay hidden across multiple wallets.

Another useful method is graph analysis, where wallets and transactions are represented as nodes and edges in a graph. Analysts can apply network theory to look for patterns such as central hubs, isolated clusters, or outliers. These visualizations help with exposing irregular flows, such as funds moving through multiple wallets in a short period which is often a red flag for money laundering (Cernera et al., 2023; Li & He, 2023). These graph models are getting increased attention and are integrated into real-time blockchain surveillance platforms due to their ability to map complex structures .

Tracking is also applied in monitoring stolen funds. After an attack, analysts follow the stolen assets across wallets and chains. They often look for exit points such as centralized exchanges where Know Your Customer (KYC) protocols to verify identity might help reveal attackers (Rattanabunno & Werapun, 2023). At the same time, analysts also observe how liquidity pools behave and monitor new token launches, as these are often where scams such as rug pulls or flash loan attacks take place.

Anomalies in transaction data refer to behaviors that significantly differ from normal user activity. These could include: out of norm token movements, huge volume transactions within a short timeframe, or a wallet making many quick transactions across different liquidity pools. Those patterns may indicate bot activity, insider trading, or scam. Platforms like Chainalysis [6]use defined rules to detect anomalies and flag them for investigation.

There is lots of potential in transaction tracking and anomaly detection to detect suspicious activities. However, there are new services, such as mixers, tumblers, and privacy coins (Monero and Zcash). They aim to increase privacy which means that they complicate the tracking process and remain a challenge for the blockchain analysts (Zhang, 2023).

Transaction tracking in blockchain networks provides means of monitoring asset flows and identifying potential frauds or illegal activities. As the cryptocurrency market grows, it is crucial to ensure safety in the blockchain systems. Combining tracking techniques with other tools is

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[6] https://www.chainalysis.com/

important for improving traceability in decentralized systems. The next section will explore how the tracking can be enhanced using machine learning techniques.

2.5 Machine Learning for Suspicious Activities in Blockchain Detection

The increasing complexity of fraudulent activities in the cryptocurrency space has led researchers to explore machine learning techniques as a way to detect suspicious activity more efficiently over larger datasets. Several studies have shown how machine learning can help detect fraud in blockchain systems. For example, Giribabu et al. (2022) conducted a study aiming to compare and evaluate different supervised machine learning algorithms in detecting frauds within blockchain transactions. They applied the following models: Logistic Regression, Support Vector Machines, Decision Trees, Random Forests, AdaBoost, Multilayer Perceptron, Naive Bayes, and Deep Neural Networks. Those models were trained on a labeled dataset of transactions, where each record was classified as either fraudulent or legitimate. After preprocessing the data that included normalization and missing value handling, the models were trained and evaluated based on accuracy, precision, recall, and F1-score. Random Forest achieved the highest performance across all metrics, followed by AdaBoost and Deep Neural Networks. The study shows the potential of supervised machine learning for fraud detection and suggests future research should explore unsupervised (clustering) approaches to address the evolving fraud patterns and limited labeled data.

Rahouti et al. (2021) conducted a survey of security threats in the Bitcoin system. The main focus was on how machine learning techniques can be used to detect and prevent fraud and anomalous activities. The authors review both supervised and unsupervised machine learning approaches with models like k-means clustering, support vector machines (SVM), and anomaly detection methods. These models have been used to identify suspicious behaviors in transaction graphs, detect fraud, and reduce anonymity in the Bitcoin network. The research also shows the limitations of current machine learning solutions which are lack of real world labeled datasets and high false positives.

Machine learning can be applied to tasks such as: clustering wallets with similar acting patterns, indicating suspicious token movements, detecting bot activity, or forecasting the possibility of rug pull schemes based on token lifecycle features. These models typically look into features extracted from blockchain data, such as: transaction frequency, token age, liquidity ratios, and wallet connectivity patterns, to develop accurate classifiers (Chawathe, 2018).

One common challenge in using machine learning for crypto fraud detection is the lack of labeled data. Many fraudulent transactions are not confirmed until long after they occur. This makes supervised learning difficult and increases the importance of unsupervised methods that can detect anomalies without explicit examples of fraud. Additionally, as the frauds are evolving the models must be regularly retrained and validated to maintain accuracy (Lorenz et al., 2020).

Another challenge is the hostile environment of DeFi. As detection methods improve, attackers adjust their strategies to escape being detected. This has led to interest in using more advanced models like Graph Neural Networks (GNNs), which can better capture the relational structure of blockchain data (Tan et al., 2021).

Machine learning provides effective tools for identifying fraud in blockchain and DeFi environments. Despite challenges, the adaptability of ML models make them a useful approach for improving security and transparency in the cryptocurrency space.

2.6 Psychological Aspects of Cryptocurrency Investments

The increasing popularity of cryptocurrencies (especially meme coins) cannot be fully explained by technological innovation or economic incentives. Much of the growth in this market has been driven by psychological and social factors that influence investor behavior. Understanding these aspects is key to know why individuals choose to participate in such a volatile and speculative digital asset market.

The article called “Financial Behaviours of Stock Market Investors” (Magesh Kumar, Sujatha & Rajesh Kumar, 2025) reviews past studies on the many ways the thoughts and feelings steer stock-market investors’ choices. It sorts over twenty “biases” into four broad groups: simple mental shortcuts (heuristics), reactions to gains and losses (prospect theory), wider market effects, and following the crowd (herding). It is because we, as human beings, cannot make truly rational decisions when investing. The feelings always mold our decision making. These theories are important to understand, because financial markets use these tactics to convince investors to buy. The study shows that mental shortcuts, especially anchoring (relying too much on first information) and overconfidence, influence investors' decisions most strongly (Magesh Kumar, Sujatha & Rajesh Kumar, 2025). The article "The fear of Missing Out on Cryptocurrency and Stock Investments: Direct and Indirect Effects of Financial Literacy and Risk Tolerance" by Gerrans, Abisekaraj and Liu (2023) shows how advertisements exploit these behaviours. For example, the NFL Super Bowl in 2022 advertised crypto with emphasizing the "Don't Miss Out" theme.

The same paper by Magesh Kumar, Sujatha and Rajesh Kumar (2025) explains some of the financial behaviours. When investors tend to take more risks while there is a chance of losing assets, it is called loss aversion. Regret aversion is when investors try to avoid the feeling of regret. Mental accounting is when investors tend to sort their financial assets into "buckets" that are emotionally satisfying but could be overall not profitable. The situation when investors mistakenly think a market trend is about to turn around so they go against the crowd is called Gambler's Fallacy Bias. Overconfidence makes investors too optimistic, so they downplay risks and ignore other important factors, which creates more uncertainty. Anchoring happens when investors latch onto the first piece of information they see and then let that "anchor" shape all their later decisions. Availability bias describes a situation when investors base their decisions on whatever examples or recent events come to mind first, instead of looking at all the relevant information. Representativeness bias happens when investors spot similarities between a current situation and a past one and assume the outcome will be the same. They are overlooking the fact that things could turn out differently.

2.6.1 Fear of Missing Out

One of the most influential psychological drivers is FOMO: Fear of Missing Out. FOMO encourages individuals to invest in cryptocurrencies out of anxiety that they might miss a potentially profitable opportunity. As Serada (2023) explains, FOMO acts as a "positive fear" that pushes individuals to invest not necessarily based on rational financial analysis, but due to anxiety over missing perceived opportunities others are benefiting from. This emotion is exaggerated through social media, where stories of ‘overnight’ millionaires and viral investment trends dominate platforms like X, TikTok, and Reddit. FOMO often overrides rational financial planning and pushes users to buy into assets at peak prices based on hype rather than informed analysis (Serada, 2023; Krause, 2025).

The article called “A critical review of FOMO behaviour among young investors” by Bo (2023) says that not only in finance, but in several areas of life, FOMO can be influential. The study lists examples such as: managers that are more likely to adopt new technology into their business operations, students that spend more time on Facebook, or Chinese customers that are more likely to use the more expensive, luxury beauty products.

In the financial markets FOMO describes the tendency to follow others’ strategies out of fear that they’ll miss out on potential gains. This behaviour often reflects in herding behaviour. It is typically from those who lack experience in the financial markets. FOMO herding leads individuals to mimic the actions of others to avoid foregoing profit opportunities in financial markets, but it is also popular during the more volatile periods. Studies show that even during the 2008-2010 financial crisis and the COVID-19 pandemic, people were more likely to impersonate this type of behaviour (Bo, 2023).

The already mentioned prospect theory (Loss Aversion, Regret Aversion, Mental Accounting) and heuristic-driven biases (Gambler’s Fallacy, Overconfidence, Anchoring, Availability Bias, Representativeness) are key drivers of FOMO herding, as investors allow feelings of regret, loss aversion, and peer pressure to guide their decisions and be drawn to assets with easily accessible track records. This means that FOMO is not only driven by herding but also increases other biases, such as loss aversion, especially among younger investors (Bo, 2023).

2.6.2 You Only Live Once

Closely related to FOMO is the YOLO (You Only Live Once) mindset, which encourages risky and thrilling/exciting behavior for the chance of high rewards. YOLO investors are often drawn to meme coins like Dogecoin, Shiba Inu, or the $TRUMP token. They view them as opportunities for fast gains rather than long-term investments. Their behavior aligns with the broader shift towards individual empowerment and democratization of finance, yet it also introduces volatility and unpredictability into the market. (Serada, 2023; Krause, 2025).

2.6.3 Herding

Herding is when people tend to copy other investors' behaviour. Most of the time it is because of the lack of experience in the financial market. For those who have less experience, this is the more rational decision to do, because gathering their own information is costly. This leads to groups of investors moving in the same direction for extended periods, creating correlated trading patterns that can cause them to make systematic mistakes. Because of herding, you need more different kinds of investments to really spread risk. Also, if everyone sticks to the crowd's choice, prices can drift away from what a company or asset is worth, so some investments end up over or underpriced (Chiang & Zheng; 2010).

2.6.4 Bandwagon Effect

The bandwagon effect is when people go along with what everyone else is doing, even if it isn't their first choice. Researchers have also shown it ties into our self‑image, materialism, and the need to both stand out and fit in (Bindra, 2022). Bandwagon effect is commonly present in everyday life. People rely on it, when checking reviews, recommendations online, because they feel more at ease when they follow the crowd (Nadroo, Lim & Naqshbandi, 2024).

2.6.5 Other Factors

Social identity and cultural belonging are additional factors that play a significant role in why people invest in cryptocurrencies. As Krause (2025) explains in his study of the $TRUMP meme coin, many users are not just looking for financial returns but rather they are using these coins to express political views or cultural affiliations. Meme coins can serve as digital symbols of identity, especially when they are linked to public figures or social movements. The humor, inside jokes, and common narratives behind these coins help create a sense of community among holders. This makes the act of investing feel both socially and emotionally meaningful.

All those psychological and social factors show that investing in cryptocurrencies is not purely a financial decision. For many participants, it is about emotion, identity, and belonging. While these motivations help explain the rapid growth and interest in crypto assets, they also point out vulnerabilities. Emotional investing can lead to impulsive decisions, reduced attention to risk, and exposure to manipulation or market crashes. Understanding these human behaviors is crucial for building safer and more transparent financial ecosystems in the digital space.

2.7 Profiling Cryptocurrency Investors

Around 2017, the number of investors of cryptocurrencies increased, even when authorities around the world advised against it. The area of profiling the investors is still under research. The main cause of this is the anonymity that comes with investing in crypto, which we already mentioned in the previous subchapters. Therefore, studies from this topic are limited (Lammer, Hanspal & Hackethal, 2019; Chhatwani, Parija, 2023).

The paper called “The Characteristics and Portfolio Behavior of Bitcoin Investors: Evidence from Indirect Cryptocurrency Investments” by Lammer, Hanspal and Hackethal (2019) drew on administrative data from a German bank to profile indirect cryptocurrency investors. These investors appeared to be mostly male, held larger portfolios, and made bigger use of the bank’s innovative offerings, so they weren’t afraid to use technology. They logged into online banking more often, traded more frequently, and maintained broader holdings, especially in individual stocks. Both their login and trading activity spiked even further after their first Bitcoin purchase. We also find that their portfolios carry higher betas, meaning that they carry higher risk. Behavioral biases like trend-chasing and a “lottery-stock” mindset may be influencing their investment choices.

Even though this study was about purchasing Bitcoin in Germany, the study also states that investors with similar assets would have resembling profiles in US and other European countries (Lammer, Hanspal & Hackethal; 2019).

The study “Who invests in cryptocurrency? The role of overconfidence among American investors” by Chhatwani and Parija (2023) examines American investors and the correlation between owning cryptocurrency and being overconfident. Apparently, the overconfident investor is 8% more likely to invest in crypto.

Another study conducted in Brazil shows that people who invest in crypto are more likely to be among the younger generation, male, risk tolerant and they are less optimistic when it comes to the situation of the economy. Both those that invest in crypto and the ones that don't, have similar backgrounds when it comes to finance education and similar fields. Also, main findings indicate that compared to early adopters, late investors are more influenced by past returns and low interest rates (Colombo, Yarovaya; 2024).

Nemeczek and Weiss (2023), like previous studies, found that those who invest in cryptocurrencies are mainly male. They are also more prone to taking the risk. They like to spend more on technological devices, food and public transport, but not on healthcare and high rent. This is the most typical for a student. They also prefer to go with their own instinct and not use any help from a financial advisor, because they say that they have a high financial literacy. Also, the more savings they have, the more likely they will buy cryptocurrencies.

3. Empirical Context

For our analysis, we chose to focus on $TRUMP, $MELANIA, and $LIBRA. At the time we began writing our project, meme coins were already a notable trend in the cryptocurrency world. However, political meme coins, like those endorsed to figures such as Donald Trump and Melania Trump, were not present in crypto space. These particular tokens became a hot topic and gained significant attention in the crypto community, which sparked our curiosity. The popularity of these coins raised important questions regarding their role in the broader cryptocurrency market, particularly in terms of how political figures and events could influence the creation and success of digital assets. This unique combination of meme culture and politics presented an intriguing area for our research.

3.1 Solana Blockchain

Solana is an open-source blockchain platform designed to support decentralized applications (dApps). Since its launch in 2020, Solana has offered one of the fastest transaction speeds and lowest fees in the blockchain space. It is popular in decentralized finance, non-fungible tokens, and meme coins (Kapron, 2025; Picardo, 2024; CoinGecko, 2025).

Solana uses a combination of technologies as its system is based on Delegated Proof-of-Stake and Proof-of-History. PoH puts a timestamp on every transaction, so the network knows exactly when things happen. This helps validators agree on the order of transactions quickly, without constantly checking in with each other (Kapron, 2025; CoinGecko, 2025). Thanks to this setup, Solana can process thousands of transactions per second with very low fees (Picardo, 2024).

The advantages of Solana are its speed, affordability, and strong developer tools. It enables real-time financial applications and microtransactions that would be too expensive or slow on many other chains. However, Solana has also faced challenges. It relies on high-performance hardware that can limit decentralization, and it has experienced network outages in the past, especially during periods of high demand (like during higher demand for $MELANIA). Despite these issues, upgrades have helped Solana recover (Kapron, 2025; CoinGecko, 2025).

Solana was chosen as the blockchain for all three tokens analyzed in this study ($TRUMP, $MELANIA, and $LIBRA). Its ability to support high transaction volumes at low cost makes it a fitting platform for meme coins that rely on hype (meaning increased demand when promoted).

3.2 $TRUMP

$TRUMP is a meme cryptocurrency launched on January 17, 2025, on the Solana blockchain (mint address: 6p6xgHyF7AeE6TZkSmFsko444wqoP15icUSqi2jfGiPN). It was introduced a few days before Donald Trump's presidential inauguration. Unlike other Trump meme coins, this token stood out as it was officially endorsed by Donald Trump (on X platform and Truth social). It was developed by CIC Digital LLC and Fight Fight Fight LLC, a company specifically formed for this project (MEXC, 2025a; Bitrue, 2025b).

As the official website of the cryptocurrency states[7], 200 million $TRUMP tokens were made available to the public at launch. 80% of the total supply is controlled by CIC Digital LLC and Celebration Cards LLC (owner of Fight Fight Fight LLC). Over the next three years, their supply is planned to be released according to a set schedule. These entities are also entitled to collect revenue from $TRUMP transactions, according to the project's terms and conditions.

The project's official website positioned $TRUMP not as an investment or financial product, but as a form of cultural expression and community engagement. According to the site, $TRUMP is meant to celebrate values such as optimism and success, and to offer a sense of shared identity among supporters. It also states that the token is not officially tied to any political campaign or government office.

Despite these disclaimers, the launch of $TRUMP is believed to be a controversial event. Because the companies hold the majority of the token supply and would profit from trading activity, many critics raised concerns about centralized control and the possibility of a conflict of interest. The timing of the launch also led the public to discuss monetizing political identity through crypto. From a market perspective, $TRUMP took off quickly and saw a huge increase in trading volume (over 300%) and market cap within its first few days. It got to the top 20

[7]Retrieved from:
https://gettrumpmemes.com/#tokenomics

cryptocurrencies by market cap. This was possible due to the online hype and promotion on platforms like X. However, within the crypto community, many professionals criticized it and viewed it as a publicity stunt since Trump commented about not fully understanding how crypto works. The coin's volatility and its centralized supply led to speculation about a potential pump-and-dump. As no sell off was organized by now, the possibility of the coin being a scheme remains a concern due to the supply schedule and the concentration of tokens by project owners. Still, $TRUMP represents a new type of risk meme coin as it includes celebrity (political) branding, online culture, and crypto trading (Tidy, 2025; Gallagher, 2025).

3.3 $MELANIA

$MELANIA was launched on January 19, 2025 just before Donald Trump's second presidential inauguration (mint address: FUAfBo2jgks6gB4Z4LfZkqSZgzNucisEHqnNebaRxM1P). The coin was officially backed by Melania Trump and developed by a company called MKT World LLC. The launch was promoted directly to her followers on X. The information about release quickly spread across social media and within the first hour it attracted nearly 20 000 holders. At the very beginning $MELANIA reached $2 billion in market capitalization (Capital.com, n.d.). As stated on the coin official website[8]: it was promoted as a digital collectible and a way for fans to connect with Melania's vision and not as an investment. The coin is believed to represent the charitable focus of Melania as the transaction fees are donated to support foster children through the Be Best campaign (Bitrue, 2025a).

The coin was surrounded by lots of controversies. One of the biggest concerns was the centralization of the token supply. Data revealed that 90% of all $MELANIA tokens were stored in a single wallet[9], which might lead to potential market manipulation. While the token allocation included categories like team vesting, community use, and liquidity, the dominance of one wallet made the token's decentralization questionable from the start (TOI Business Desk, 2025).

The launch of $MELANIA had an immediate effect on the performance of the $TRUMP token. It is most likely that $MELANIA got the attention of the same audience of political traders as

[8] https://melaniameme.com/
[9] Data analysis done by Bubblemaps: https://app.bubblemaps.io/sol/token/FUAfBo2jgks6gB4Z4LfZkqSZgzNucisEHqnNebaRxM1P?id=qL34suI5QlNCyAyIdN0S

$TRUMP. As a result, many investors shifted their money from $TRUMP to the new coin. This move in sentiment caused $TRUMP’s value to drop shortly after $MELANIA was announced. Although both coins were presented as digital collectibles rather than serious investments, they ended up competing over investors (Newsweek, 2025).

In the months following its launch, $MELANIA experienced a huge price drop. After reaching an all-time high of over $13 on January 20, 2025, the coin's value dropped by over 97% by May 2025. Despite its initial hype, the coin lost the investors' support. Beyond its price drop, $MELANIA has faced other controversies, such as accusations of insider trading. Just before the official launch, 24 wallets bought $2.6 million worth of tokens and through that made nearly $100 million in profit. $MELANIA’s token structure and lack of information and transparency have also raised concerns. Out of the 1 billion total tokens, 30% went to the team, with 10% unlocked just 30 days after launch and the rest planned to be released over the next year. This short period increases the risk of early sell-offs that could hurt smaller investors. $MELANIA’s ties to public figures have also raised ethical and legal issues. In early 2025, Senator Chris Murphy proposed the MEME Act to stop public officials from promoting meme coins. He used the two coins ($MELANIA and $TRUMP) as examples of projects that could be used for personal gain (MEXC Blog, 2025b).

3.4 $LIBRA

The $LIBRA token was launched on the Solana blockchain on February 14, 2025 (mint address: Bo9jh3wsmcC2AjakLWzNmKJ3SgtZmXEcSaW7L2FAvUsU). It became one of Argentina’s most infamous and controversial crypto. It was promoted by Argentine President Javier Milei on his social media accounts (Buenos Aires Times, 2025). The coin was presented on the official website[10] as a private initiative meant to help the national economy by supporting small businesses and entrepreneurs. The project’s message: “The world wants to invest in Argentina,” was published across platforms to give a sense of national purpose.

$LIBRA was created by Kelsier Ventures, who had previously met with President Milei. The project was branded as part of the “Viva La Libertad” campaign. It was supposed to attract

[10] https://www.vivalalibertadproject.com/

capital into Argentina. However, the fact that several people involved had ties to Milei raised concerns about whether the project was independent or political (Blockchain Council, 2025).

Shortly after the announcement, $LIBRA's value collapsed by close to 90%. This drop caused suspicion and public backlash. Milei quickly deleted his original post and issued a follow-up stating that he had no direct involvement in the project and withdrew his support after learning more about it (TRM Labs, 2025).

