Retail investor behavior and sentiment surrounding the $TRUMP meme coin

Senior Year Project – Final Report

Fall/Spring 2024-2025

A project submitted in partial fulfillment of the
Lahore University of Management Sciences
of
BSc (Honours) in
Management Sciences

Lahore University of Management Sciences

18 May 2025

Project Detail

Type (Nature of project)	*Semester Based*			
Area of specialization	*DISC/OB/MGMT/MKTG/ACF*			
SPROJ Code	*MGS 491*			
Project Group Members				
Sr.#	Campus ID	Student Name	Email ID	*Signature
(i)	25110235	Muhammad Usama Habib	25110235@lums.edu.pk	
(ii)	25110079	Muhammad Haris Khan	25110079@lums.edu.pk	
(iii)	25110198	Salman Khan Shafi	25110198@lums.edu.pk	

*The candidates confirm that the work submitted is their own and appropriate credit has been given where reference has been made to the work of others

Plagiarism Free Certificate

This is to certify that I am _Muhammad Usama Habib___ S/D/o __Muhammad Rehan___group leader of SPROJ under the supervision of _Dr. Ussama Yaqub __ at Suleman Dawood School of Business at Lahore University of Management Sciences (LUMS). I declare that my SPROJ report has been checked by my supervisor and the similarity index is _9_% is less than 15%, an acceptable limit by HEC. The report is attached herewith as Appendix A.

Date: _17 May 2025_ Name of Group Leader: __Muhammad Usama habib___ Signature: ___Usama habib____

Name of Supervisor:	_Dr. Ussama Yaqub	Co-Supervisor (if any):	______________________
Designation:	__Assistant Professor __	Designation:	______________________
Signature:	______________________	Signature:	______________________

Table of Contents

Abstract

This study investigates retail investor behavior and sentiment surrounding the $TRUMP meme coin, particularly in the context of a suspected rug pull. Using Reddit data and Kraken price information, we conduct sentiment analysis and topic modeling to examine whether users knowingly invested despite scam indicators, and whether sentiment shifted meaningfully after the rug pull. Findings reveal that many users expressed skepticism while still participating, often with short-term speculative intent. Post-rugpull sentiment remained largely unchanged, suggesting pre-existing awareness of fraudulent risk. Our study bridges a critical gap in existing literature by combining natural language processing with time-aligned financial data.

1. Introduction

The rise of meme coins marks a new era of speculative digital finance, where social media narratives often drive market behavior more than traditional financial fundamentals. These tokens, frequently born from internet jokes, political movements, or viral moments, are embraced for their humor, hype, and high-risk potential. The $TRUMP meme coin exemplifies this phenomenon, launched amidst polarizing political sentiment and framed as both satire and opportunity. Unlike traditional cryptocurrencies with utility or technological innovation, meme coins thrive on community discourse, reflexive belief systems, and often, ironic detachment from value claims.

In this context, we investigate two core questions:

(1) To what extent did Reddit users invest in the Trump meme coin despite recognizing it as a potential rug pull, and did their sentiment indicate speculative short-term intent?

(2) Did the occurrence of the rugpull significantly impact the sentiment of Reddit users, or did sentiment remain stable, suggesting prior awareness of the coin's fraudulent nature?

These questions matter because they illuminate the psychology of high-risk retail investing in the age of internet-native assets.

We leverage sentiment analysis, topic modeling, and speculative intent tagging to analyze Reddit discourse surrounding the $TRUMP meme coin. This research contributes to the growing literature on financial meme culture by quantifying retail investor sentiment over time and correlating it with market price behavior.

2. Literature Review

Recent academic work has increasingly acknowledged the speculative and socially driven nature of meme coins. One foundational study presents a broad overview of meme coins as high-risk, high-volatility assets with little fundamental value, often fueled by social media virality and retail investor hype [1]. This highlights how meme coins attract impulsive participation, especially among younger investors, yet leaves unaddressed the question of whether investors are aware of the risks or participating ironically. Building on this, another article narrows its focus to the $TRUMP meme coin, critiquing its centralized tokenomics and celebrity-driven narrative. While it identifies red flags such as founder-held supply and poor transparency, it lacks any user-level behavioral analysis, which our study provides through Reddit sentiment mining [2].