On-chain analysis by TRM Labs (2025) showed patterns that indicated possible market manipulation. Roughly 20 minutes before the President's tweet, one of the wallets received 1 million $LIBRA tokens and added them to a liquidity pool on Meteora (DeFi platform). This wallet then distributed tokens to other addresses that also contributed to the same pool (likely to fake the interest). Then, large amounts of funds were pulled from the pool, which led to a quick drop in the price. TRM found that more than $7.8 million worth of Solana (SOL) was moved through wallets likely belonging to the $LIBRA team. All that money was eventually sent to one wallet that held about $90 million in crypto. These findings caused speculation that the project was a planned and coordinated pump-and-dump or rug pull (TRM Labs, 2025).

4. Methodology

In this chapter, we explain how we approached the project from a practical point of view, including how we worked with the data, the tools we used, and how we built and tested our solution. Generative AI was used during the writing process to support phrasing improvements and brainstorming. The tool was used as a writing assistant, not as a source of content or analysis. All conclusions and analytical work remain our responsibility. All the code we used throughout the project is available on GitHub: https://github.com/lau0606/master_thesis.

4.1 Analysis of Cryptocurrency Transaction on Blockchain

4.1.1 Dataset

Getting the dataset for the task was quite a challenge as there is a limited amount of datasets available for academic use. After reaching out and researching, we managed to get access to Solana Raw Blockchain Data published by Pinax on Snowflake platform[11]. The dataset included all Solana blockchain transactions for January 2025. After contacting creators, we were granted access to data for February 2025 as well. In this research, we covered the timeframe from the respective launch dates for each token: January 17th ($TRUMP), January 19th ($MELANIA), and February 14th ($LIBRA), until February 28th.

Wallets that performed more than 1000 transactions were excluded, as we associated them with centralized exchanges and they don't represent the behavior of individual traders. These wallets handle thousands of users at once, so their transactions are usually just deposits, withdrawals, or internal transfers and not actual trading decisions. Including them would make it hard to analyze patterns like spotting snipers or people trying to manipulate the market. Additionally, in our work we included 300 wallets for $MELANIA and $LIBRA tokens and 292 wallets for $TRUMP to simplify the process of visualization and analysis (including the time spent on loading the data and performing tasks).

[11] Retrieved from: https://app.snowflake.com/marketplace/listing/GZTSZ33VCBM/pinax-solana-raw-blockchain-data

We identified a number of data quality issues in the transaction dataset. It was mostly related to the way transactions were recorded on the Solana blockchain. We needed to work on those inconsistencies to ensure that the analyses conducted later in the study would be based on the most reliable and accurate data.

On the Solana blockchain, it is common for a single block to contain multiple transaction IDs (tx_id), and for a single tx_id to include few transfers involving different tokens. However, in the dataset used for this project, these relationships were not always saved correctly. In a few cases, the dataset contained transactions that had the correct tx_id and block number, but the internal transfer details (e.g., sender, receiver, token type, or amount) were mismatched. To correct this issue, we downloaded all transactions from Solscan in which more than a million tokens were transferred to give us a reference. We made a script which compared each entry in the original dataset against the corresponding verified transactions. If a transaction in the dataset could not be matched exactly to a verified one (based on multiple attributes such as tx_id, amount, and token), it was considered incorrect and removed.

The dataset also included a large number of duplicate entries. After we identified them by comparing key attributes such as tx_id, wallet addresses, token type, and transfer amount, we made sure to remove these duplicates.

Since the dataset did not contain token prices, price estimates were added manually. For the initial launch period (2 first days), we extracted prices from graphs available on CoinMarketCap[12] to have the most reliable solution we can get. As this task was too consuming due to the amount of data, we decided to retrieve daily closing prices from CoinMarketCap and implemented it in a new column to our dataset.

4.1.2 Wallet Mapping and Suspicious Transactions

In order to gain insight into individual wallet behavior, we designed a visualization that we refer to as the wallet map (or bubble map). This tool plots key behavioral metrics like a profit and loss

[12]Retrieved from:
https://coinmarketcap.com/currencies/melania-meme/
https://coinmarketcap.com/currencies/official-trump/
https://coinmarketcap.com/currencies/libra-viva-la-libertad-project/

mapping, cluster mapping, and suspicion mapping defined by us using the suspicion score (described in further part). The implementation was done in Python with the use of libraries like: pandas for data handling, scikit-learn for clustering, and bokeh for constructing the HTML interface.

The idea behind the map was to arrange wallets such that users could visually distinguish between different levels of engagement and profitability. The horizontal axis (x-axis) represents each wallet's total profit or loss which was calculated as the USD value of tokens sold minus the value of tokens purchased. The vertical axis (y-axis) represents the number of trades executed by each wallet. A value of 0 corresponds to the average trade count across all wallets. Wallets positioned above that conducted more trades than average, while those below it were less active than the average. Each wallet was plotted as a bubble whose size reflects the absolute profit (scaled using the square root function for better visual separation). The colors change depending on the visualisation types (specific color meaning is described in the research findings section).

To visualise behavioral patterns, we applied the KMeans clustering algorithm. This unsupervised technique grouped wallets into five clusters based on similarities in two metrics: profits and trading activities.

Following, to detect suspicious wallets during the early trading phase of meme tokens, we conducted a wallet level analysis on all three tokens. The goal was to visualize wallet behaviors, assess profit/loss, and flag suspicious activity using a transparent and repeatable methodology. In order to do so, we created a scoring system called the suspicion score. The idea was to combine a few signs of suspicious behavior into one metric. We looked at five specific criteria:

1. Conducted at least one transaction within the first five minutes of token launch.
2. More than three transactions in the first 15 minutes.
3. Realized gains exceeding $1,000.
4. Held more than 2% of the token's circulating supply.
5. Classified as a wash trading wallet.

Each of these criteria was chosen because they indicate patterns often seen in suspicious or bot behavior during early token launches. Trading within the first five minutes might indicate sniping as bots try to buy tokens before regular users can react. Making more than three trades in the first 15 minutes shows high activity which might suggest automated trading or attempts to manipulate price swings. Earning over $1 000 in profit in such a short time isn't suspicious on its own, but when combined with other behaviors, it can indicate someone took unfair advantage of early price movements. Holding more than 2% of the total supply gives a wallet power over the token's market. If such a wallet suddenly dumps its tokens, it could hurt the price or decrease investor confidence. It's worth noting that wash trading behavior was initially not included in the suspicion score. However, during the analysis, we realized that many wallets showing wash trading patterns were not being marked as suspicious. To fix this, we added wash trading as a fifth criterion in the suspicion score. These criteria were selected based on insights from the literature review conducted earlier in this thesis. We assigned one point for each of the criteria listed above. Then, we calculated the suspicion score by adding those points for each wallet. A suspicion score of 2 or higher (out of 5) was used as the threshold for marking a wallet as suspicious.

In addition to the suspicion score, we also marked wallets involved in sniping or wash trading based on patterns we observed in the transaction data. We used a rule that if a wallet made a transaction within the first 3 minutes of a token launch it was marked as a sniper (since snipers perform transactions quicker and not following human reaction and decision time). To detect wash trading, we looked for wallets that performed at least 6 transactions (buying and selling) within a 5 minute window and where the combined volume was at least $100. These conditions were chosen to filter out normal trading and focus on wallets that appeared to be creating fake activity by trading with themselves or through repeated buys and sells.

4.1.3 On-chain Behavior

To analyze transaction data from the Solana blockchain, we built a data processing pipeline in Python. The used libraries were: Pandas for data analysis, Matplotlib for visualisations, and Os for managing files.

We started by cleaning the dataset to make sure it was consistent which included removing duplicate transactions. We cleaned up column names to make them easier to read and converted the block_time column to datetime format. After that, we renamed it and used it as the index for all our time analysis.

Once the data was clean, we grouped transactions by token and calculated several key metrics on an hourly basis. These included total token volume, the number of unique wallets per hour, how many new wallets joined, the number of transactions, and the average transaction size. To detect suspicious behavior, we used two rules. First, we labeled "sniper" transactions as any buy trades that happened within the first three minutes of the token's first recorded trade. Second, we flagged "wash trading" if a wallet completed at least six back-and-forth (buy-sell) transactions within a five-minute window, and the total volume of those trades was at least $100. These metrics were chosen to help with understanding the overall trading activity and how users behaved in the early trading period for each token.

We then generated visualisations for each metrics. To make our analysis more readable, we removed the highest outliers (0.5 percentile) as they influenced the scale. The actual data was kept in full and saved separately for reference. For each token, we created a CSV file with the full dataset of calculated metrics that can be found on our github.

4.2 Analysis of Discussion about Tokens

4.2.1 Dataset

To get a deeper understanding of the blockchain data's analysis and the psychological side of the crypto phenomenon, we needed to perform text analysis. Because news articles often use formal language that doesn't reflect the average crypto investor's voice, we decided to collect data from social media instead. While Twitter is one of the largest platforms for these discussions, its free API was too limited for our purposes. Reddit, however, hosts large, topic-focused communities. Its discussions are organically generated, topically diverse, and often rich in sentiment language. This made Reddit the ideal choice for our analysis.

We registered a Reddit script application, Python 3.10 with PRAW, to obtain a client_id, client_secret, and username/password for read-only access. Subreddits were gathered in different types of topics, mainly cryptocurrencies, but also technology and economics (see table 4). All subreddits were checked using the key words including: trump, melania, libra, official trump, memecoins, melania coin. The date range was defined as the coin launch to February 28, 2025 (to comply with the Solana dataset that we managed to get access to). All relevant posts were retrieved and comments to be stored did not get a limit either. The code can be found in the file ‘commentdownloader.ipynb’.

Table 4. Subreddit with relevant threads that were used for creating datasets

Subreddit	Coin	File Name
r/AskConservatives	MELANIA	askconservatives_melania.csv
r/AskConservatives	TRUMP	askconservatives_trump.csv
r/TheRaceTo10Million	MELANIA	therace_melania.csv
r/TheRaceTo10Million	TRUMP	therace_trump.csv
r/solana	MELANIA	solana_melania.csv
r/solana	TRUMP	Solana_trump.csv and solana_trump_2.csv
r/solana	LIBRA	solana_libra.csv
r/AskTrumpSupporters	TRUMP	trump_supporters_trump.csv
r/WallStreetBetsCrypto	TRUMP	wallstreetbets_trump.csv
r/WallStreetBetsCrypto	MELANIA	wallstreetbets_melania.csv
r/WallStreetBetsCrypto	LIBRA	wallstreetbets_libra.csv
r/CoinBase	TRUMP	coinbase_trump.csv
r/CoinBase	MELANIA	coinbase_melania.csv
r/economy	TRUMP	economy_trump.csv
r/economy	MELANIA	economy_melania.csv
r/economy	LIBRA	economy_libra.csv
r/CryptoMarkets	MELANIA	CryptoMarkets_melania.csv
r/CryptoMarkets	TRUMP	CryptoMarkets_trump.csv
r/CryptoMarkets	LIBRA	CryptoMarkets_libra.csv
r/CryptoCurrency	TRUMP	CryptoCurrency_trump.csv and

Subreddit	Coin	File Name
		CryptoCurrency_trump_2.csv
r/CryptoCurrency	MELANIA	CryptoCurrency_melania.csv
r/CryptoCurrency	LIBRA	CryptoCurrency_libra.csv
r/technology	TRUMP	Technology_trump coin.csv
r/technology	MELANIA	Technology_melania coin.csv
r/economicCollapse	TRUMP	economicCollapse_trump.csv
r/economicCollapse	MELANIA	economicCollapse_melania.csv

The following fields were saved to CSV files:

- Thread title
- Thread URL
- Thread time utc
- Thread score
- Comment time utc
- Comment score
- Comment text

We treated thread title and comment text as the main inputs for sentiment analysis. The UTC timestamps let us track how investors' discussions evolved over time, especially during coin "pump and dump" phases. The thread and comment scores let us weigh each comment by its popularity. Following table shows the size of created datasets and the distribution of the number of threads, and number of comments for each coin (table 5).

Table 5. The dataset size

Coin	$TRUMP	$MELANIA	$LIBRA
Number of Threads	354	120	37
Number of Comments (before cleaning)	56 775	15 886	1 963

We first prepared the raw CSVs for text analysis by merging each coin's files into a single dataset: one file for $LIBRA, one for $TRUMP, and one for $MELANIA. Then we performed different data processing to ensure that our datasets were consistent and ready for further analysis.

4.2.2 Topic Modelling

To better understand the themes and discussion patterns in Reddit comments related to meme coins, we applied topic modelling using the BERTopic framework. This approach allowed us to extract topics from unstructured text data and track how discussions changed over time.

Overview of BERTopic

BERTopic is a topic modelling technique that combines transformer-based embeddings, dimensionality reduction, and clustering based on density. It outperforms traditional models like Latent Dirichlet Allocation (LDA) in short-text and semantic contexts by using pre-trained language models such as BERT. Instead of relying on word frequency counts, BERTopic captures relationships between words and documents (Grootendorst, 2022).

The topic modelling pipeline we used in this project is based on BERTopic, which combines few techniques to identify and describe themes in text. First, each Reddit comment was turned into a numerical vector using the all-MiniLM-L6-v2 model from SentenceTransformers. This model captures not just the meaning of individual words, but also the context they appear in, therefore making it ideal for understanding informal and slang language like meme coin discussions. After that, we used UMAP to reduce vectors into a lower-dimensional space so that they could be grouped more easily. To form the actual topics, we applied HDBSCAN which is a clustering algorithm that doesn't require us to define the number of topics ahead of time. Finally, to make the topics easy to interpret, BERTopic uses a technique called class-based TF-IDF (c-TF-IDF), which highlights the most important words for each topic by comparing them to the rest of the dataset.

Data Preprocessing

We began by preprocessing the text data to remove noise and standardize the format. We merged the files and then we applied general text cleaning to produce cleaned_libra.csv, cleaned_trump.csv, and cleaned_melania.csv. During cleaning, we converted all text to lowercase, removed URLs, stripped out special characters and collapsed extra spaces (code available in the file: data_preparation_m.ipynb). We applied a minimum length filter to remove very short comments (fewer than 4 words after cleaning). We also deleted the duplicates of comments as those suggested bot behaviour, advertisement, or information about removed comments by user or moderator. Each cleaned document was stored in a new column and used as input to the embedding model. After all the preprocessing, we were left with: 45 654 comments for $TRUMP, 12 813 comments for $MELANIA, and 1 476 comments for $LIBRA.

Topic Reduction and Selection

After the initial topic modelling, the number of generated topics was overwhelmingly high, from 50 to over 150 topics for the coins, with some clusters being overly specific or containing very few documents. To improve interpretability, we used BERTopic's reduce_topics() method to merge similar topics and reduce repetition. Topic reduction was guided by manual inspection of topic keywords, visualization of topic distribution and distances while monitoring the number of documents assigned to the outlier topic "-1". In order to reduce the number of comments in the outlier group, we have experimented with the parameter min_cluster_size of HDBSCAN which sets the minimum number of comments needed to form a topic. By increasing this value, we made sure that only more substantial and meaningful groups of comments were turned into topics. This helped avoid having too many tiny or overly specific topics and made the overall topic structure clearer and easier to interpret. We settled on a model with a different number of relevant topics for each coin: $TRUMP with 10 topic groups, $MELANIA with 9, and $LIBRA with 8.

Visualization

To get a better understanding of how the topics relate to each other, we created a few visualizations using BERTopic. The intertopic distance map shows how similar or different the topics are by placing them in a graph. Topics that are closer together share more semantic content. We also used that map to visualize how big each topic is in terms of the number of documents it contains, which helped us identify which topics were most dominant in the dataset. Additionally, the topic hierarchy gave us an overview of how similar the topics are based on their keyword distributions. Once the model was finalized, we saved the key results, including the main topics, top keywords for each topic, and some representative example posts. All code and outputs can be found in our GitHub repository.

4.2.3 Sentiment Analysis

For our sentiment analysis, we relied mainly on NLTK. It is a natural language toolkit, which helps working with human language data. It provides modules for common NLP tasks like tokenization, stemming, tagging, and parsing (NLTK, n.d). We also used Pandas for data handling, Matplotlib for plotting, and NumPy for efficient numerical operations.

To compare different approaches, we incorporated two sentiment models into our pipeline. VADER (Valence Aware Dictionary and sEntiment Reasoner) is a rule-based tool tuned for social-media text. It uses a lexicon of sentiment-intensity scores and simple heuristics for things like all caps, degree modifiers ("very"), punctuation (e.g., "!!!"), and emoticons. VADER outputs positive, negative, and neutral scores plus a single "compound" score (−1 to +1) that summarizes overall sentiment (Geetha, 2023). TextBlob, by contrast, is a higher-level library built on NLTK that returns a polarity score (−1.0 to +1.0) and a subjectivity score (0.0 to 1.0). Because TextBlob uses a more general lexicon, it can sometimes miss the slang or emoji nuances found in Reddit comments (TextBlob, n.d). By running both, we could see how a social media focused model versus a general purpose one handled our crypto discussions.

Before running any sentiment models, we applied a cleaning to our merged, raw files. We stripped out all URLs and Reddit mentions, because they didn't add useful semantic content. We then removed every punctuation mark and digit so that our analysis would focus solely on words.

In a separate preprocessing function, we tokenized each text into individual tokens (words) and then lemmatized them, reducing each token to its dictionary form. This step also included filtering out common stop words, ensuring that only meaningful terms remained.

To study how sentiment shifts over a coin's life cycle, we divided each coin's data into three periods: launch, pump, and after-pump/dump (table 6).

Table 6. Defined dates of phases for each token

Phase	$TRUMP	$MELANIA	$LIBRA
Launch	17.01-19.01.2025	19.01-21.01.2025	14.02-15.02.2025
Pump (Peak)	20.01-01.02.2025	22.01-23.01.2025	16.02-18.02.2025
After	02.02-28.02.2025	24.01-28.02.2025	19.02-28.02.2025

The launch phase captures initial reactions and baseline optimism when the coin debuts. The pump phase covers the price change driven by hype, where sentiment typically peaks. Finally, the after-pump/dump phase lets us analyze the sentiment as the coin's value stabilizes or crashes.

The enrich_sentiment_with_votes function works in three main steps. First, it applies the sentiment analyzer (VADER or TextBlob) to each entry's cleaned text and extracts the raw sentiment scores. Then, it pulls in the corresponding vote count (thread or comment score) and multiplies it with the raw sentiment to produce a "weighted_sentiment": metric ensuring that more-popular posts carry more influence. Finally, it adds both the unweighted and weighted sentiment columns back to the DataFrame and returns the enriched dataset for downstream analysis.

Keeping both unweighted and weighted sentiment lets us answer two different questions: unweighted sentiment shows "What's the general tone if every voice counts equally?" while weighted sentiment reveals "What's the tone according to the most-liked or most-disliked comments?"

To directly compare VADER's compound scores and TextBlob's polarity scores, each of which can have different ranges and variances, we standardized both sets of results by converting them into z-scores.

4.2.4 FOMO/Hype Analysis

We began by loading the three raw, merged datasets into pandas DataFrames, parsing both thread_time_utc and comment_time_utc as datetime objects. This makes it simple to work with dates and times later on.

For cleaning these datasets for the FOMO/Hype analysis, we created a full_text column here too, which combines the thread_title and comment_text columns into one. The column with the URL did not seem to be relevant for us, so we dropped it and we also cut everything out which was after the date 28th February 2025.

To identify posts showing "fear of missing out" (FOMO) and general hype language, we created two sets of regular‑expression patterns. FOMO_PATTERNS captures phrases like "next $XYZ," "not financial advice," "yolo," "moonshot," and multiplicative gains (e.g., "10x"). HYPE_PATTERNS looks for words like "exploding," "everyone's buying," "join telegram," and "going viral."

Using a helper function, we checked each comment's text for these patterns. If a comment contained any FOMO or hype term, we assigned a 1; otherwise, we assigned a 0. This produced two new columns in each DataFrame: fomo_flag and hype_flag.

We resampled each dataframe by hour and summed the fomo_flag and hype_flag counts. Then, with a 24-hour rolling window, we calculated the mean and standard deviation of those hourly counts and converted each hour's count into a z-score. Any hour with a z-score above 2 was marked as a significant "spike" (for FOMO) or "wave" (for hype).

We applied these tagging and burst-detection steps separately to the Trump, Melania, and Libra datasets, resulting in three time series that highlight when each community experienced unusually large bursts of FOMO or hype.

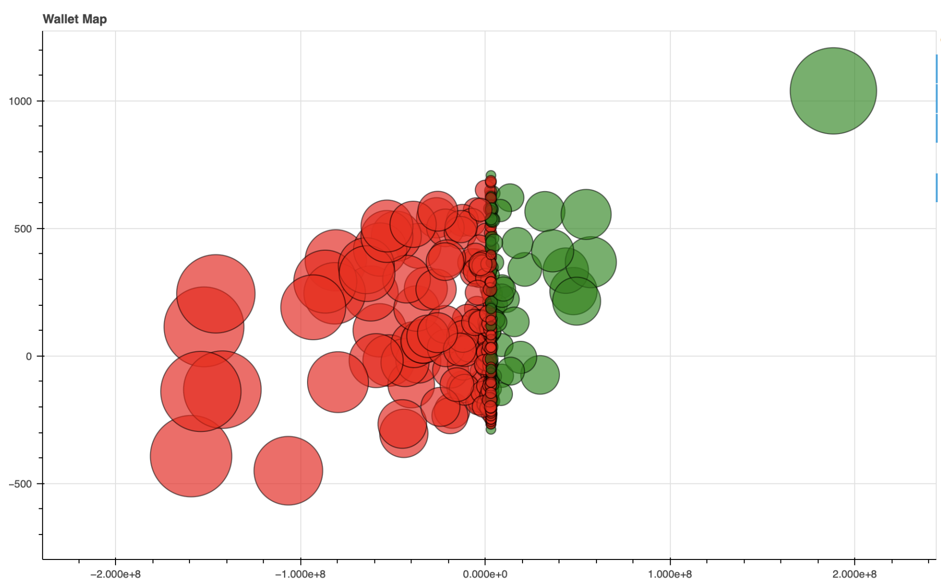
5. Research Findings

5.1 Blockchain Analysis Findings

This section presents the main findings from the on-blockchain wallet analysis of the meme tokens $TRUMP, $MELANIA, and $LIBRA during their early trading periods. We used four visualizations: profit and loss distribution, clustering, suspicion scoring, and scam type detection.

Profit and Loss Analysis

One of the first patterns that stands out from the wallet analysis is the imbalance between wallets that made a profit and those that suffered a loss (see graph 1).



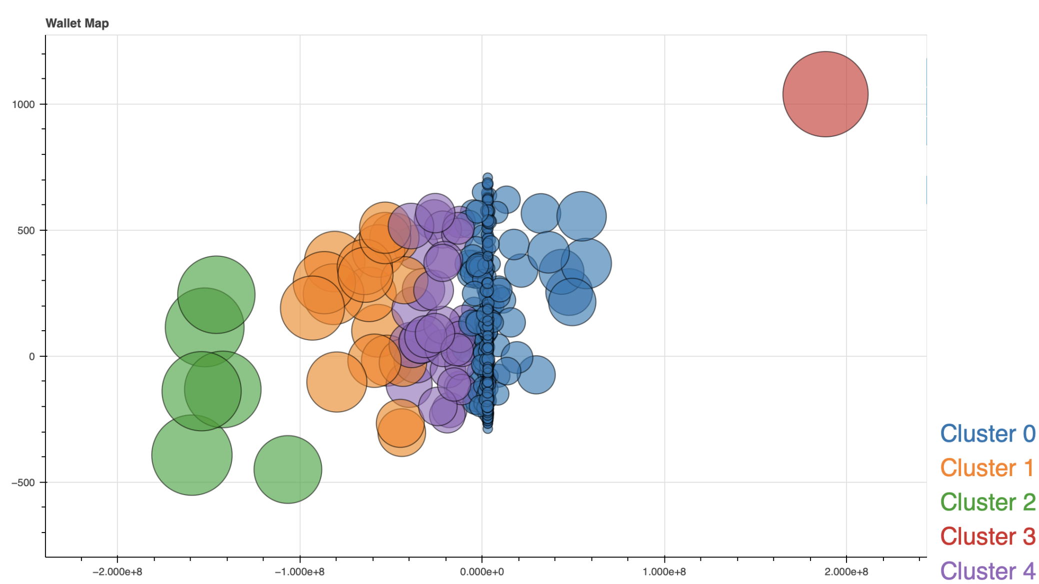
Graph 1. Profit and loss distribution

Across all three tokens combined, only 335 wallets ended up making profit (marked in green), while 548 wallets were in loss (marked in red). When we break this down by token, $LIBRA had the highest number of profitable wallets (126). On the other hand, $TRUMP had the fewest profit wallets (100), and $MELANIA fell in between with 109. However, it is important to notice that even though more wallets profited in $LIBRA, the profit was in total smaller. The distribution indicated that wallets for $LIBRA that had profits earned usually from 200 to 7 000

USD. In comparison, wallets for $MELANIA and $TRUMP had profitable wallets over 1 million USD. There are also visible wallets far from the main group. These outliers likely represent early buyers (possibly insiders) who sold at or near the peak before prices crashed. The large red areas represent wallets that entered too late or held on too long and were caught in the price downturn. This pattern of a small number of wallets making huge profits while most others lose money seems to be typical of meme coins. It brings up questions about fairness, especially since early price movements happen so quickly that only those with perfect timing or special access benefit. For everyday traders, it's an important note that early meme coin trading can be risky and unpredictable, and being even a few minutes late can make a big difference.

Cluster Behavior Analysis

Clustering was used to group wallets based on behavioral similarities, such as transaction patterns, timing, and interaction intensity with each token. The majority of wallets for all three tokens fell into a dominant cluster 0 but the distribution depends on the token (see graph 2).



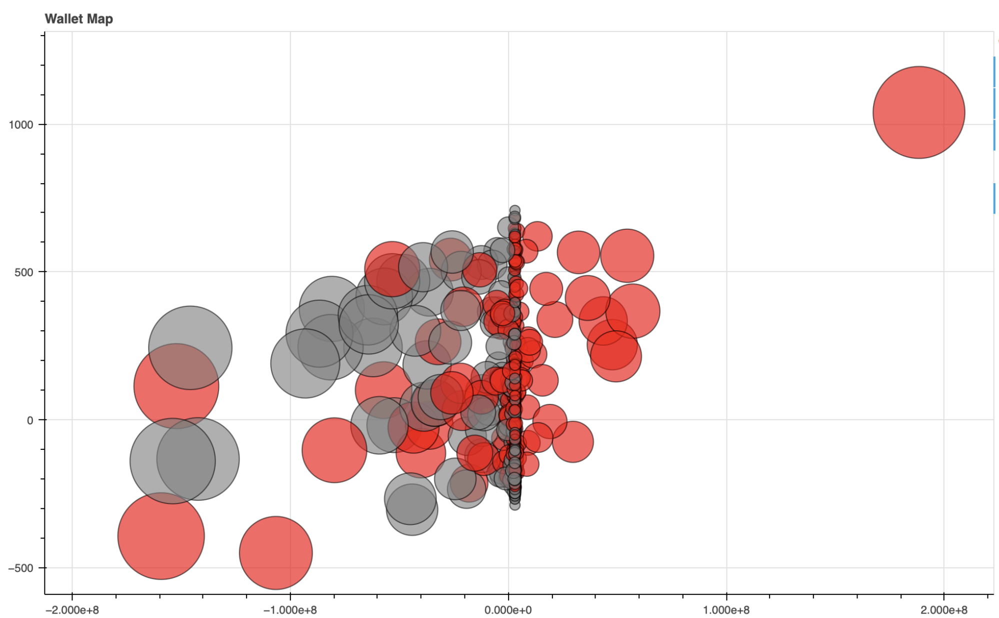
Graph 2. Wallet clusters across all tokens

For $LIBRA there was little cluster variation. Out of 300 wallets, 297 belonged to Cluster 0 . Only three wallets fell outside this main group: two in Cluster 4 and one in Cluster 1. This suggests that most wallets in the $LIBRA token followed very similar trading patterns. In

$MELANIA, clustering was a bit more varied. While 290 wallets were part of Cluster 0, seven wallets ended up in Cluster 4, with 2 in Cluster 1 and 1 wallet in cluster 2. These outliers represent wallets that follow different strategies, such as lower transaction frequency or volume behavior. It is worth mentioning that the wallets who are in other clusters than cluster 0 were at loss. $TRUMP showed the most diverse clustering outcome. Although 243 wallets were in Cluster 0, 57 wallets were split across four other clusters. This suggests that traders may have been experimenting more with different strategies, or reacting to less predictable price swings without the comparison to previous political meme tokens.

Suspicious Behavior, Wash Trading and Sniper Bots

The analysis of suspicious behavior in meme coin trading shows patterns indicating manipulation across all three tokens.

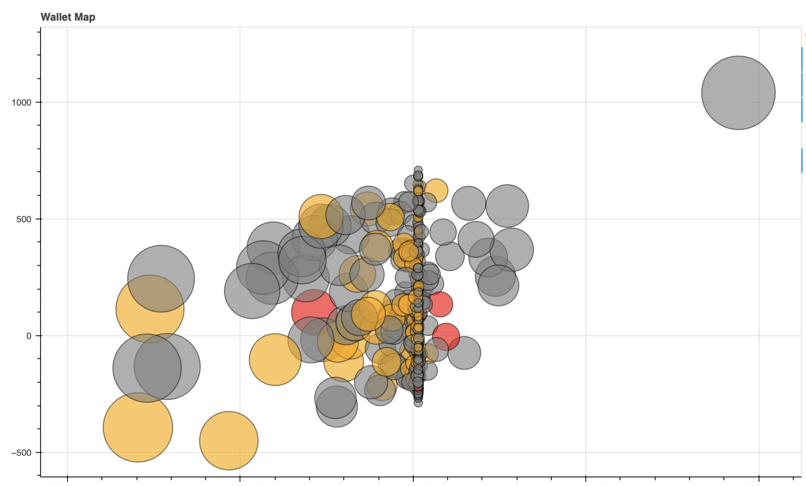


Graph 3. Distribution of suspicious wallets based on suspicion score

Suspicious wallet activity was visualized in Graph 3, where red bubbles represent wallets flagged as suspicious and grey bubbles represent non-suspicious wallets. As described in the methodology, wallets were labeled suspicious if they fulfilled at least two out of five specific criteria. Since one of the criteria is about making more than $1,000 in profit, many profitable wallets appear red in this graph. But the label was not applied based on profits alone as they also had to demonstrate other behaviors or unusual trading patterns, such as highly active behavior in the early minutes of the token launch or holding large portions of the token supply. This means that being marked suspicious shows potential manipulation or unfair advantage.

It is worth noting that the suspicious label was not exclusive to profitable wallets. In fact, many of the wallets with the highest losses were also flagged as suspicious. This may indicate failed attempts at manipulating the market that did not pay off as not all unfair trading strategies lead to gains.

Looking at the numbers, $TRUMP and $MELANIA had the highest number of suspicious wallets with 162 and 156, while $LIBRA followed with 132. This shows that suspicious activity was not an issue of one token, but rather a common issue affecting those political coins.



Graph 4. Distribution of wash trading and sniping among wallets

Graph 4 highlights wallets involved in specific types of scams. We can see the wallets involved in wash trading (yellow), sniping (red), and other wallets (grey). One of the interesting patterns is that the majority of wallets identified as wash traders ended up losing money. This suggests that their efforts to create fake market activity through artificially increasing trading volume may have backfired or were not profitable in meme coins volatile conditions.

In terms of numbers, $TRUMP had the most wash traders with 101 wallets, followed by $MELANIA with 91, and $LIBRA with 68. What stands out is the low number of wallets marked as snipers. There were 2 sniper wallets for $TRUMP and $MELANIA, and 6 for $LIBRA. One wallet on $LIBRA was flagged as both a sniper and a wash trader. Even though people often say that sniper bots take over new token launches, our result might seem surprising as not many snipers were detected. One explanation could be that token launch mechanisms on Solana have improved and it is harder for snipers to gain an advantage. Another possibility is that sniper bots are now more advanced and behave in ways that are harder to spot using the rules we applied in this analysis.

These findings show that while suspicious activity is commonly present in meme coins and takes many forms, profit is not guaranteed. Even manipulative strategies often result in losses.

$TRUMP

The trading activity of the $TRUMP token on the Solana blockchain changed through three phases between January 17 and February 28, 2025. The initial period following the launch was characterized by high levels of user activity. During this phase, the number of new wallets entering the space reached 33 370 per hour, with an average of 13 971. The number of unique wallets transacting during this period reached 78 047 and averaged 37 830 per hour. The transaction count during the launch phase reached a maximum of 409 669 transactions in an hour with an average of over 225 000. Those numbers indicate significant interest in the early launch as users joined and interacted with the new token.

We also noticed signs of potentially manipulative trading activity. The number of transactions flagged as possible wash trades reached a maximum of 290 997. It suggests an intentional attempt to inflate trading volume. A single transaction was identified as a potential sniper trade, which might seem unusually low for the meme coin space.

In the following period, January 20 to February 1, 2025, a decline in most metrics was observed. The number of new wallets decreased to the average of 1 448 per hour, while the number of unique wallets fell to an average of 6 470. Transaction activity remained high but reduced compared to the launch period. The peak was 325 970 and a mean of approximately 57 170 transactions per hour. Wash trading activity continued with the average of 48 154 suspicious transactions per hour.

From February 2 to February 28, 2025, trading activity declined further. The number of new wallets averaged 271 per hour. Unique wallet activity decreased to a mean of 1 255. Transaction counts fell to an average of 14 122 per hour. The average transaction size also decreased, reaching a mean of 35 216 tokens. Wash trading could still be observed but at lower intensity, with an average of 11 160 flagged transactions per hour. No additional sniper activity was identified during this final phase, which is understandable as snipers hit in the early phases of tokens.

In summary, the $TRUMP token experienced a very active launch period which was characterized by high user participation. However, much of those transactions appear to be artificial activity. This was followed by a decline across all metrics. This suggests that initial interest was not kept through time. All observed patterns are consistent with the typical lifecycle of speculative meme token launches.

$MELANIA

The $MELANIA token showed a pattern typical for hyped meme coins. It started with a strong launch and was followed by a short raise in activity that eventually fell. In the first few days after its launch (January 19 to 21, 2025), the token experienced very high levels of engagement. The number of new wallets reached up to 45 713 per hour and unique wallet participation to 75 361 per hour. This indicates the widespread early interest likely caused by the hype. Transaction activity was also intense as the hourly counts reached up to 396 064 and averaged around 108 900.

This early phase was also marked by signs of wash trading. On average, nearly 80 000 transactions per hour were flagged as potential wash trades. The peak of suspicious transactions was 260 010. As in the case of $TRUMP, these levels suggest that much of the trading volume may have been artificially inflated to generate attention. A single sniper transaction was detected during the launch period, but overall sniper activity remained minimal.

In the days that followed (January 22 to January 23, 2025), activity dropped but did not stop. New wallet creation fell to an average of 858 per hour, while unique wallet participation averaged around 2 800. Transactions decreased to about 26 200 per hour on average. At the same time, the average transaction size dropped to around 59 600 tokens which indicates a shift away from large trades. Wash trading was still present but lower (around 22 600 transactions) which suggests that manipulation stayed present even as activity on the blockchain slowed.

From January 24 through the end of February, engagement with the token declined even more. New wallets fell to an average of just 161 per hour, and unique wallets transacting dropped to about 541. Transaction counts averaged 5 500 per hour. Wash trading was still detectable but the number dropped to an average of just over 4 000 flagged transactions per hour. Same as in the case of $TRUMP, no sniper activity was identified during this final phase.

The $MELANIA token saw a very active launch period that was likely boosted by artificial trading behavior as well as the hype from the launch and, at that moment, the success of the $TRUMP coin. There was a brief period of interest followed by a decline across all mentioned indicators. The trends observed suggest that while the token initially drew attention, much of it may have been driven by manipulation or initial hype rather than honest user engagement.

$LIBRA

The $LIBRA token experienced a very sharp rise in activity following its launch on February 14, 2025. However, this initial enthusiasm faded quickly. In the first two days, the project drew significant attention. There were up to 47 747 new wallet creations in a single hour. Unique wallet activity was also strong during this period. It peaked at 52 783 per hour. These figures point to a high level of interest right after the token went live which was likely due to the marketing. Transaction activity was also intense. The number of transactions peaked at close to 438 000 per hour but the average was just under 48 000.

However, our analysis revealed that a large part of the activity may have been manipulated as there were clear signs of suspicious trading. Wash trading was especially present as hourly counts reached up to 276 135 flagged transactions with average nearly 30 000. In contrast to other tokens, $LIBRA also showed more sniper activity identified as attempts to purchase immediately after liquidity was added.

Between February 16 and 18, activity dropped across all key metrics. The number of new wallets fell to an average of just 329 per hour, while unique wallet participation declined to around

1 200. Transaction counts also decreased to 6,000 on average per hour. Wash trading continued, but with just over 4 000 flagged transactions per hour.

From February 19 onward, activity declined even further. New wallet creation dropped to just 20 per hour on average, and unique wallets fell to about 128. Transactions went to under 400 per hour. Overall engagement had dropped to minimal levels.

What sets $LIBRA apart is how quickly this shift occurred. While other tokens showed a gradual decline, $LIBRA's decrease in interest happened within just a few hours after launch. This is visible in the large gap between its peak values and overall averages in the early days. For example, while hourly peaks in the launch phase reached 47 747 new wallets and 437 929 transactions, the corresponding averages were much lower at 4 032 and 47 805. This contrast between early peaks and much lower averages suggests the token got a brief attention, likely thanks to the marketing, bots or insiders, but interest disappeared almost immediately. The drop in both price and trading volume points to a rug pull as liquidity was likely removed shortly after launch. This caused the project to collapse within hours.

In summary, $LIBRA followed a pattern similar to other speculative meme coins, but with a much faster collapse in user activity. While the launch attracted interest, the engagement period lasted only a few hours before activity dropped strongly. The decline in price and trading volume shortly after launch strongly indicates that liquidity was pulled or reduced, which points to a potential rug pull. As a result, trading activity and user participation declined almost entirely within hours of launch.

5.2 Topic Modelling Findings

Topic Modelling for $TRUMP

After applying BERTopic, we identified 10 topics including one large outlier group labeled as Topic -1. The topics reveal a range of conversations surrounding the $TRUMP meme coin from political reactions and market behavior to cultural commentary. Table 8 below presents the distribution of comments across topics.

Table 7. Distribution of comments per topic

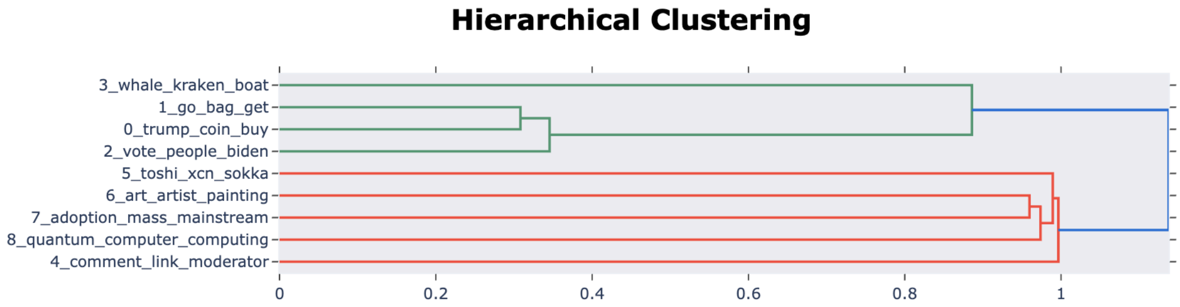
Topic number	-1	0	1	2	3	4	5	6	7	8
Number of comments	18 935	18 513	4 061	3 613	320	64	58	36	28	26

Visualizations

As mentioned above, after processing and cleaning the data, BERTopic identified 9 topic clusters and one outlier group. The charts below help illustrate how these topics are distributed and how they relate to one another.

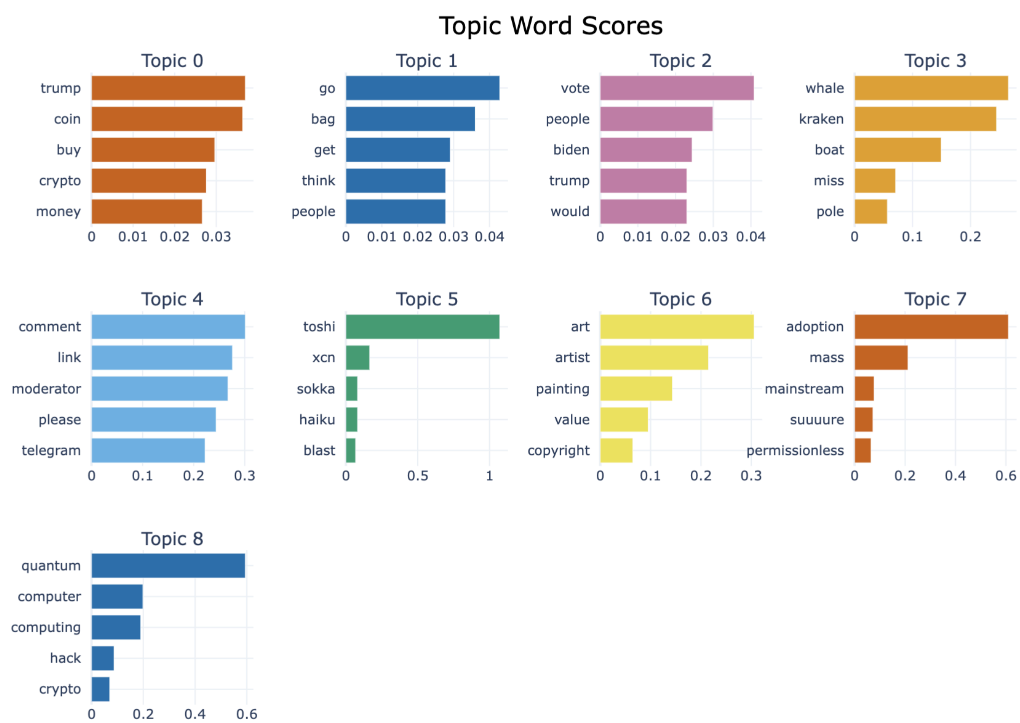
Graph 5. The intertopic distance map for $TRUMP

We used the Intertopic Distance Map from the BERTopic model, to better understand the semantic structure of discussions around the $TRUMP meme coin, (graph 5). In this visualization, each bubble represents a topic. Its position shows how similar it is to others based on comment content. The size of the bubble shows the proportion of comments assigned to that topic. For $TRUMP, the map shows a few dominant clusters grouped in the center. It suggests overlapping conversations and shared language. Several smaller and more distant bubbles suggest specific discussions that differ from the core themes.



Graph 6. Hierarchical clustering for $TRUMP

We used hierarchical clustering to further visualize the structure between topics (graph 6). The graph reveals two broad clusters. One group (marked in green) contains topics that relate like trading behavior, political discussion, and public reaction (Topics 0, 1, 2, and 3). These are more focused on the coin. The second group (shown in red) includes loosely connected or distinct topics, such as moderator comments (Topic 4), artistic or AI-related tangents (Topics 6 and 8), or humorous references.