Complementary perspectives explore the cultural symbolism of the $TRUMP coin, describing it as performative politics masquerading as financial innovation [3]. These analyses are rich in narrative but do not quantify user reactions or investment motives, a gap addressed through our LDA and speculative keyword tagging. Regulatory implications are also discussed in recent literature, particularly the push to reclassify meme coins and NFTs as cultural collectibles [4]. This raises questions about investor protection in the absence of oversight but stops short of analyzing how users respond in real-time to such risks. Our work captures that window through sentiment tracking around the rugpull event.

Further, transactional data studies reveal the asymmetric payoff structure of $TRUMP, where early entrants (often insiders) profit disproportionately while latecomers are left with losses [5]. Yet these findings stop short of answering whether retail investors sensed this risk beforehand or were blindsided. We build on this by showing that over half of speculative comments had negative sentiment, suggesting a degree of risk awareness. Sentiment has also been formally integrated into pricing models, where meme coin volatility is shown to be sentiment-driven rather than fundamentals-based [6]. However, these models often rely on sentiment indexes or Twitter data, whereas we use subreddit comments as a more context-rich source.

The sociopolitical dimension of meme coins is another emerging theme, with researchers arguing that political tokens like $TRUMP or LIBRA threaten democratic integrity by doubling as unregulated campaign finance tools [7]. While alarming, these insights remain theoretical. Our study operationalizes public reaction to such threats via post-tagging and sentiment shifts. In contrast, quantitative papers on meme coin prices tend to ignore sentiment altogether. For instance, a time series forecasting study on Pepemon tokens models volatility accurately but does not explore behavioral or hype-driven inputs [8]. We take a reverse approach by focusing on how price changes correlate with retail discourse, particularly during critical windows like a rugpull.

Early whitepapers on meme tokens often describe them as culture-first, logic-second digital assets, but rarely go beyond surface-level hype analysis [9]. Our study uses NLP to extract dominant scam-related keywords and topics, thus grounding these cultural observations in measurable data. Lastly, a broader Web3 governance article touches briefly on meme coins but lacks relevance to our $TRUMP-specific focus [10]. It is therefore excluded from our core literature review but noted for context.

.

3. Methodology

This study adopts a mixed-method research design, integrating natural language processing (NLP), topic modeling, keyword tagging, and statistical testing to analyze user sentiment and behavior surrounding the $TRUMP meme coin. The methodology leverages two primary data sources: textual data from Reddit and historical price data from Kraken, structured to align temporally for comparative analysis.

3.1 Data Collection

Reddit data was collected from the primary subreddit dedicated to the $TRUMP meme coin, including both posts and their corresponding comments. While comments themselves did not include exact timestamps, each was matched with its parent post using the permalink. The post timestamp was used as a proxy for the comment's time, allowing us to assign a 4-hour bin to each comment. This approach, while not precise, enabled reasonable aggregation for trend-based analysis across the coin's lifecycle.

In parallel, we used historical 4-hour interval data for the TRUMP/USDT trading pair from Kraken, capturing variables such as open, close, high, low, and volume. This allowed us to align sentiment metrics from Reddit with actual market price movements over identical time windows.

3.2 Sentiment Analysis

We applied the pre-trained cardiffnlp/twitter-roberta-base-sentiment model using Hugging Face Transformers and PyTorch to classify each Reddit comment as **positive**, **neutral**, or **negative**. This Robertaa model was fine-tuned on social media text, making it suitable for Reddit's informal and meme-heavy language. Each comment was also assigned a **confidence score**, quantifying the model's certainty in its classification.

To prepare for sentiment labeling, we first removed null entries and standardized the text input format. Predictions were executed in batches, and results were appended to the original dataset. Sentiment labels were also numerically encoded (positive = 1, neutral = 0, negative = -1) to compute aggregate sentiment averages per time window.

3.3 Speculative Intent Detection

To assess short-term investment behavior, we developed a simple keyword-based flagging method. Comments were marked as speculative if they included common hype-driven or exit-intent phrases such as "quick flip," "get in," "get out," "exit early," "10x," "pump," or "moon." This allowed us to isolate comments reflecting high-risk, profit-first motivation. We further filtered by engagement (minimum upvotes ≥ 5) to avoid noise from fringe or troll comments.