Graph 7. Topic word scores for $TRUMP

We looked at the top keywords that the model found most important for each topic (graph 7). This helps us with understanding what people were talking about while discussing $TRUMP. For example, Topic 0 includes words like “trump,” “coin,” “buy,” and “crypto,” which points to people discussing the token. Topic 2 has words like “vote,” “people,” and “biden,” which shows interest in political conversations tied to Trump as a public figure. Some topics were a bit more surprising. For example, Topic 6 brings up words like “art,” “artist,” and “painting” and Topic 8 mentions “quantum,” “computer,” and “hack.” Looking at these keywords helped us make sense of the model’s output and showed how differentiated Reddit discussions can get, even when the topic starts out focused on just one coin.

Results Overview

Topic group -1 gathers all the comments that didn’t fit into any specific cluster. With over 18 000 comments, it forms the biggest chunk of the dataset. We believe that it is actually quite normal when dealing with social media discussions. On Reddit, people don’t always stay on-topic but rather they invite sarcasm, trolling, and general chaos especially in meme coin threads. When we look at the content, it becomes clear why these comments were too messy for the model to group. There’s a little bit of everything: jokes about “fartcoin,” political takes, speculations about the economy, promotion of other coins, random personal complaints, and conspiracy theories. Some users are excited and hopeful (“This could be huge for adoption!”), others are purely cynical (“Grift of the century”), and some just want to ride the hype for quick profits no matter the ethics or outcome. A few users reflect on how strange it feels to see a meme coin become a serious trading asset. There’s also a number of unrelated spam and promotions.

Topic 0 is all about early reactions to the $TRUMP token mostly from people who bought it right after the launch. Many comments are centered around buying strategies, price speculation, quick profits, and excitement about how fast the token was growing. It's clear that a lot of users saw this as a meme coin opportunity to make fast money rather than a long-term investment. Some users report making huge gains, while others talk about where and how to buy the coin. There’s also a mix of sarcastic comments joking about a “Trump coin reserve” or making comparisons to past grifts (exploitations) like Trump’s NFTs, watches, or the “Trump Bible.” At the same time, there’s a lot of noticeable skepticism. A lot of users call $TRUMP a scam, a “pump and dump,” or just a grift for quick cash. Still, they often follow that up with the will to invest no matter the consequences. That shows how meme coin investors sometimes value profits over principles. This topic also includes a few users calling out the reputational risk of a U.S. president launching a coin like this, but those voices are overtaken by the excitement (or sarcasm) about making a quick money. Topic 0 captures the beginning of the $TRUMP coin lifecycle that includes part hype, part disbelief, part “get in early and exit fast.” It's mostly focused on quick money.

Topic 1 shows a mix of sarcasm, confusion, and criticism. Users are watching token and price development in real time and many are overwhelmed. There’s a strong sense of disbelief that this is really happening again and that others are still falling for what they see as an obvious grift “I can’t believe people fell for it a second time” or “he did it before and will do it again.” Another theme is people feeling stuck after buying in too late or predicting others will be left with worthless tokens. There’s also a lot of political complaints. It's less about the coin and more about how the community feels watching others buy, sell, and react in real time.

In Topic 2 the focus is on political and ethical concerns surrounding the $TRUMP coin. It is seen not just as a meme asset, but as a symbol of how far the line between government, crypto, and personal gain are blurred. The tone in this cluster is heavier as users are processing what they see as a change in basic norms. Many comments question the legality of a sitting U.S. president creating, promoting, and (potentially) profiting from a crypto token. There’s discussion of presidential immunity, conflicts of interest, and whether laws even matter anymore if there are no consequences. Phrases like “he’s a convicted felon,” “this has to be illegal,” and “the secret ingredient is crime” repeat with sarcasm or with frustration. A key theme is also blame. Some users focus on the people who voted for Trump as president, decided not to participate in the election, or believed this term would be different this time. There's a division between those who expected this and those who still seem surprised. Users outside of the U.S. are also shocked as $TRUMP becomes less about crypto and more about what people feel it says about America.

Topic 3 is dominated by disgust at what users call as the latest grift from Donald Trump. The language is intense and repetitive. Different variations of the word grift, like “grifter” and “griftception”, appear nearly in every comment. The vocabulary shows how users associate the $TRUMP coin with fraud, exploitation, and personal enrichment at the public's expense. Many commenters are not shocked Trump would do this but they expected it. What makes them frustrated is that the scam is working and it attracts new investors. As one user puts it, people are “eating it up.” This topic isn’t just about $TRUMP but about crypto’s image. Users worry that this type of fraudulent tokens decreases the entire industry’s credibility. This cluster also reflects a loss of faith in institutions. Users say that “everyone is grifting” from politicians to influencers to average token holders looking for the next pump. Some users admit they missed out and are experiencing FOMO, while others refuse to participate by calling it “poison.”

Topic 4 consists of all the technical comments related to Reddit moderation. The majority of comments in this cluster consist of automated messages from Reddit’s bots flagging or removing posts for including banned Telegram links, referral codes, or promotional content. Many users either shared or reacted to links for trading bots, Telegram groups, and other tools used to gain early access to meme coins or coordinate trades. While this topic does not reflect opinion about the coin, it shows the environment in which meme coin trading happens: one where bots, trading groups, and aggressive promotion tactics play a significant role. This reveals the exploitative nature of meme coins, where users who are not parts of these networks may be in a disadvantage.

Topic 5 focuses on trading behavior and the tools people use to track meme coins like $TRUMP. Most of the comments focus on platforms like Dexscreener or Dextools, which are used to track new coin launches and price movements in real time. Some users share their strategies for spotting early listings and flipping tokens for quick gains, while others express regret over missing out (related to FOMO) or getting in too late. There’s a strong sense of urgency as many want to figure out how to buy coins before they even appear on Dexscreener. They are often mentioning bots or private alerts. Users talk about how important timing is in the crypto space.

Topic 6 talks about the online investigation that users follow in order to check the reliability of meme coins. Many Reddit users referenced Coffeezilla’s videos or speculated about upcoming online investigations targeting the $TRUMP token and related scams. These comments show how YouTube investigators have become trusted figures in the crypto community. Users waited for Coffeezilla’s review and cited his past videos as a reason for their investment decisions or skepticism. The repeated mention of “the video” also proves that social media (in this case YouTube content) shapes sentiment and awareness in crypto spaces.

Topic 7 collects the discussion around the $TOSHI token. Users compared $TOSHI to $TRUMP, debated whether to switch investments, or hyped it as the "next big thing." The tone was enthusiastic with references to “Toshi time” or being part of the “Toshigang.” Some users shared trading strategies or claimed recent profits, while others warned about the token being potential rug pull. It is a small theme that was just a side topic in all the discussions about meme coins.

Topic 8 focuses on chart analysis, price movements, and technical indicators. Users shared confusion or skepticism about the accuracy of the displayed charts. Some users joked about the volatility (“charts that go to shit quickly”). This topic reflects the more analytical side of the community, where users attempt to make sense of the chaos by tracking price data. The surprising part is how small this topic is considering its focus on actual analysis and informed decisions in crypto space.

Topic Modelling for $MELANIA

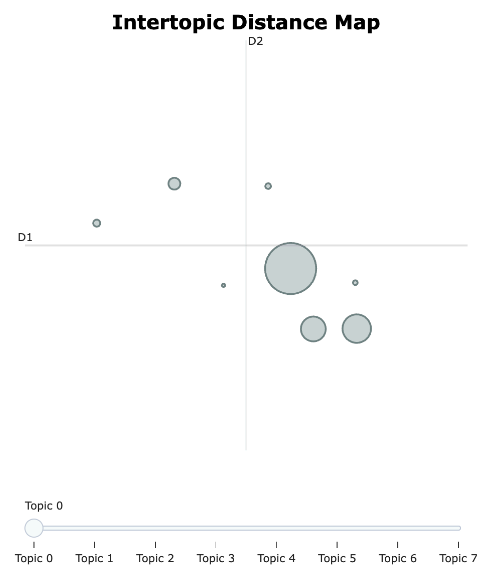
After the preprocessing and cleaning steps, using BERTopic we identified 8 topics and one large outlier group (Topic -1), which captured comments that did not cluster into any single coherent theme (see table 8 below). The distribution of these topics helps illustrate which themes dominated the conversation and which were led on the side.

Table 8. Distribution of comments per topic.

Topic number	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Number of comments	4 242	5 207	1 621	1 233	281	100	64	44	21

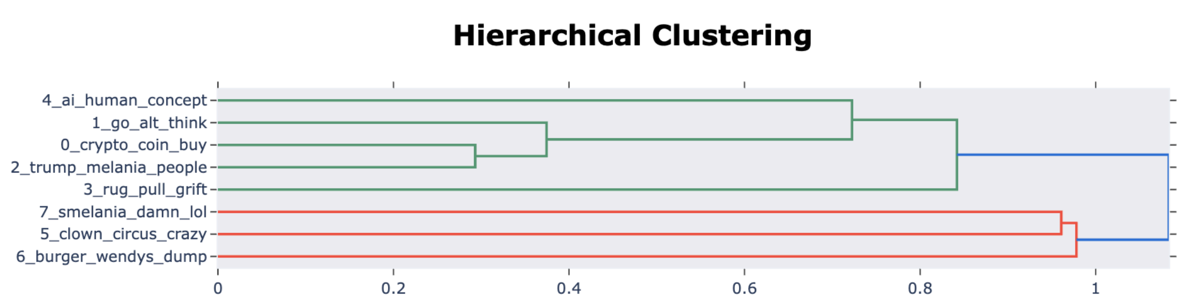
Visualization

We once more visualized the structure and relationships between topics using the same three graphs as dring $TRUMP analysis: an intertopic distance map, a hierarchical clustering dendrogram, and bar charts of the top keywords in each topic cluster .



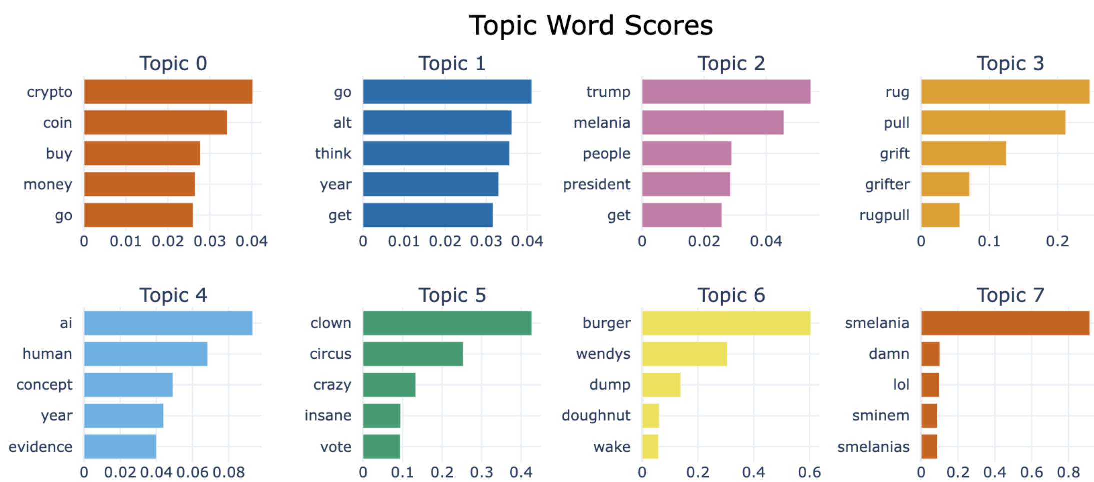
Graph 8. An intertopic distance map for $MELANIA

In the case of $MELANIA, four topics appear tightly grouped on the right side of the map (graph 8). It suggests their similar language and likely connected themes such as trading behavior, coin performance, and reactions to the launch. This clustering reflects how many users were focused on the financial and political implications of the coin. Few topics are scattered farther away as they likely focus on sarcasm, hype or humor that, as shown in other cases, often appears in meme coin conversations.



Graph 9. Hierarchical clustering for $MELANIA

Graph 9 shows how topics relate to each other based on their semantic content while discussing $MELANIA. For example, Topics 0, 1, 2, and 3 are all grouped within the same green branch as they share focus on cryptocurrency behavior, political figures like Trump and Melania, and scam discussions. On the other hand, Topics 5, 6, and 7 form a separate cluster with pop culture references, food jokes, or humor.



Graph 10. Topic word scores for $MELANIA

Graph 10 presents bar charts of the top five keywords associated with each topic. These keywords provide insight into the core ideas in each group. For instance, Topic 0 is full of terms like "crypto," "coin," and "buy," that suggest investing talk. Topic 3 contains words like "rug," "pull," and "grift," which points to scam discussions. Interestingly, Topic 6 appears to be dominated by words like "burger" and "wendys," which need further look to understand. Finally, Topic 7 revolves around the term "smelania," which is a mocking nickname that seems to have gone viral in the Reddit threads.

Results Overview

Topic -1 represents the large outlier group that BERTopic could not assign to any single thematic cluster. As expected with informal online discussions, this category is a mix of everything from sarcasm and political rants to random jokes. What stands out most is the wide emotion range: some users make fun of those who lost money, others criticise the crypto industry, capitalism, or American politics. Many posts show confusion and disbelief that something like $MELANIA exists and is being taken seriously. Some comments compare the token to other scams, while others try to analyze price movements or insinuate insider trading. The tone varies between amused, angry, and resigned.

Topic 0 is focused on advice, safety tips, and early reactions from crypto users who interact with $MELANIA. Many of the comments show concerns about scams, wallet security, and instructions on how to avoid common mistakes. Posts in this topic warn others about interacting with suspicious airdrops, signing unknown transactions, or trusting random links. Additionally, users discuss whether the coin launch is something problematic like a grift or laundering scheme. While some see the project as just another predictable pump-and-dump scheme, others worry that it could damage crypto's reputation through the political connection.

Topic 1 shows a strong emotional reaction from the community. It combines disbelief, sarcasm, and tiredness of users. Most comments are not centered on the coin's price or features, but on the absurdity of the situation, which is the fact that the first lady has a meme coin, and how that reflects the state of both crypto and politics. There's a tone of cynicism as people joke about living in a simulation or compare the next four years of political life to a circus. Despite the humor, many comments show hopelessness from users who see the coin as a symbol of how far the crypto has drifted from its original values.

Topic 2 of the $MELANIA coin discussions reveals the political chaos and emotions surrounding the involvement of public figures, like Donald Trump and Melania Trump, in meme coin launches. Unlike some other clusters that focus more on market reactions, this group includes commentary about the perceived corruption, manipulation, and decrease of public trust. Many users are mad that meme coins are tied to the U.S. presidency. The comments show the worry for long-term consequences of those projects. Few contributors criticize the normalization of grifting or state pump-and-dump schemes. For some, it's a sign of democratic collapse. There are comparisons to dystopian films like *Idiocracy*, and users voice concern that crypto is now being used as a tool for money laundering, backdoor political funding, or means for the leaders to extract more wealth from everyday people.

Topic 3 revolves around the idea of a rug pull. Many Reddit users in this topic are debating whether what happened with $MELANIA and $TRUMP really counts as a rug pull in the traditional sense. Some argue that the drop in price is simply part of volatility and not evidence of intentional fraud. Others insist that the timing, wallet behavior, and huge profits taken out by insiders indicate an effort made to exploit hype and then abandon the coin which would fit the rug pull definition. There are sarcastic views like “rugged by the president” or “griftception.” The theme of grifting or using one's position for personal gain also appears frequently. Commenters link the behavior not just to crypto schemes but to corruption. There’s even speculation about future rug pulls and market implications. This topic also shows how terrible users feel when hype turns into loss.

The main theme in topic 4 is the commodification of ideas. It talks how in today's financial and digital environment, intangible concepts can be ‘packaged’ and sold. A repeated phrase throughout this topic is the criticism of “selling the idea of a thing.” Users express this idea using comparisons to advertising, marketing, or historic bubbles like tulip mania, when people paid huge sums for tulip bulbs before the market crashed in the 1600s. The tone is mixed: some find this fascinating or funny, while others express frustration at how easily these concepts gain interest of people. Other thoughts range from commentary on AI, marketing, and “the future of humanity,” to expressing views on capitalism and meaning. This topic shows us that in crypto space, success isn’t about technical merit but rather it’s just about convincing others that an idea is worth chasing.

In Topic 5 most comments use circus and clown metaphors to describe the behavior of Donald Trump, the meme coin launches, and the political landscape in the U.S. Users refer to the political environment as a joke with phrases like “we elected a clown and got a circus” appearing a few times throughout the comments. While some comments are sarcastic, others show embarrassment over the state of American democracy. The repeated use of visual metaphors like “freak show,” or “bingo clown card” suggests helplessness. Overall, this topic reflects users processing the situation not through direct critique of the coin itself, but by commenting on how unbelievable the situation is.

Topic 6 is small and full of jokes built around the idea of financial loss and market crashes. "Going to work at Wendy’s" is a common phrase in communities as it implies someone lost so much money that they now need to get a job flipping burgers. Users talk about "burgers dumping" which in slang means that Americans (burgers) are selling the assets/tokens.

The tone of Topic 7 is mocking and the topic centers around the nickname “Smelania”. Most of the comments joke about how the coin's name looks silly and similar to a school insult. It’s a small topic that shows how branding missteps or name choices can quickly turn into community memes.

Topic Modelling for $LIBRA

After preprocessing, cleaning, and filtering for relevance, BERTopic identified 7 coherent topics and one large outlier group (*Topic -1*), which contained comments that did not fit into any cluster (table 7).

Table 9. Distribution of comments per topic

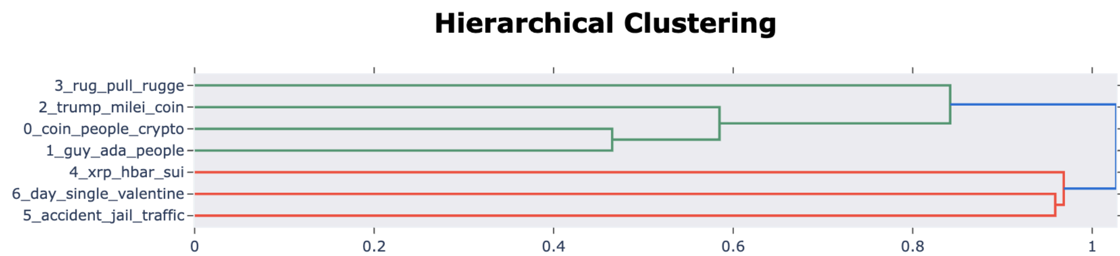
Topic number	**-1**	**0**	**1**	**2**	**3**	**4**	**5**	**6**
Number of comments	412	664	163	132	52	32	11	10

Visualization

We further visualized these topics using the same graphs as in the case of other coins (graphs: 7, 8, and 9).

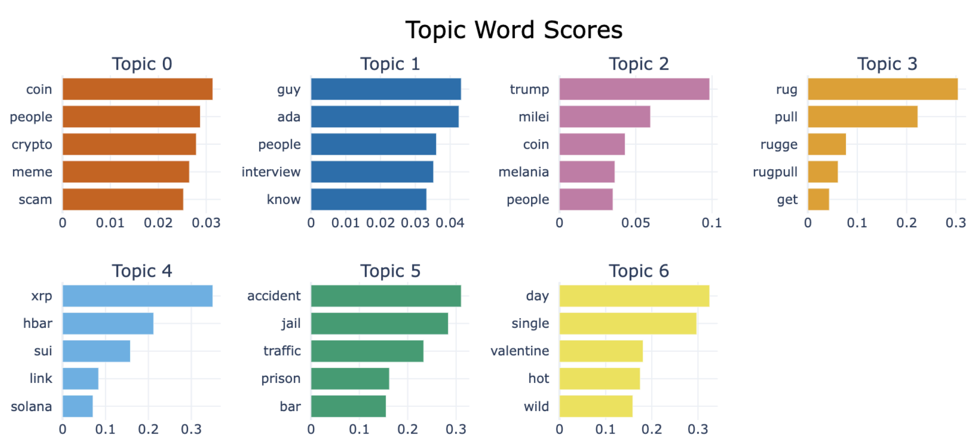
Graph 11. An intertopic distance map for $LIBRA

To better understand the semantic structure of discussions surrounding the $LIBRA meme coin, we used the Intertopic Distance Map available with the BERTopic model (graph 11). The Intertopic Distance Map confirms that while there are a few core themes dominating $LIBRA coin discussion, the other topics are semantically diverse.



Graph 12. Hierarchical clustering for $LIBRA

The hierarchical clustering tree graph provides an additional view on the semantic relationships between the identified topics (graph 12). Topics connected by green branches (such as Topic 0, Topic 1, Topic 2, and Topic 3) form a group centered around cryptocurrency discussions, public figures, and scam-related language. In contrast, Topics 5 and 6, grouped under red branches, stand apart as semantically different and likely reflect off-topic or, at the first glance, contextually unrelated conversations.



Graph 13. Bar Chart of Key Words in each Topic Cluster

Graph 13 provides an overview of the most important terms associated with each identified topic in the $LIBRA Reddit dataset. This visualization gives insight into what people were talking about most when discussing $LIBRA. Some topics very clearly relate to core crypto themes, like coins, scams, or references to other tokens, while others reveal broader online conversations. The diversity of topics suggests that discussions around $LIBRA didn't just revolve around the coin itself, but were influenced by cultural and community language as well as news.

Results Overview

Topic -1 is what BERTopic assigns to comments that don't fit well into any specific theme or cluster. In the case of the $LIBRA dataset, it holds quite a large number of comments. We believe that this is common in social media data, where people often respond with short or sarcastic remarks that don't contain enough consistent language to form a clear topic. Looking through the content in this cluster, we can see a wide mix of off-topic jokes, unrelated political commentary, and broken sentences, for example: "lol we really live in the matrix". Some comments mention the coin briefly but without meaningful context, for example: 'find a casino and win back all the money you lost in crypto (...)'. These types of comments are difficult for a model to categorize probably due to the lack of structure. The presence of this large outlier group still tells us something important: conversations about meme coins are often chaotic and fragmented. Here people are just as likely to post memes, jokes, sarcastic or trolling comments as they are to talk about actual investment decisions. Even though this topic doesn't give us a specific theme, this mess shows the broader meme coin culture where hype and speculation go together.

Topic 0 was the biggest theme in the $LIBRA discussion. It mostly reflects a general sense of frustration and skepticism toward meme coins and the crypto space. Many users shared their personal experiences with scams, pump-and-dump schemes, and lost money. There's a clear feeling of disappointment, especially with how easily people fall for these projects over and over again. Memecoins like $LIBRA are seen not as serious investments but as gambling tools used by influencers or even politicians to take advantage of hype. What's also interesting is that many comments go beyond just this coin. They mention other scams (like FTX or Luna). Some users suggest the political distrust as world leaders or public figures are involved. People seem to start to lose faith in crypto's potential because they keep seeing the same scam patterns repeating.

Topic 0 represents users who feel let down by the system. Instead of excitement or hope, this topic is filled with warnings and a strong sense that things in the meme coin have gone too far. It highlights how $LIBRA wasn't just seen as a risky coin but as another example of how hype can lead to real financial loss.

Topic 1 focused on community responses to suspected insider activity, sniper bot use, and the manipulation in meme coin launches. A repeating reference throughout the comments is the interview with Coffeezilla (a popular crypto journalist known for uncovering scams) which seems to start discussions on unethical behavior behind the $LIBRA coin. Many Reddit users express strong emotions: from disbelief and aversion toward the behavior of influencers and founders, to sarcasm and amusement at others' financial losses. The tone is mocking toward those described as naive. Several comments accuse the coin's promoters and early investors of organizing a "pump and dump" while posing as regular community members. The idea that the wallets that made profits likely belonged to insiders or snipers caused anger. However, many users seem entertained by the drama. References to watching others get "rekt" (crypto slang for losing big) like it's a reality show suggest that meme coin investing has become a form of entertainment more than finance. However, this doesn't take away from the frustration people feel toward the lack of transparency and the normalization of manipulative tactics through meme coins. Topic 1 shows both the community's distrust in crypto influencers and the helplessness many feel when participating in markets that seem rigged from the start.

Topic 2 focuses on the political and social implications of meme coin launches by recognizable people like Javier Milei, Donald Trump, and Melania Trump. The comments clustered in this topic show public reactions to the potential involvement of political leaders in crypto scams. Many users comment on how the release of $LIBRA, following $TRUMP and $MELANIA, appears to be part of a growing trend where politicians either directly endorse or indirectly profit from meme coins. The tone is critical and skeptical, especially toward Milei. Users discuss how Milei's libertarian image and outsider status made him seem appealing to audiences new to crypto. However, his involvement in $LIBRA is seen as a betrayal of those standards. There are users that stated that they initially had hope in Milei's economic reforms but they feel let down by the coin launch controversy. Commenters point to how the launch of $TRUMP created an example for other political meme coins. Overall, the comments from topic 2 reflect not only frustration with losses but also an irritation with normalizing of manipulation by public figures.

Topic 3 captures all ironic comments about rug pulls that involve politicians. Many Reddit users joked about how common these scams have become with comments like "one rug pull, everybody knows the rules" and "we need presidential rug pull bingo cards." In this group it is important to notice that rug pulls are no longer shocking. They've become part of the meme coin and are treated as entertainment. Many just laugh at the absurdity. However, few users question why people still fall for those coins after many examples of scams. Topic 3 shows how users use humor to cope with repeated losses and distrust in both crypto and politics.

Topic 4 is mostly about people sharing which altcoins (alternatives to Bitcoin) they like and why. Coins like XRP, HBAR, SUI, and Solana come up a lot as users casually compare them or share which ones they've held the longest. Few comments show strong loyalty to tokens (like XRP) while others are a bit more cautious since they admit that they are feeling unsure about altcoins in general. Users also share advice of not getting caught up in hype and doing proper research before entering the crypto market. Overall, the tone is friendly and informal. Everyone seems to have their 'favorite' coin. It is clear that some users are in it for potential gains, while others are just interested in the concept and enjoy being part of the conversation. This group represents the comments that are not about hype or emotions but just exchange of opinions and advice.

Topic 5 is small but intense. Most of the comments express frustration and anger toward the people behind the meme coin scandal. They call them out as criminals who should be in jail. Users draw comparisons to other crypto frauds and use strong language to suggest that what happened with $LIBRA wasn't just a mistake but it was theft. The main theme is clear: people feel cheated and want justice. There's a sense that too many in the crypto space get away with unethical behavior and that there is time for accountability.

Topic 6 is lighter in tone and does not connect with the main discussion. Here, users joke about the release date that was on Valentine's Day. They compare the experience of losing money on a meme coin to getting "dumped" or being single. Some comments are just random or funny responses that don't add much to the original topic but show the casual and meme based style of Reddit crypto threads. This cluster doesn't offer deep insights into the coin itself.

5.3 Sentiment Analysis Findings

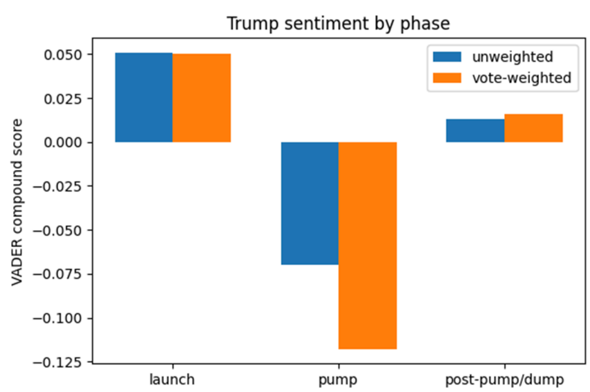
In this chapter, we bring together the quantitative results and graphical summaries of our sentiment analysis to reveal how the users of Reddit reacted to each coin's life cycle. We examined the launch, pump, and post-pump/dump phases for $TRUMP, $MELANIA, and $LIBRA. We used both VADER and TextBlob scores (weighted and unweighted) and standardized them into z-scores. While all figures are available in the appendix, only those related to the $TRUMP token are included in the main text for ease of reading.

$TRUMP

Table 10. $TRUMP sentiment results

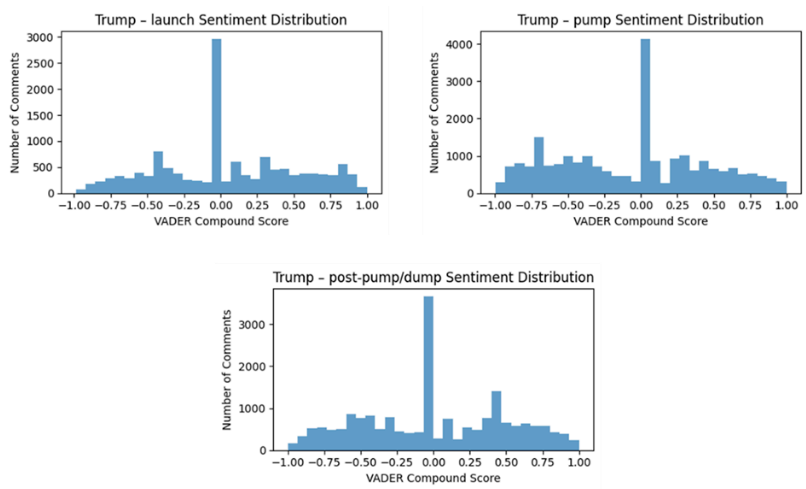
Model	Phase	Number of comments	Unweighted score	Weighted score
VADER	Launch	13318	0.050727	0.050193
	Pump	23688	-0.069798	-0.117750
	Dump	19756	0.013098	0.015688
TextBlob	Launch	13318	0.053004	0.053222
	Pump	23688	0.022362	0.009272
	Dump	19756	0.088082	0.088148

VADER Model



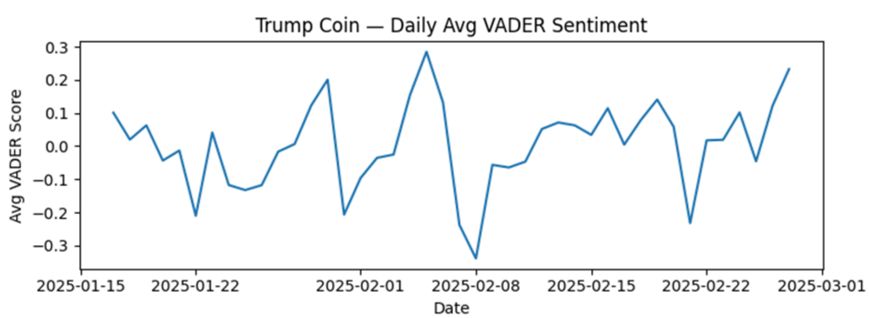
Graph 14. $TRUMP sentiment by phase with VADER model

During the launch period, both the weighted and unweighted metrics sit just above zero, showing a mildly positive tone overall. The unweighted and weighted means suggest that highly upvoted comments reflected the general sentiment of the launch discussion rather than differing from it (table 10 and graph 14).



Graph 15. $TRUMP sentiment distribution by phase with VADER model

The histogram for this phase reveals a pronounced spike at 0.0 and a roughly symmetric spread of moderately positive and negative scores, confirming that most comments clustered around neutrality with a slight positive tilt (graph 15).



Graph 16. $TRUMP daily average sentiment with VADER model

In the pump period sentiment shifted overly negative. This widening gap implies that the most highly voted comments were more negative than the average, possibly reflecting growing skepticism or frustration as prices peaked (table 10 and graph 14). The distribution histogram shows a heavier left tail compared to launch, with more comments scoring below –0.5 (graph 15). On a day-by-day basis, the average VADER score dipped as low as –0.33 around early February, underscoring a clear shift toward negative discussion during the pump (graph 16).

After the price correction, the $TRUMP coin community rebounded to a slight positivity. Although sentiment returned close to neutral, the weighted score remains marginally higher, suggesting that upvoted comments leaned just a bit more positive in the aftermath (table 10 and graph 14). The histogram for this phase again shows the familiar central spike at zero, but with a small positive skew relative to the pump phase (graph 15). The daily average plot highlights scores climbing from around –0.15 after the dump to above +0.2 by late February (graph 16).

TextBlob Model

In the launch period, the average TextBlob shows similarity to the VADER model.

Although, during the pump period, positivity persisted but at a much lower level. Still above neutral, the sharp reduction in the weighted score implies that the most popular comments were less enthusiastic than the average. The distribution shows a modest right tail but also a noticeable concentration of slightly negative scores, indicating a mix of critical remarks (table 10).

This consistent uptick in the dump period implies that commenters were more optimistic or reflective after the dump. The post-pump histogram resembles the launch-phase shape but with a slightly heavier right-hand tail, showing more strongly positive outliers. The daily average plot corroborates this rebound: polarity climbs steadily after the pump, peaking in mid-February around 0.25 before settling back near +0.08 by the end of the period (table 10).

$MELANIA

Table 11. $MELANIA sentiment results

Model	Phase	Number of comments	Unweighted score	Weighted score
VADER	Launch	9771	-0.034997	-0.028136
	Pump	649	-0.086190	-0.097212
	Dump	5465	0.041339	0.000512

Model	Phase	Number of comments	Unweighted score	Weighted score
TextBlob	Launch	9771	0.065085	0.071965
	Pump	649	0.023092	0.045300
	Dump	5465	0.039796	0.032105

VADER Model

In the launch period both figures indicate a slightly negative backdrop at debut, with highly upvoted comments pulling sentiment a bit closer to neutral (table 11 and figure 4). The distribution histogram shows a central spike at 0.0, which means neutral language, surrounded by a fairly even spread of mildly positive and negative scores, with a small bend towards the negative side (figure 5).

During the pump, negativity deepened. The fact that the weighted score is more negative than the unweighted (table 11 and figure 4) suggests that the most popular comments were even more critical or pessimistic during the price spike. The sentiment distribution broadens here, showing a heavier left tail (more scores below -0.5) compared to launch, which aligns with a rise in negative reactions as hype peaked (figure 5).

After the dump, sentiment rebounded to a modest positive level. While the average comment was mildly upbeat, the most-upvoted remarks remained essentially neutral (table 11 and figure 4). The post-pump histogram mirrors the launch phase in shape but with a slight right-hand skew, indicating more positive outliers (figure 5). On a daily basis, sentiment shows pronounced volatility. It fluctuated around zero for most of the period before a sharp spike above 0.8 around mid-February and a gradual taper back toward +0.2 by late February (figure 6).

TextBlob Model

Both the weighted and unweighted scores point to a modestly positive reception at debut, with the weighted mean slightly higher (table 11 and figure 15). It indicates that comments receiving more community endorsement tended to be even more upbeat than the baseline. The histogram shows most comments clustered around neutrality, with a right-leaning tail of stronger positive remarks (figure 16).

During the pump phase, the unweighted polarity drops to 0.0231, while the weighted mean rises to 0.0453 (table 11 and figure 15). The divergence here suggests that although the average comment was only mildly positive, the most-upvoted comments were noticeably more enthusiastic. The sentiment distribution stays around zero, with fewer extreme values except for a handful of strongly positive outliers (figure 16).

Both the weighted and unweighted scores in the dump phase are slightly positive but lower than at launch (table 11 and figure 15). The weighted score dips below the unweighted, suggesting that highly upvoted comments were somewhat less positive than the average. The histogram has a mild skew toward positive values (figure 16). The daily average plot shows sentiment bouncing back and forth around neutrality, with occasional spikes above 0.2 (figure 17).

$LIBRA

Table 12. $LIBRA sentiment results

Model	**Phase**	**Number of comments**	**Unweighted score**	**Weighted score**
VADER	Launch	361	-0.068691	-0.043458
	Pump	657	0.050951	0.068749
	Dump	945	-0.045363	-0.040604
TextBlob	Launch	361	0.036333	0.038507
	Pump	657	-0.010164	-0.023694
	Dump	945	0.048690	0.050411

VADER Model

In the launch period the values indicate an overall negative tone at launch (table 12 and figure 7). The fact that the weighted score is closer to zero suggests that the most-upvoted comments were slightly less pessimistic than the average.

During the pump phase, the sentiment flipped positive (table 12 and figure 7). This upward shift implies that as Libra’s price surged, the tenor of discussion turned upbeat and highly-endorsed comments were even more optimistic. The distribution shows both a central neutral spike and a significant right tail. Despite the small sample size, the positive tilt is clear (figure 8).

After the dump, sentiment dipped back into negative (table 12 and figure 7). Again, the weighted score is slightly less negative, indicating that popular remarks were marginally more moderate. The histogram illustrates two dominant spikes, showing a return of critical language (figure 8).

TextBlob Model

At launch, both scores sit just above zero, indicating a mildly positive initial reaction to Libra (table 12 and figure 18). The slightly higher weighted mean suggests that the most-upvoted comments tended to be more upbeat than the overall average. The launch-phase histogram shows a tall neutral spike at 0.0, flanked by a modest right-hand tail, meaning most discussion was neutral or gently positive (figure 19).

During the pump, the values are negative. Although these values are near zero, they indicate a slight shift toward negativity (table 12 and figure 18), especially in the most popular comments. This suggests that, unlike Trump or Melania, the Libra community grew mildly critical or wary. The distribution tightens around neutral, with a small bulk of slightly negative scores and relatively few strong positive outliers (figure 19).

After the dump, sentiment rebounds (table 12 and figure 18). The nearly identical weighted score implies that prominent comments mirrored the average mood. The post-pump histogram again shows a central cluster at zero but with a clearer positive skew. More comments scored between 0.1 and 0.3, indicating optimism returning to the discussion (figure 19).

5.3.1 Comparing the Two Models

$TRUMP

VADER registers a strong positive departure from its overall mean in the launch phase, whereas TextBlob sits essentially at zero (very slightly negative unweighted, barely positive when weighted). This suggests VADER perceived launch comments as unusually upbeat compared to its own baseline, while TextBlob saw them as unremarkable. Both models agree that the pump phase is significantly negative, with z-scores near –1.0. TextBlob's weighted score is marginally closer to VADER's, indicating both lexicons flagged an equally strong downturn in tone when prices peaked. Here both models flip positive, but TextBlob's rebound is far more pronounced (-1.0) than VADER's slight uptick (+0.3) (figure 10, 11, 21, 22).

$MELANIA

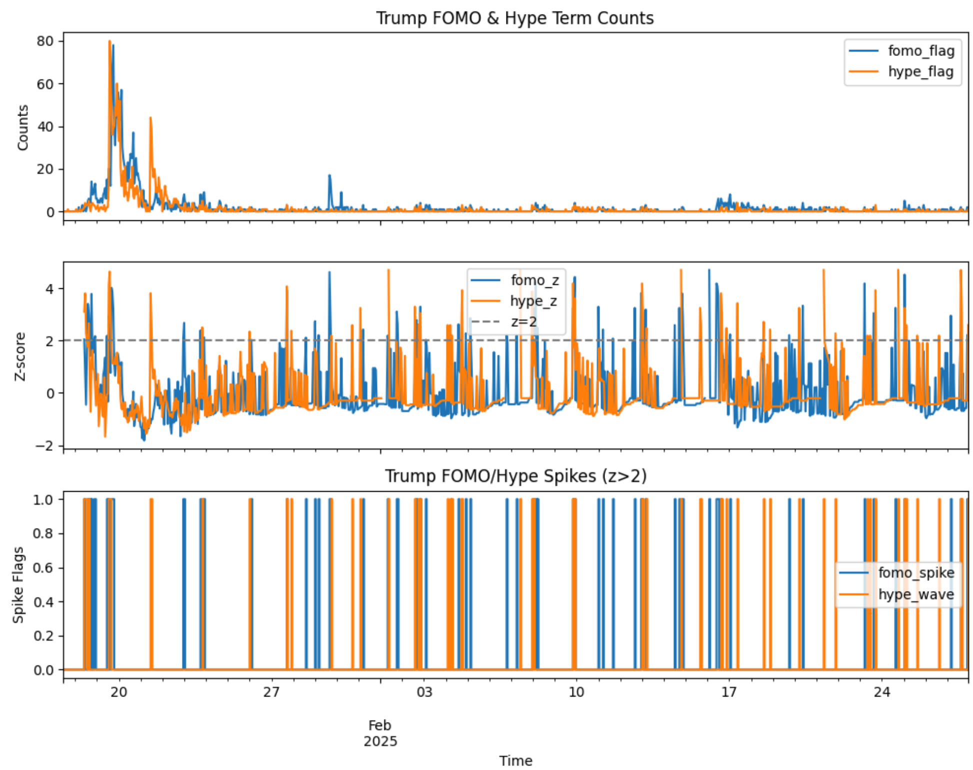
VADER's weak negative signal (unweighted slightly below average, weighted slightly above) contrasts sharply with TextBlob's strong positive spike. This divergence implies that TextBlob's lexicon found launch comments unusually friendly relative to its own distribution, whereas VADER saw them as essentially neutral. Both models record a negative pump; VADER's weighted score is slightly stronger in the negative direction, while TextBlob's weighted z-score is closer to zero—suggesting that popular comments were less downbeat under TextBlob than under VADER. VADER marks a very strong positive rebound (+1.06), but TextBlob remains near or below zero once weighted. Because of this, only VADER interprets the aftermath as unusually upbeat and TextBlob sees the post-dump phase as average or even moderate (figure 10, 11, 21, 22).

$LIBRA

At launch, VADER shows a negative tone, while TextBlob finds a moderately positive shift. This indicates disagreement on earlier skepticism versus mild optimism. The most dramatic contradiction is that VADER sees the pump as highly positive, yet TextBlob marks it as highly negative. This suggests the two lexicons respond very differently to hype-driven language around Libra's price surge (figure 10, 11, 21, 22).

5.4 Hype/FOMO Analysis Findings

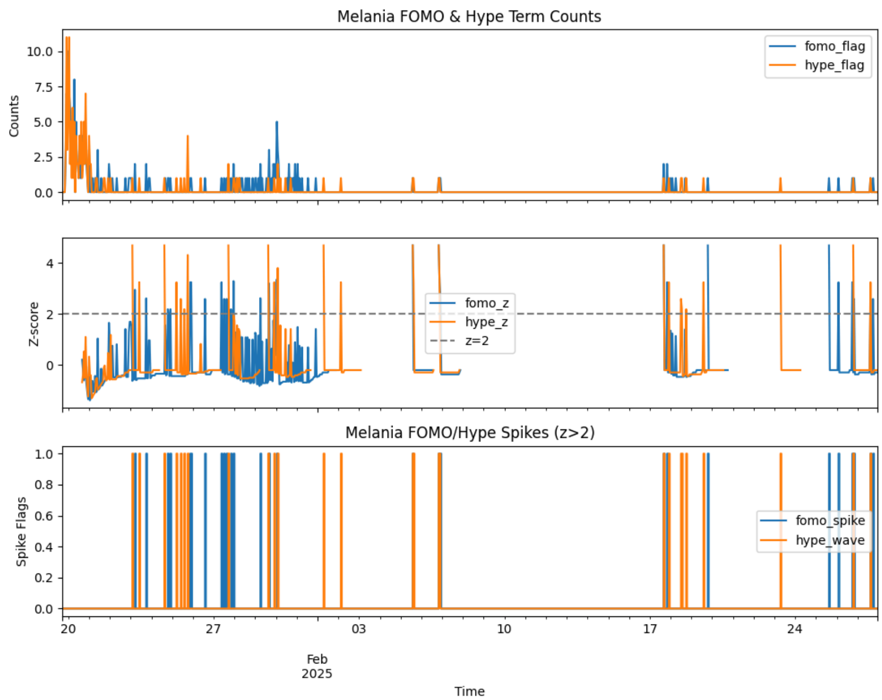
$TRUMP



Graph 17. Trump coin FOMO & Hype graphs

In the top panel, $TRUMP FOMO and hype counts spike above 40 mentions per hour around the launch and pump phase, at times even reaching 80. After that initial surge, both FOMO and hype flags continue to pop up throughout the late launch and post-pump periods, though never as intensely as during the early pump. The middle panel shows many hours where both fomo_z and hype_z go above 2, confirming these are true bursts compared to the previous 24-hour window. In the bottom panel, dozens of fomo_spike and hype_wave flags appear not only at peak hype but also before and after, indicating that excitement and hype around $TRUMP persisted well beyond its top price (graph 17).