3.4 Topic Modeling (LDA)

We implemented Latent Dirichlet Allocation (LDA) to identify latent themes within the comment corpus. The text was preprocessed with stopword removal, tokenization, and vectorization using bi-grams. We used CountVectorizer from scikit-learn with ngram_range=(2,2) and fit a 5-topic LDA model. Each topic was interpreted based on top weighted terms and manually labeled as:

1. Scam/Rug Pull Concerns
2. Moderation & Reddit Comments
3. Trump & Political Reactions
4. Sarcasm, Grift & Humor
5. Coin Speculation & Crypto Trading

We then assigned each comment to its dominant topic and analyzed topic-level sentiment trends over time.

3.5 Temporal Aggregation & Price Merging

Each comment's proxy timestamp was converted into a time bin using .dt.floor('4H').

Sentiment scores were aggregated per time bin to generate a time series of average sentiment. This was merged with Kraken's pricing data on the same time key, allowing us to overlay price and sentiment trends.

3.6 Statistical Testing (RQ2)

To test whether the rugpull event had a statistically significant impact on sentiment, we conducted an independent two-sample t-test. We compared average sentiment scores from the 4-hour intervals **before** and **after** January 20, 2025, 16:00 (the rugpull timestamp). While this does not control for other confounding events, it provides a baseline measure of post-event sentiment shift.

All data processing, modeling, and analysis were implemented in Python using the following libraries: pandas, numpy, matplotlib, seaborn, scikit-learn, torch, transformers, wordcloud, and re. These tools collectively supported data cleaning, sentiment inference, topic modeling, statistical testing, and visualization generation throughout the study.

4. Findings and Analysis

This section presents the results that directly address our two research questions and interpret them in the context of Reddit user behavior around the $TRUMP meme coin.

To investigate RQ1, we analyzed sentiment-labeled comments alongside speculative keyword tagging. The bi-gram word clouds (Appendix Figures A1–A3) show that terms commonly associated with speculative trading—such as "quick flip," "get out," "10x," and "pump dump"—appear across all sentiment categories, indicating the presence of speculative discourse regardless of sentiment polarity.

These visualizations also reveal interesting nuances: the positive sentiment cloud features ironic optimism such as "can't wait," "golden age," and "end poverty," satirically paired with "rug pull" and "pump dump." The neutral cloud shows terms like "bot action," "hawk tuah," and "market cap," referencing both moderation language and viral meme culture. Notably, "hawk tuah," a popular meme phrase linked to another meme coin scam, illustrates the layered irony users employed when engaging with $TRUMP. The negative cloud features heavy warnings like "lose money," "money laundering," and "ponzi scheme," reinforcing that many users viewed the project as fraudulent from the outset.

We then isolated comments containing speculative keywords and filtered them for higher engagement (upvotes ≥ 5) to focus on impactful discourse. Figure 1 displays the sentiment breakdown among these speculative comments: 58.5% were negative, 34.7% neutral, and only 6.7% positive. This distribution implies that a majority of speculative participants were either skeptical or ironic in tone. In other words, users were aware of the coin's inherent risks but still expressed intent to "get in and out" quickly-emphasizing the irony of knowingly participating in what they believed could be a scam. This answers RQ1 by confirming that speculative sentiment coexisted with an awareness of fraud.