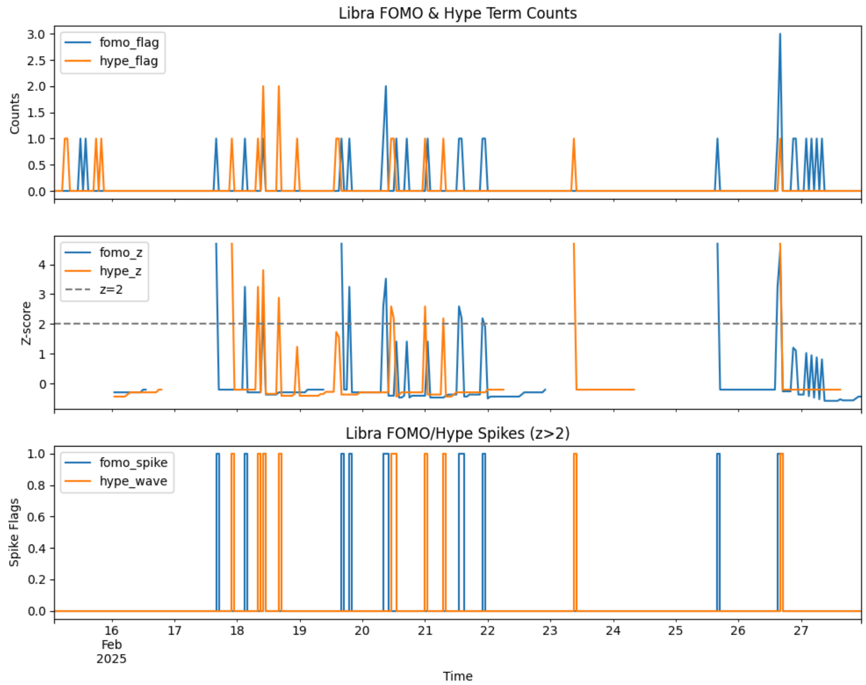
$MELANIA



Graph 18. Melania coin FOMO & Hype graphs

$MELANIA's raw FOMO and hype counts are much lower than $TRUMP's. During the launch, the FOMO and especially the hype counts reached the climax (10 mentions per hour), but during the pump phase we could count much less mentions. On the second panel, we still see several hours where both fomo_z and hype_z cross the threshold, producing a handful of fomo_spike and hype_wave flags. However, after the early February dump phase, FOMO and hype mentions nearly vanished, showing that community excitement was short-lived and tied closely to the initial price rise (graph 18).

$LIBRA



Graph 19. Libra coin FOMO & Hype graphs

Libra generated the least discussion of all three. Hype mentions slightly outnumber FOMO ones, but both stay sparse across launch, pump, and dump phases. Unlike $TRUMP, $MELANIA and $LIBRA's hype-term frequency doesn't drop off during the dump phase. Instead, both FOMO and hype flags appear at almost equal rates throughout. The z-score panel confirms each event crosses our z > 2 threshold, and the spike panel logs hype_wave and fomo_spike events mainly throughout what we defined as dump phase for Libra (graph 19).

6. Discussion

6.1 Blockchain Transparency

One of the biggest paradoxes we encountered during this research is the idea of blockchain "transparency." In theory, every transaction is publicly available, which we discussed through our literature review. In practice, understanding what's happening on-chain is nearly impossible without advanced tools and significant technical effort, especially during the chaotic launch phase of meme coins. The data is out there, but that doesn't mean it's usable.

If you want reliable and structured blockchain data, you often have to pay for it. This is very frustrating in a system that claims to be decentralized and democratized. Platforms like Solana promote their speed and openness, but once you attempt to analyze behavior, access is often limited to paid services. The dataset we worked with from Snowflake was the best free option available, and even then, it was messy, incomplete, and had to be manually cleaned and verified against external sources like Solscan. Those processes took lots of time and energy just to get something usable.

This experience shows a serious accessibility problem. Regular investors, journalists, researchers, or educators shouldn't need subscriptions or insider knowledge just to make sense of public data. If blockchain is supposed to work for individuals, then the current situation is a failure. Transparency that requires money or technical specialization to access isn't real transparency. The data might be public, but making sense of it requires significant financial resources.

6.2 Profit Distribution

Our profit and loss analysis confirmed a pattern that meme coin launches benefit a small group while the majority lose money. Out of 892 wallets analyzed, only 335 ended up with a profit. That's less than 38%. 548 wallets were in loss and 9 broke even.

The largest profits were not spread evenly. In $TRUMP and $MELANIA, a few wallets made over $1 million each. These wallets typically bought within the first few minutes of launch. This early activity reflects either automated trading (such as sniping bots) or insider knowledge and access. In both cases, it puts regular investors at a disadvantage.

While unequal profit distribution is common in many markets, the speed and scale at which it occurs in meme coin launches is particularly troubling. It shows that meme coin trading is biased from the start. Profitability depends more on position and speed than strategy.

Those findings show that most people enter meme coin markets too late, without realizing how much of the value has already been extracted. The system rewards a few and harms the rest. The way meme coins launch and trade often reflects the same concentration of power found in traditional finance even though they claim it is a decentralized system.

6.3 Suspicious Wallet Patterns

Our suspicion score was built on an idea that some behaviors cannot be ignored as they seem manipulative. Trading in the first few minutes, holding more than 2% of the supply, and reaching profits early cannot alone prove bad intent. However, when added together, they show a pattern that's hard to explain as coincidence. These are behaviors often seen in sniper bots or insider wallets. By combining them into a score, we pointed to wallets that deserved more in-depth attention.

While the score cannot determine intent, it works as a tool for narrowing down wallet behavior that deviates from the norm. It might be especially useful during the early moments of a token launch. This allows researchers and users to focus on wallets that meet risk indicators defined through suspicion score.

The tools for transaction classification (manipulative/safe) are important which shows the score across all three tokens. 450 out of 892 wallets were marked as suspicious which is above 50%. In addition, over 28% of wallets showed signs of wash trading. This presence confirms that the scale of suspicious activity is too large to ignore. It points out the need for better monitoring tools and mechanisms to prevent exploiting users.

One of the very important insights from our analysis is that suspicious behavior doesn't guarantee profit. Out of the 450 wallets flagged as suspicious, over 160 of them ended up at a loss. Despite attempting to influence the market, lots of these wallets failed to turn a profit. This challenges the commonly present assumption that manipulators always benefit at the expense of regular users. In reality, many of these attempts fail. It might be due to the strategy failing to generate enough hype or it's also possible that the growing number of similar scams means they now interfere with each other.

This finding is important for two reasons. First, it shows profit alone is not the only indicator of manipulation. Second, it highlights how fraud in DeFi is evolving. As more players use the same tactics (like bots, early entry, and fake volume) the effectiveness of these strategies is not equal. They’re no longer a ‘safe’ win, but a gamble. What we see in the data is a shift from scams to a messy area where manipulators lose. And that’s something worth paying attention to.

6.4 The Psychology of Meme Coins

Reddit sentiment analysis showed constant investor interest even after dump phases. Sentiment didn’t drop to overly negative for any of the coins after dump phases, which means according to the discussions, people still felt more positive in investing in these cryptocurrencies.

As our literature review showed us, investor behaviour in these markets is strongly influenced by psychological and social factors. Despite the price drops and volatility, investors persisted with their participation, so we can say that meme coins (and cryptocurrency market) are not driven by financial returns alone but by deeper, emotional, and social dynamics. For example, when we looked at who is buying cryptocurrencies, we found that many investors’ enthusiasm could be compared to the one present when buying lottery tickets. These investors tend to be overconfident and risk-taking.

We also looked at FOMO and hype behaviour. Obviously, the hype and FOMO feelings died down a bit after the launch and pump phase, but these feelings were still present in the comments.

Topic modelling also revealed that investors are invested in the subject. A big portion of Reddit discussion is focused on the excitement of early trading, speculative behaviour, and the hope for quick profits. For example, Topic 0 for $TRUMP and $MELANIA includes a lot of buzzwords like "buy," "coin," "crypto," which shows early excitement and anticipation of making fast profits.

6.5 Political Names in Meme Coins

Tokens like $TRUMP, $MELANIA and $LIBRA are heavily tied to the public personas of popular public figures. The early hype of these coins, driven by political figures like Donald Trump, Melania Trump, and Argentine President Javier Milei, led to a rush of speculative investments, often driven more by political alignment or support for the figure rather than any value in the token itself.

However, as is typical with many meme coins, once the initial excitement faded, the tokens experienced significant price collapse, leaving many investors at a loss. This was especially true for $MELANIA and $LIBRA. For example, $MELANIA had 90% of its tokens stored in a single wallet, raising suspicions of market manipulation and potential rug pulls. The centralization of control is a common trait in these tokens, which alters the natural decentralized ideals of cryptocurrency, creating vulnerabilities for investors.

Moreover, the public backlash following the price collapse, especially among those who felt baited or manipulated, shows how these tokens may blur the lines between legitimate community-driven projects and manipulation schemes. This situation emphasizes how celebrity tokens can distort investor expectations. Investors feel more secure in the legitimacy of these coins due to them associating them with familiar political figures. The idea of a "celebrity endorsement" gives a false sense of security, making investors exposed to scams more.

7. Conclusions

This thesis focused on how meme coin behavior can be analyzed during the early stages of trading. The goal was to identify manipulation and understand investor decisions. Our approach focused on blockchain transaction data with Reddit discussions, and the results helped us answer the main research questions.

The first question was how early transaction flows can be visualized to detect suspicious or manipulative wallet behavior. We addressed this through the wallet map, which plotted each wallet's total profit or loss, number of trades and trading behaviors. By using a suspicion score based on five specific criteria, we were able to flag wallets that followed typical scam behavior. Visual tools made it possible to spot patterns that would be hard to see in raw data.

The second question focused on whether any recurring patterns show up in tokens affected by scams like rug pulls or sniper bots. Across all three tokens we saw few signals. Many suspicious wallets traded in the first few minutes, and over 28% of all wallets showed signs of wash trading. While sniper bots were less common than expected, rug pull behavior was clearly visible in $LIBRA. Here, wallets linked to the project added and quickly removed liquidity, causing a rapid price collapse. All those behaviors are repeated across tokens, which shows that scams follow similar patterns that can be tracked with the right tools.

The third research question asked how blockchain transparency holds up in practice. In theory, blockchain is fully transparent. As this research revealed, that transparency is difficult to work with. While all transaction data is technically public, accessing it in a usable form is not easy or costly. Most datasets providers require paid subscriptions. The free data available often lacks elements like token prices or is faulty. The Solana dataset we used had issues and missing information. It required cleaning and checking with platforms like Solscan. We had to manually verify and add parts of the data before we could begin our analysis. This shows that transparency is not enough as the data must also be accessible and understandable if it's going to be useful to regular users.

The last question was why people continue to invest in meme coins, even when the main profits have already been taken. The answer came through our Reddit analysis. Discussions were heavily influenced by FOMO, hype, group behavior, and identity. Many users openly acknowledged the risks or even called the tokens scams, but still participated. Investment decisions were often emotional or socially motivated rather than based on any analysis. Meme coins are treated less like financial assets and more like trends, where getting in, even too late, feels better than missing out entirely.

All our findings show that there is a present imbalance in outcomes. Profitability is often limited to a small group of wallets with early access or quick buyers. In contrast, the majority of participants entering after the initial phase experience financial losses. At the same time, the presence of emotional aspects such as hype, FOMO, and social belonging helps explain investment behavior even after profit opportunities have disappeared.

8. Limitations and Further Research

It is important to note that our project has limitations and most of them are related to the quality and structure of the datasets used.

8.1 Limitations

Solana Dataset

While this thesis provides insights into the behavior of wallets involved in meme coin trading on Solana, the research faced limitations due to the quality and structure of the dataset used in the analysis. These limitations should be taken into consideration when interpreting the results.

One of the main challenges was the initial absence of price data. Without knowing the token prices at the moment of each transaction, it was impossible to determine wallet profits or losses. Although historical price information was later added to estimate USD values, this may not accurately show the actual transaction conditions due to the volatility of these assets. As a result, any conclusions about profitability should be seen as approximations.

Another limitation is the structure of the transaction data. In many cases, the dataset only identified the wallet sending the tokens and the amount transferred without identifying the recipient. This makes it difficult to track token flows or interactions between wallets. Additionally, the treatment of transaction fees adds a layer of complexity. On Solana, each transaction carries a small fee, but the dataset did not always distinguish between the fee and the transferred amount. This made it difficult to determine net wallets' value which could influence metrics used to flag suspicious behavior.

A further limitation relates to how transaction data was recorded. Although our methodology included steps to identify and remove mismatched transactions, some transactions in the dataset might not be correct. While we were able to validate and correct a subset of transactions, limited financial resources prevented us from a verification of the entire dataset. The data provider offered little support when discrepancies were reported and assured us that the dataset is precise. However, our check confirmed that certain entries were incorrect and there is a risk that some of the transactions used in our analysis may be inaccurate or misleading. Given that access to other datasets was paid, we had to accept this limitation.

Lastly, when working with the blockchain data it's impossible to know the intent behind a transaction. Even if certain patterns look suspicious, we can't say for sure whether someone is trying to manipulate the market or just acting by coincidence. This means we have to be careful when labeling wallets as malicious or manipulative. Tools like suspicion scoring and clustering can help with marking unusual activity, but they cannot explain the motivations behind wallet activity.

Reddit Dataset

For our language processing tasks, we initially planned to gather data from X as it is one of the most popular platforms for discussions and information sharing related to topics like cryptocurrency, technology, and finance. However, due to the high cost of the API, which was beyond our student budget, we searched for alternative sources and decided that Reddit could serve as a suitable option.

One limitation of using Reddit as our one data source is that it may introduce a potential bias, as the information gathered could be one-sided. Most of the data came from subreddits focused on cryptocurrency, which might lead to a "crypto-positive" view. While we attempted to reduce this bias by scraping data from some other subreddits like economic or political ones, we still faced challenges. There were limited subreddits that discussed the relevant coins, which further limited the diversity of viewpoints. Because of the limited subreddits and threads talking about the relevant coins, we also had very limited sample sizes to work with.

Despite these constraints, the thesis demonstrates a method for connecting transaction flows with community sentiment. It gives the basics for further research into meme coins and shows the importance of improved transparency in crypto markets.

8.2 Further Research

Due to the big issues with the dataset, the main goal would be to search for a better one that would upgrade the analysis. Also, another thing that should be done is expanding the dataset to include a broader range of tokens from various blockchains which would allow for a more thorough understanding of meme coin dynamics. It would involve comparing meme coin behaviour across different blockchains such as Ethereum, Binance Smart Chain, or Polygon.

The current study is based on historical data. However, real-time data analysis could offer more immediate applications, such as fraud detection and investor alerts during the early stages of token launches. Developing systems capable of analysing on-chain activities in real time could allow for the identification of suspicious activities, for example sniper bots and wash trading, as they happen.

Another potential direction for future research involves integrating psychological factors with wallet transaction data to develop an even deeper understanding of investor behavior in meme coin markets. Building on the current analysis of wallet activity and Reddit sentiment, future studies could explore how behavioral drivers such as FOMO, YOLO, and herding influence trading decisions in the early stages of a token's life cycle. These factors could be incorporated into machine learning models to simulate or predict short-term investor responses to market events, particularly during periods of rapid price movement or social media hype.

9. Summary

Working with Solana and Reddit showed that blockchain raw data is useless if people can't understand it. Most investors are lacking the tools to read through transaction logs. Simplifying the complexity is the way to make this information usable. That's why we focused on creating visual tools.

The wallet map made it possible to see patterns in trading behavior: who profited, who lost, who traded like a bot, and who acted early. It replaced lines of transaction data with interpretable maps. Clustering and suspicion scoring gave structure to the data in order to help users spot outliers and potential manipulation without needing technical skills. Additionally, Reddit sentiment graphs, topic modelling, and FOMO spikes made it clear when hype was rising, when sentiment turned negative, and what kind of language dominated each phase. These tools together showed the connection between what was happening on-chain and what was being said online.

Without visual tools, the promised transparency of blockchain stays out of reach for most people. This project aimed at creating tools for both researchers and users to make sense of behavior in a space full of scams, bots, and emotional trading. This project is a starting point and not a final solution. But it shows that with the right tools, complexity doesn't have to be a barrier.

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- Official $MELANIA website: https://melaniameme.com/
- Official $LIBRA website: https://www.vivalalibertadproject.com/
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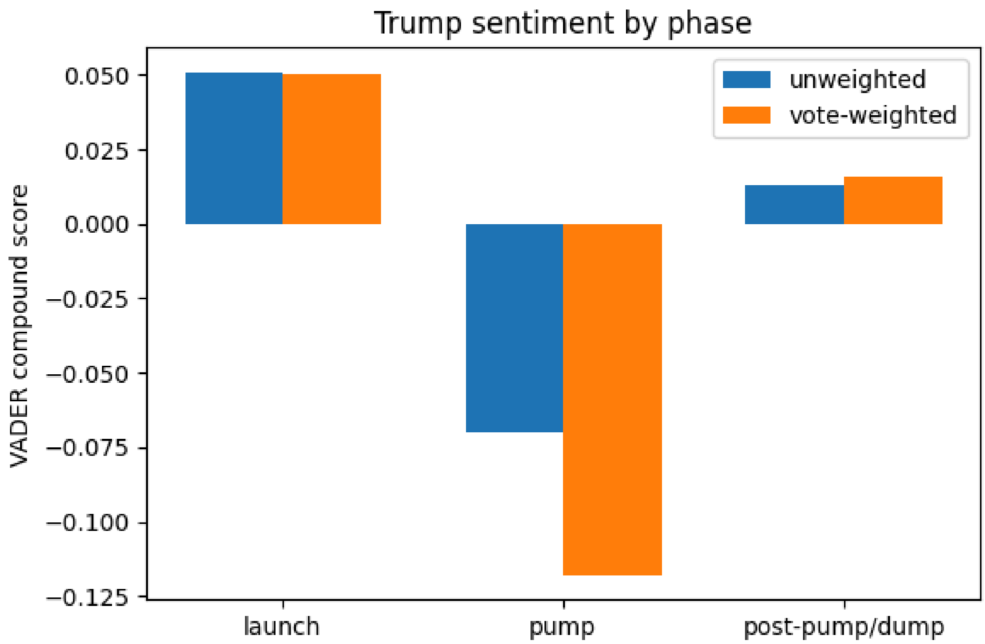
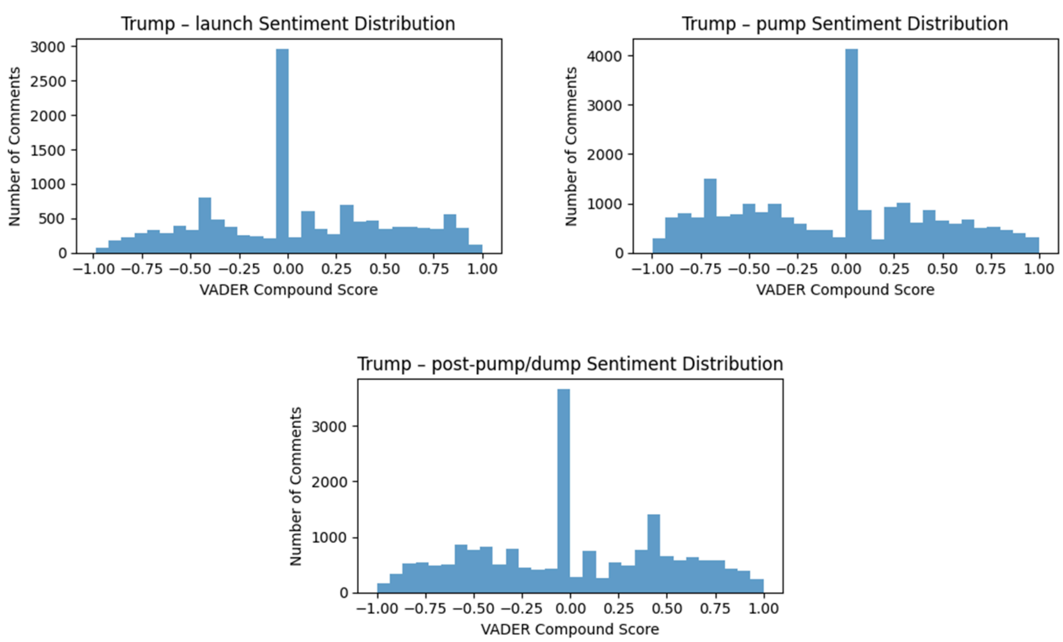


Figure 1. Trump sentiment by phase with VADER model



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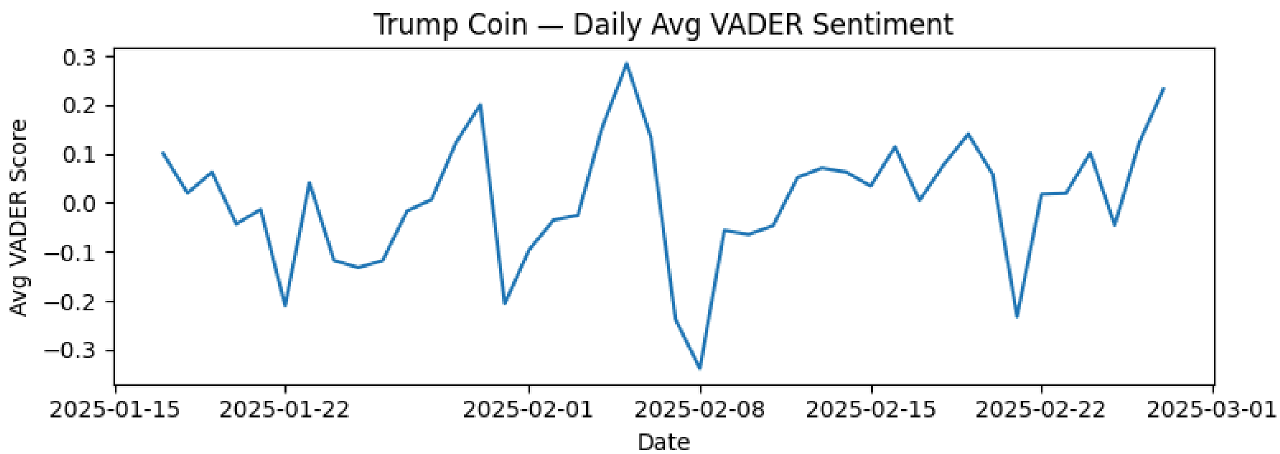

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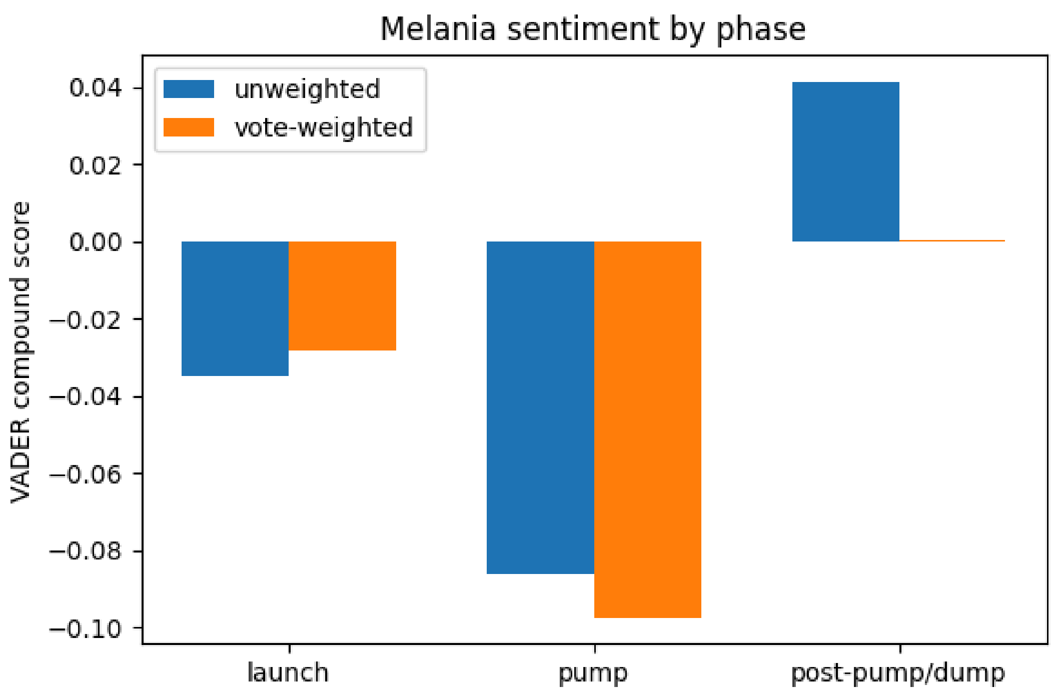

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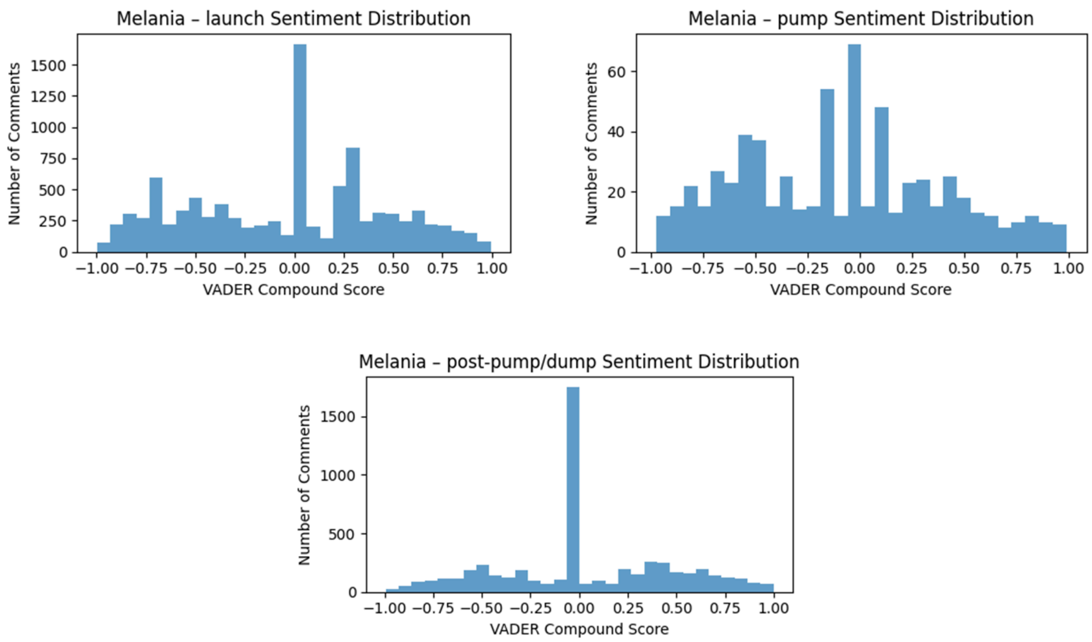

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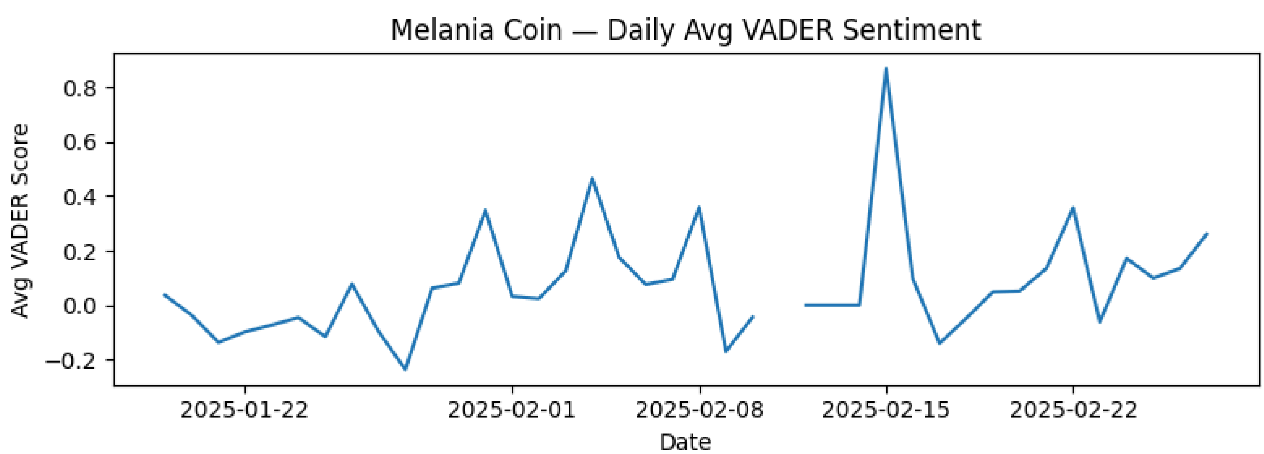

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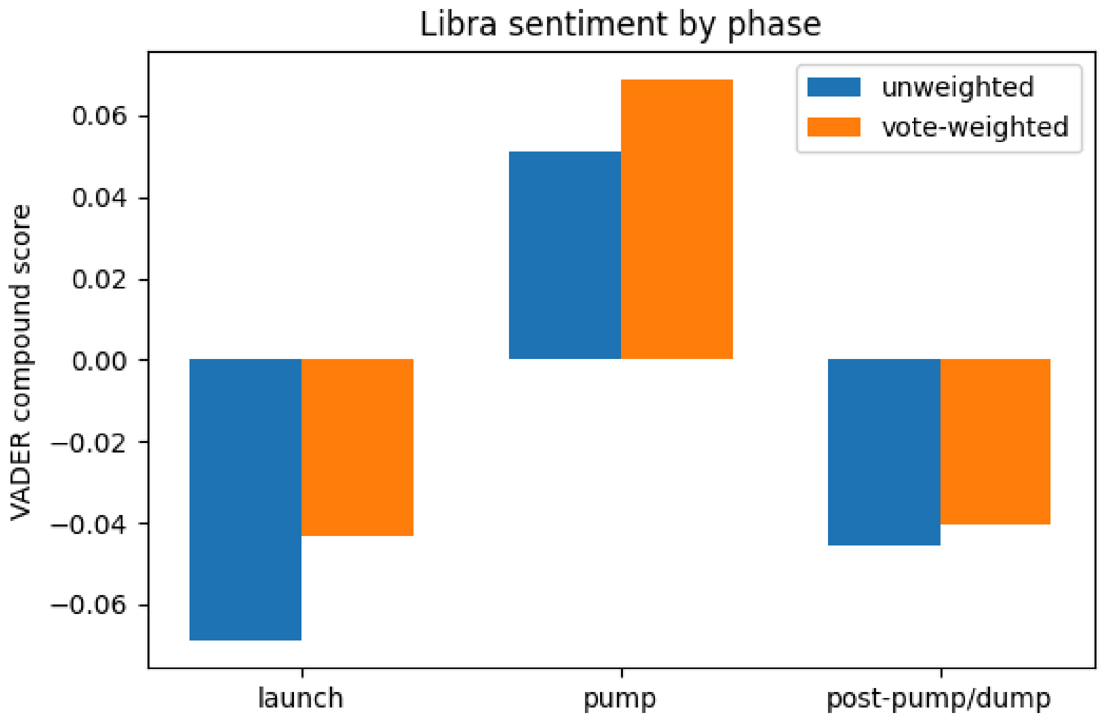

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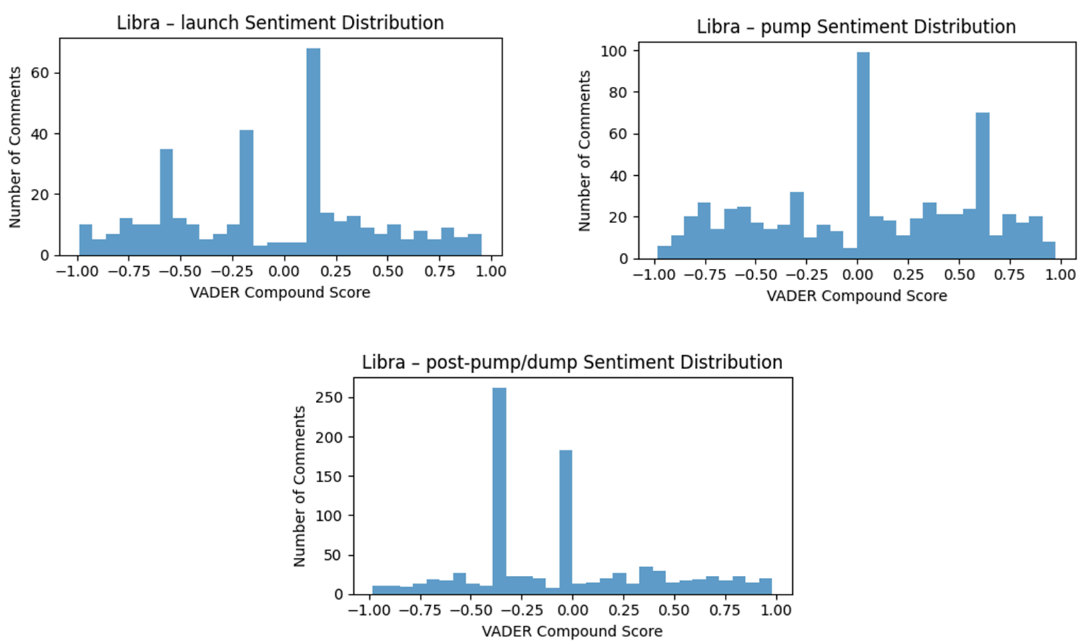

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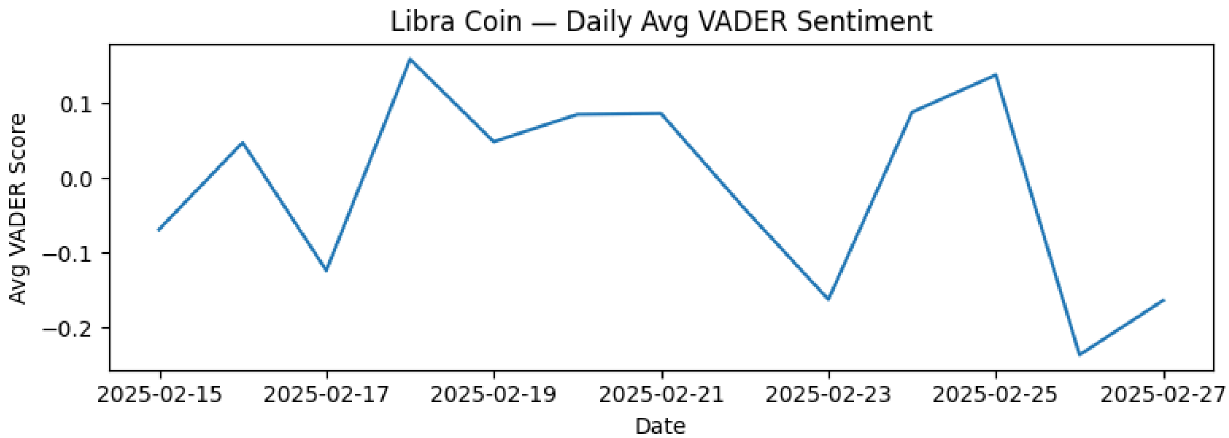

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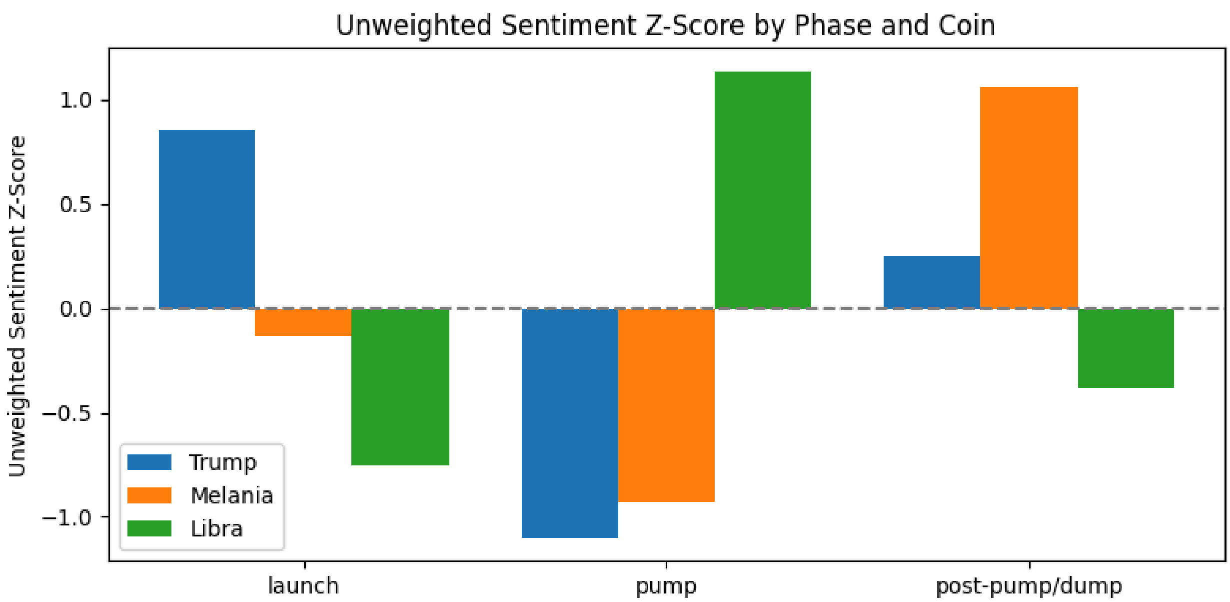

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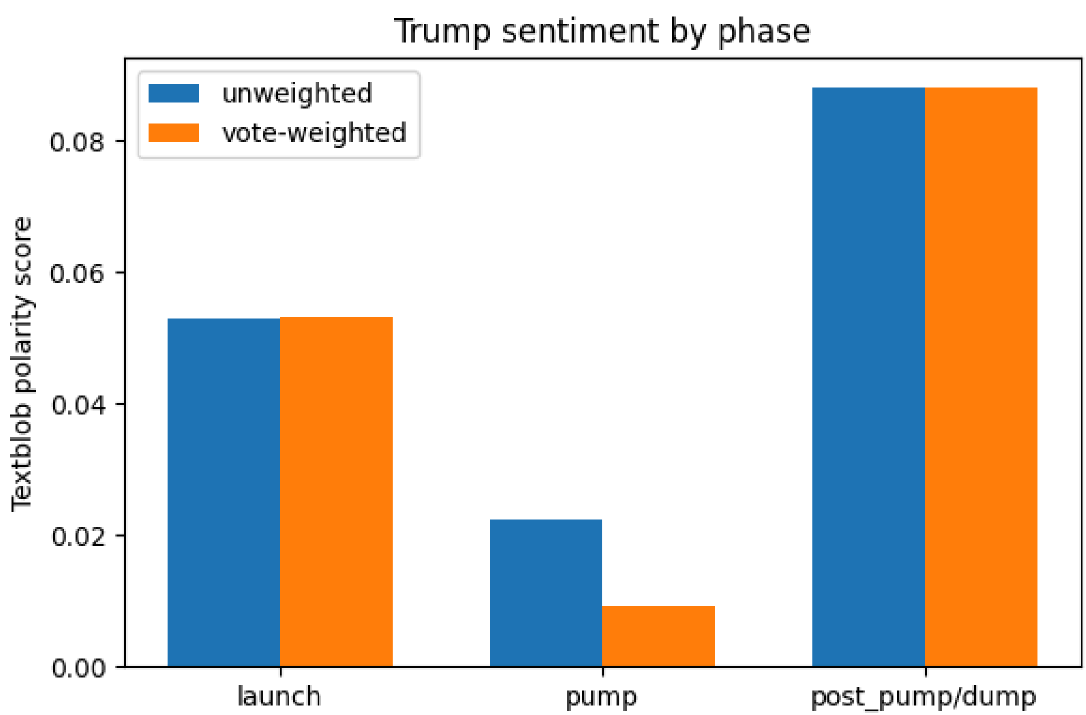

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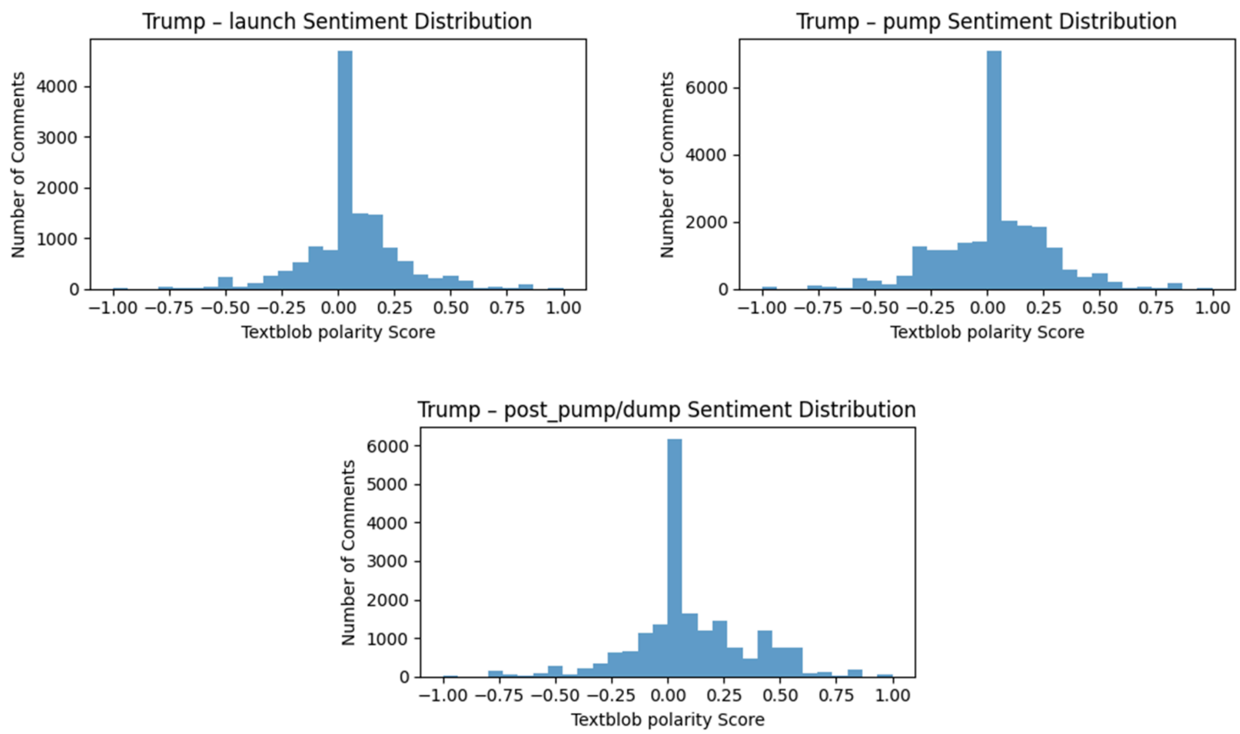