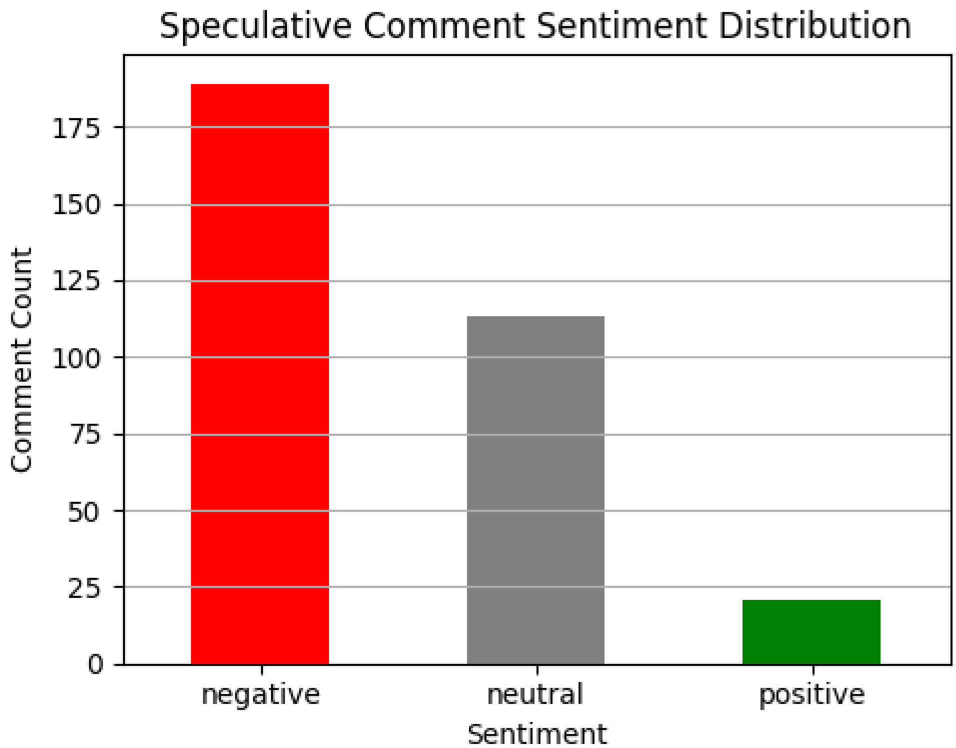

Figure 1

To answer RQ2, we compared average sentiment before and after the rugpull event on January 20, 2025 at 16:00. The mean sentiment score pre-event was -0.387, which declined marginally to -0.418 post-event. This small change was not statistically significant, as indicated by a two-sample t-test result (t-stat = 0.30, p-value = 0.776). Figure 2 shows the sentiment-price overlay graph, where no sharp sentiment collapse is visible after the rugpull.

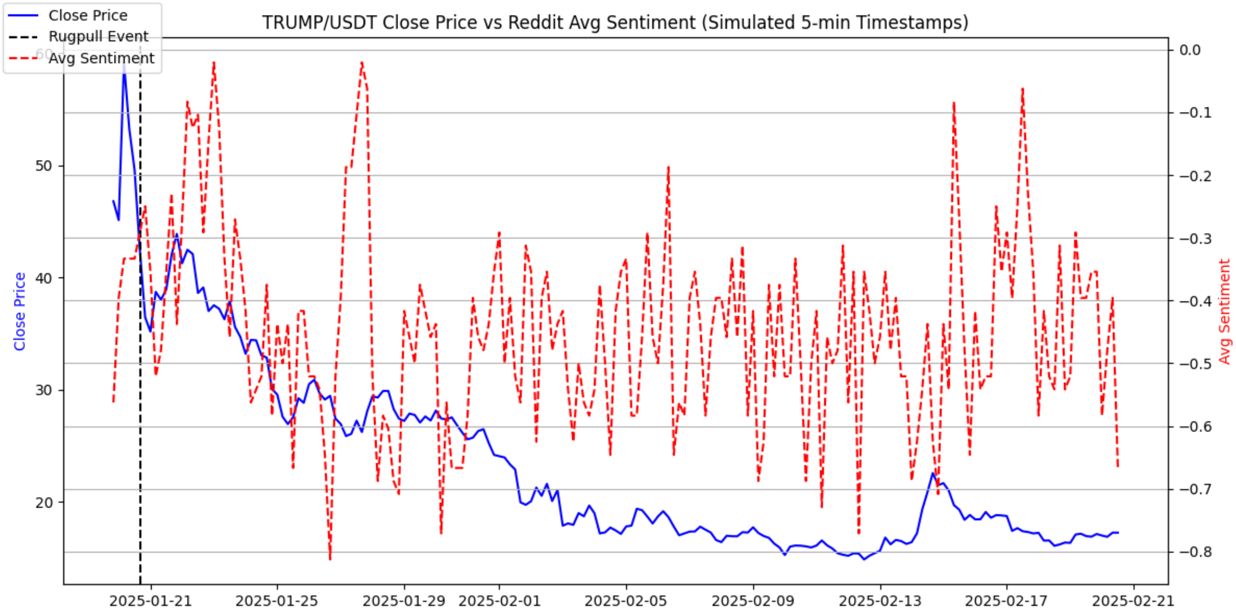

Figure 2

This finding suggests that Reddit users were not shocked or disillusioned by the rugpull because their sentiment was already largely negative. The rugpull validated their expectations rather than altering them. The consistency in sentiment scores reinforces the hypothesis that the fraud was anticipated, and many users engaged with a reflexive understanding of the risk.