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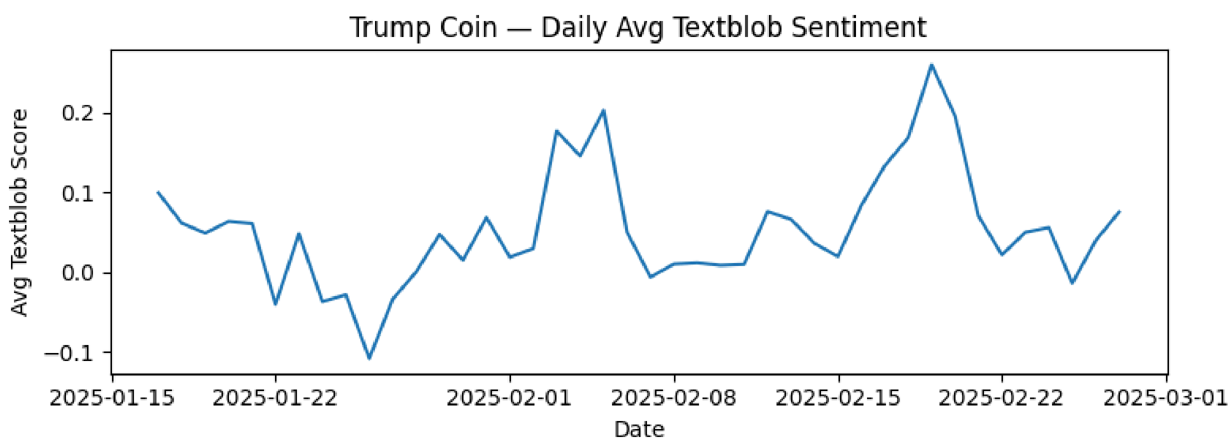

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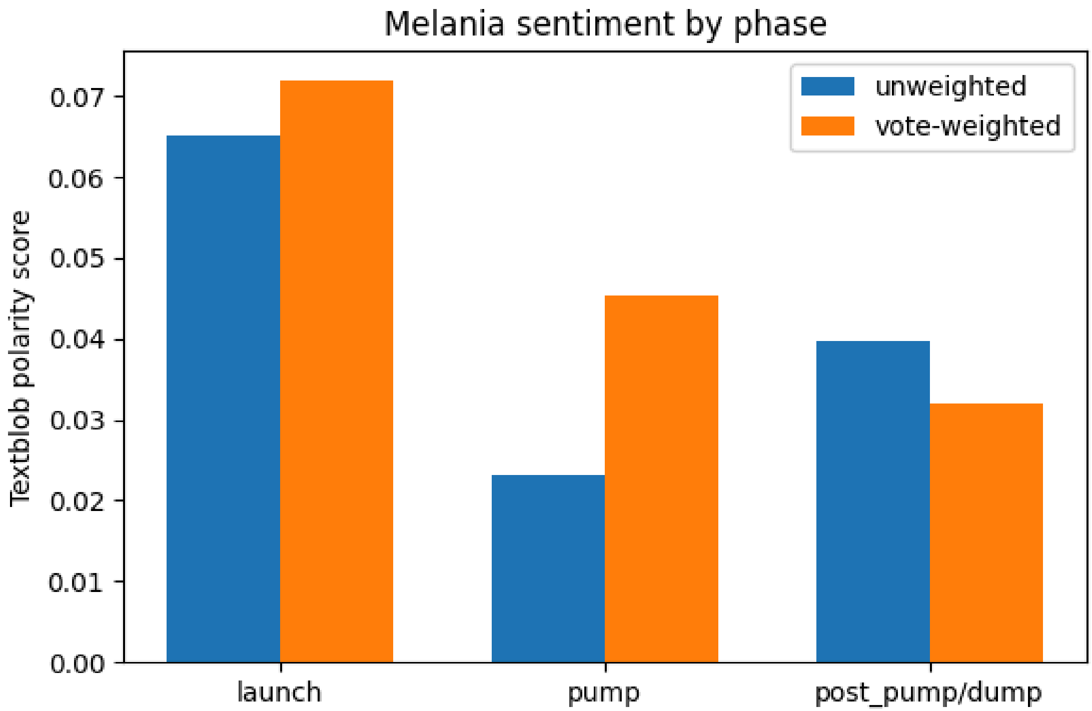

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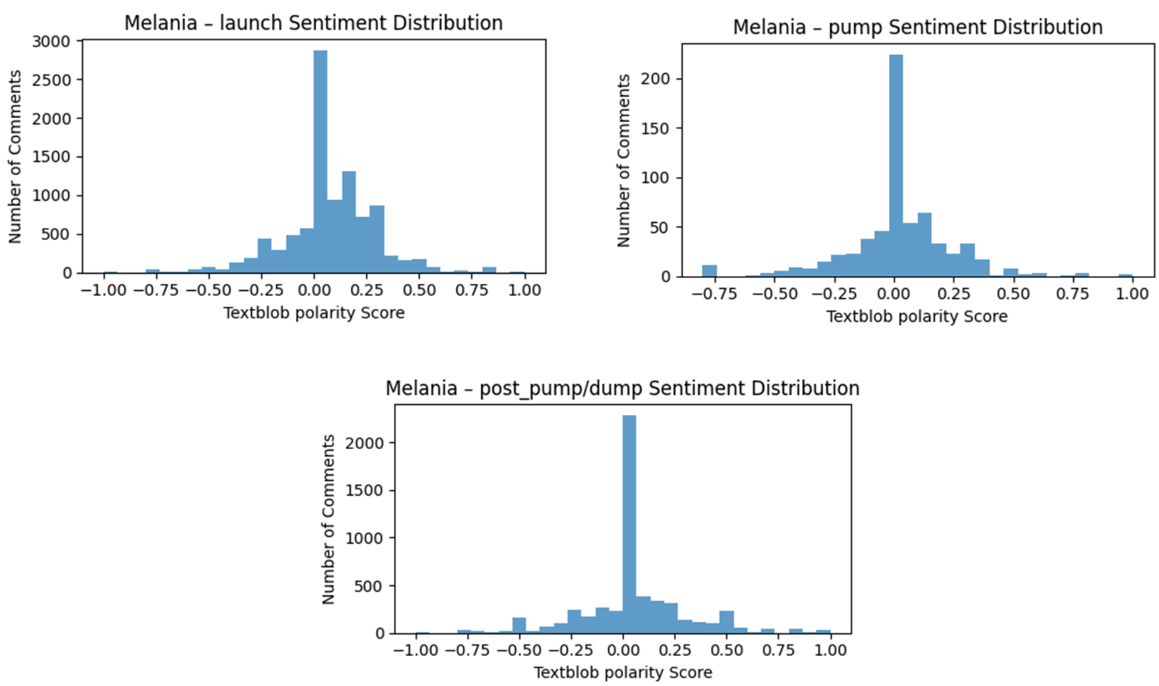

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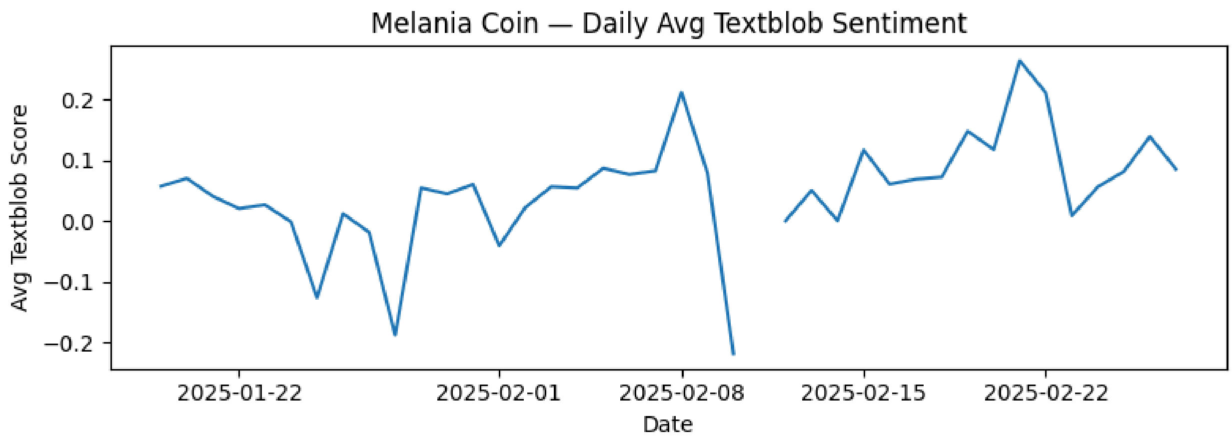

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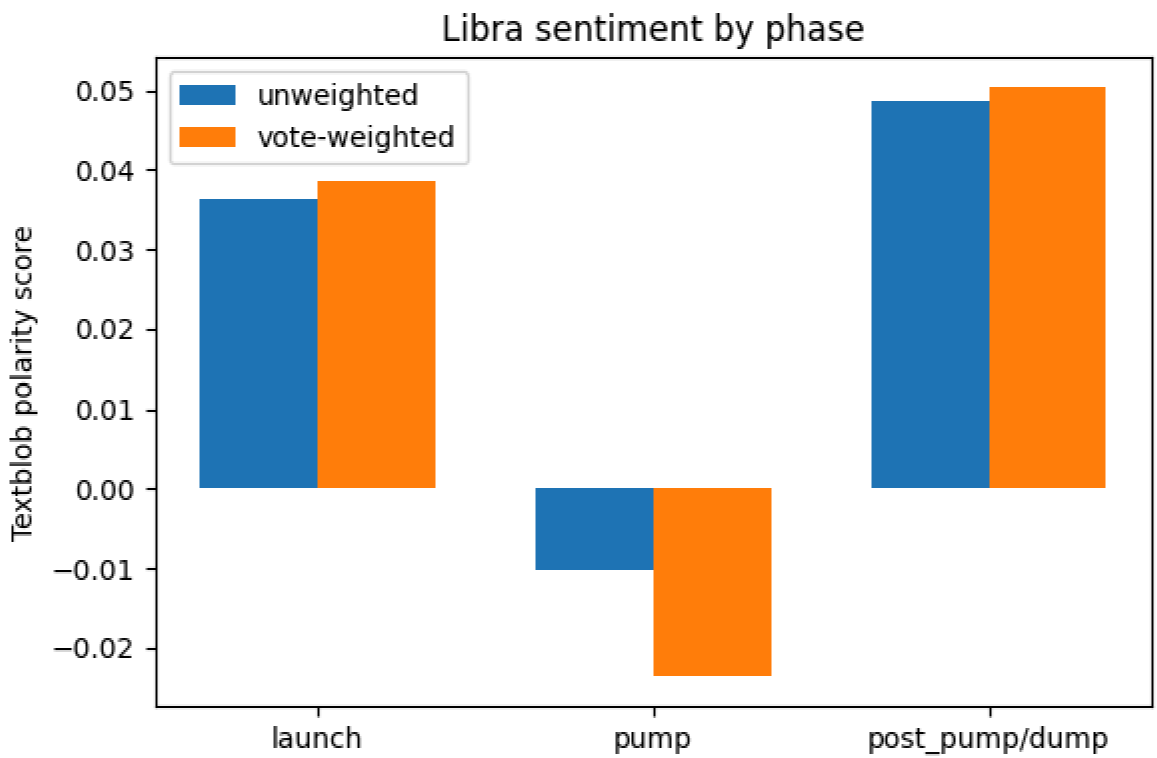

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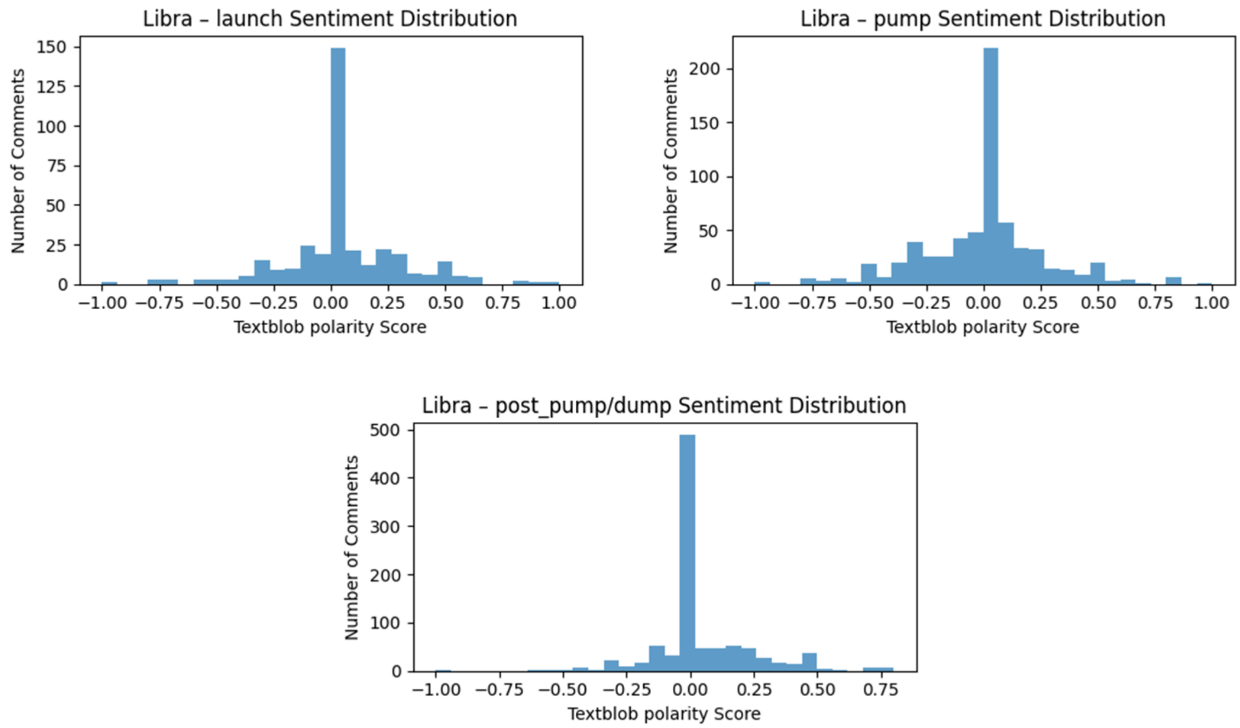

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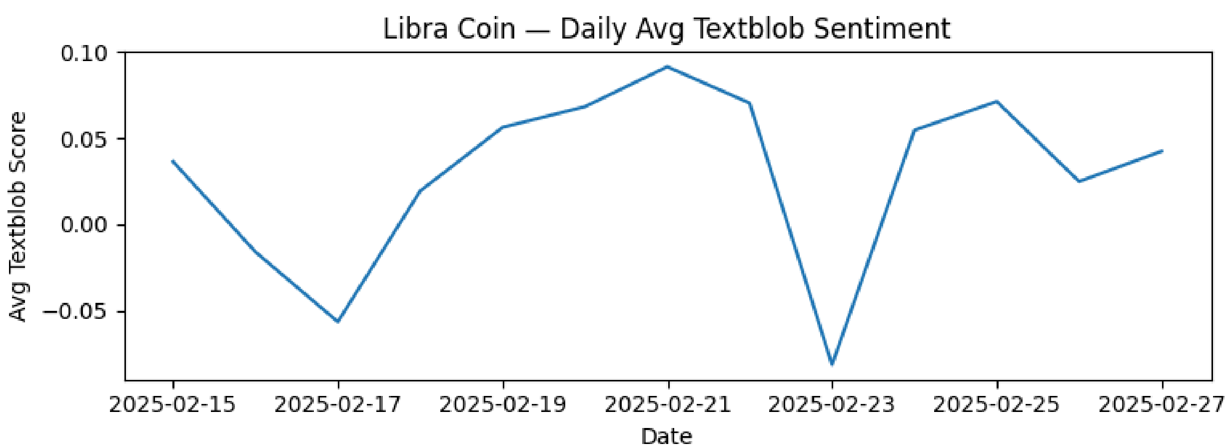

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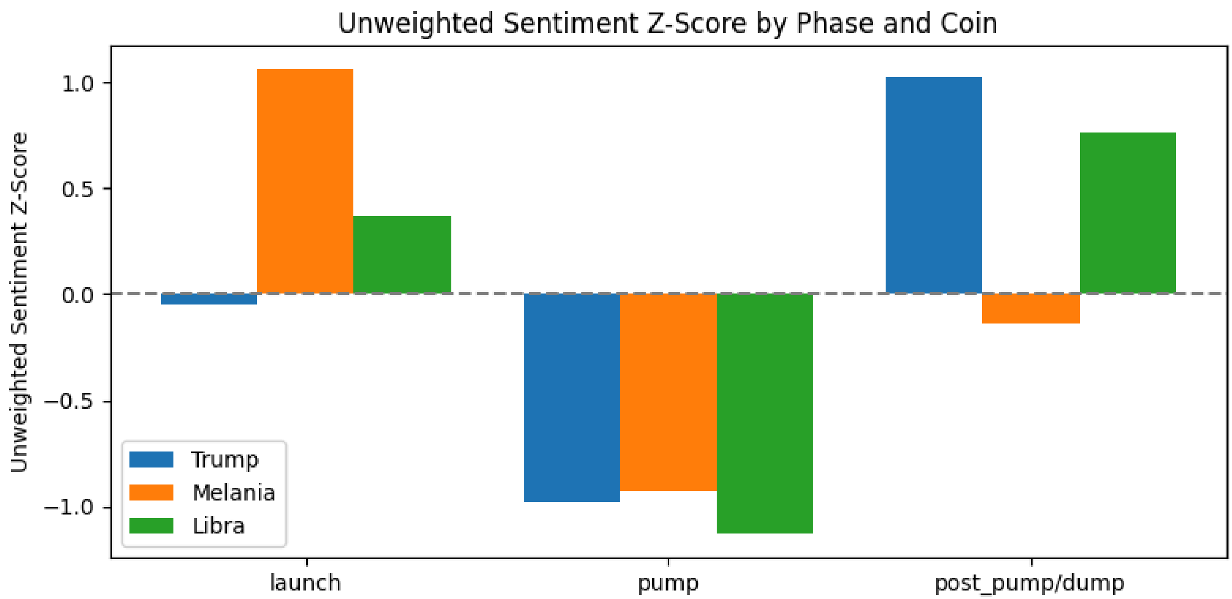

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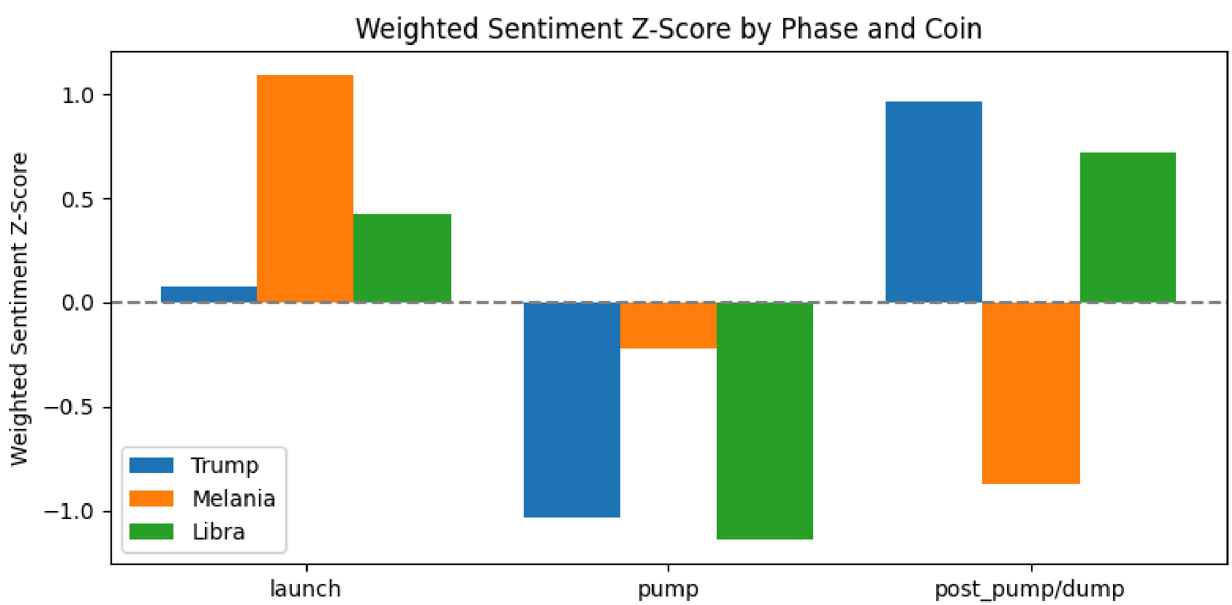

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