Topic modeling further supports this. Figure 3 illustrates topic-wise sentiment trends over time. Notably, the topics labeled “Scam/Rug Pull Concerns” and “Sarcasm, Grift & Humor” consistently exhibited negative sentiment throughout the dataset’s timeline. These topics did not experience a post-rugpull drop, affirming that the themes of distrust and irony were present from the start.

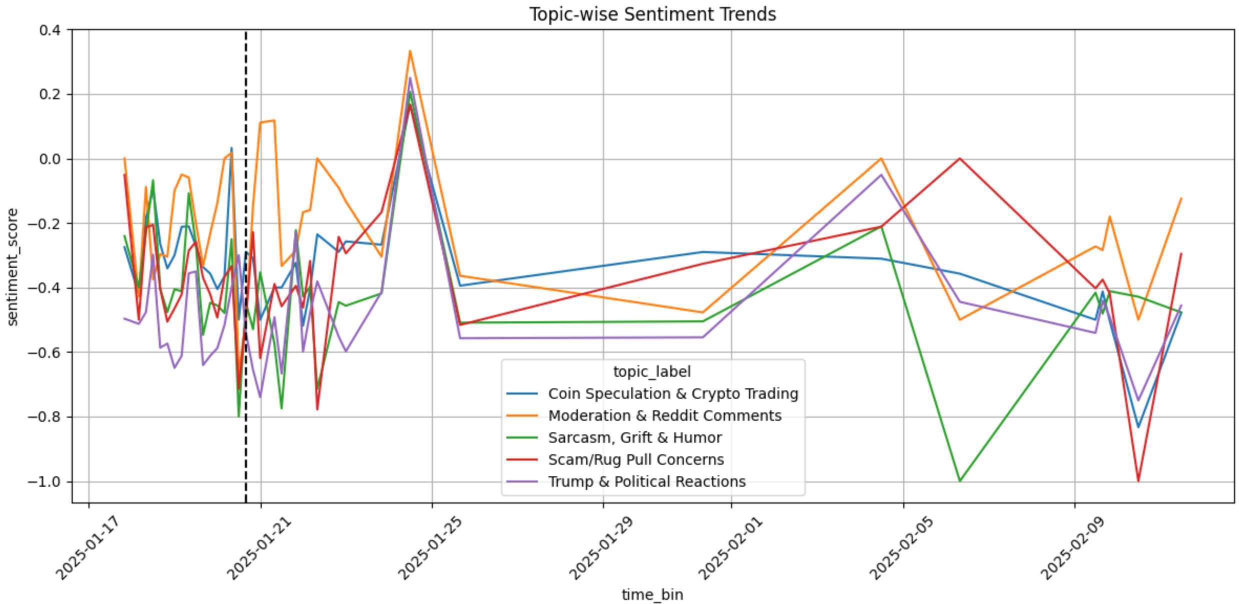

Figure 3

Together, these findings strongly support both research questions: Reddit users displayed speculative intent even when aware of fraud, and their sentiment remained largely unchanged after the rugpull-highlighting the paradoxical nature of meme coin communities where irony, skepticism, and profit-chasing coexist.

To address the second question, we compared pre- and post-rugpull sentiment. The average sentiment before the rugpull was -0.387, while after the event it slightly declined to -0.418. A t-test produced a p-value of 0.776, indicating that the change was not statistically significant. This result suggests that users' sentiment remained broadly negative and stable, reinforcing the notion that the rugpull was anticipated (Figure 2).

Topic-wise sentiment trends (Figure 3) show that topics such as "Scam/Rug Pull Concerns" and "Grift & Humor" had consistently negative sentiment throughout. Sentiment did not sharply decline post-event for any topic, further supporting the hypothesis of prior user awareness.

5. Limitations and Future Implications

While this study provides novel insights into investor sentiment within meme coin communities, it is not without limitations. First, due to the absence of comment-level timestamps during Reddit extraction, we used each comment's parent post timestamp as a proxy for temporal alignment. This may have introduced slight misalignment in 4-hour sentiment aggregation, though the impact was minimized through large sample size and binning. Second, although Twitter (now X) was initially considered as a complementary data source, recent API policy changes require paid access, making it unfeasible for large-scale academic analysis.

Additionally, our speculative keyword tagging relied on a predefined list and may have overlooked nuanced or sarcastic forms of investor intent. Similarly, while Latent Dirichlet Allocation (LDA) helped uncover thematic trends, the interpretation of topics required human labeling, introducing potential subjectivity.

That said, this study lays important groundwork for future research. With access to richer cross-platform data (e.g., Discord, Telegram, YouTube comments), future analyses could uncover multi-platform hype cycles. Supervised machine learning models could also be trained to detect speculative or scam-aware language more precisely.

Our findings demonstrate that meme coin participants often engage with irony, fully aware of the potential for scams, yet still driven by short-term gains. This paradox is central to understanding modern financial behavior in digital communities. With slight methodological improvements and broader data integration, this type of analysis could support early detection systems for future meme coin frauds and help inform regulators and investors alike about emerging scam patterns in real-time.

6. Conclusion

This study provides empirical evidence that retail investors engaged with the $TRUMP meme coin while being aware of its fraudulent nature, motivated by speculative short-term goals. Despite the rugpull event, sentiment remained consistently negative, suggesting that many users were not deceived but chose to participate knowingly. This behavior underscores the unique psychological profile of meme coin investors-characterized by irony, reflexivity, and risk tolerance.

By combining sentiment analysis, topic modeling, and market data, our study contributes a multi-dimensional perspective to the evolving literature on financial memes and speculative investing. As meme coin phenomena continue to blur the lines between culture and capital, understanding investor mindset becomes critical for both regulators and market observers.

Appendix

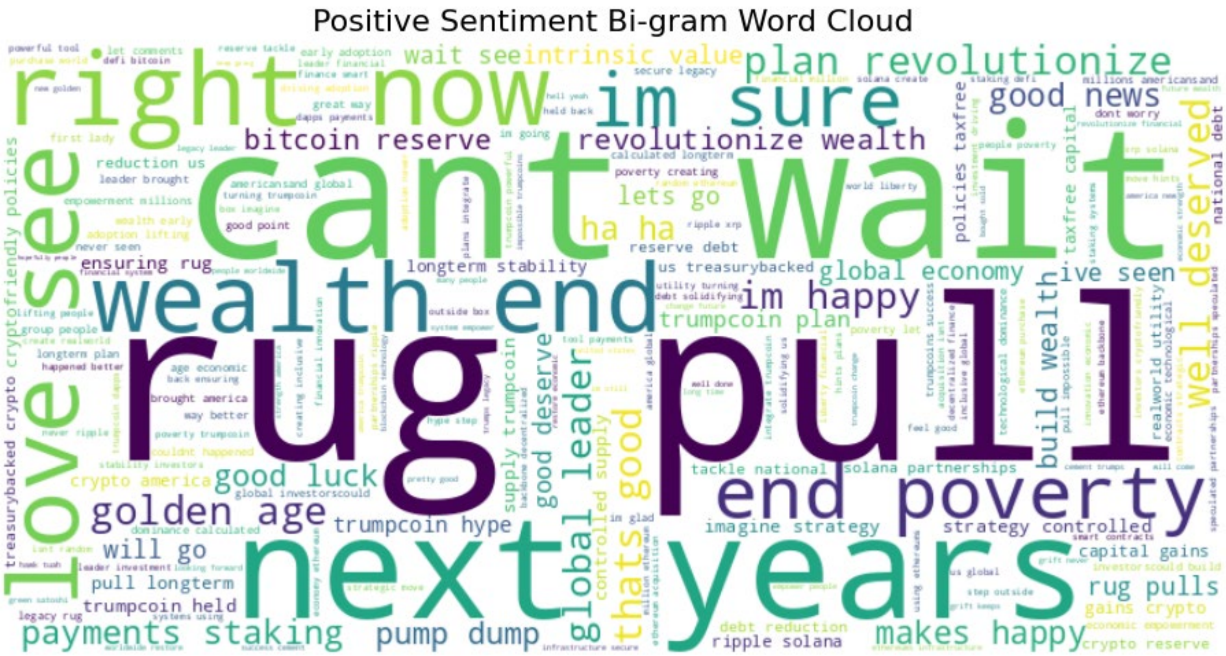

Figure A1. Positive Sentiment Bi-gram Word Cloud

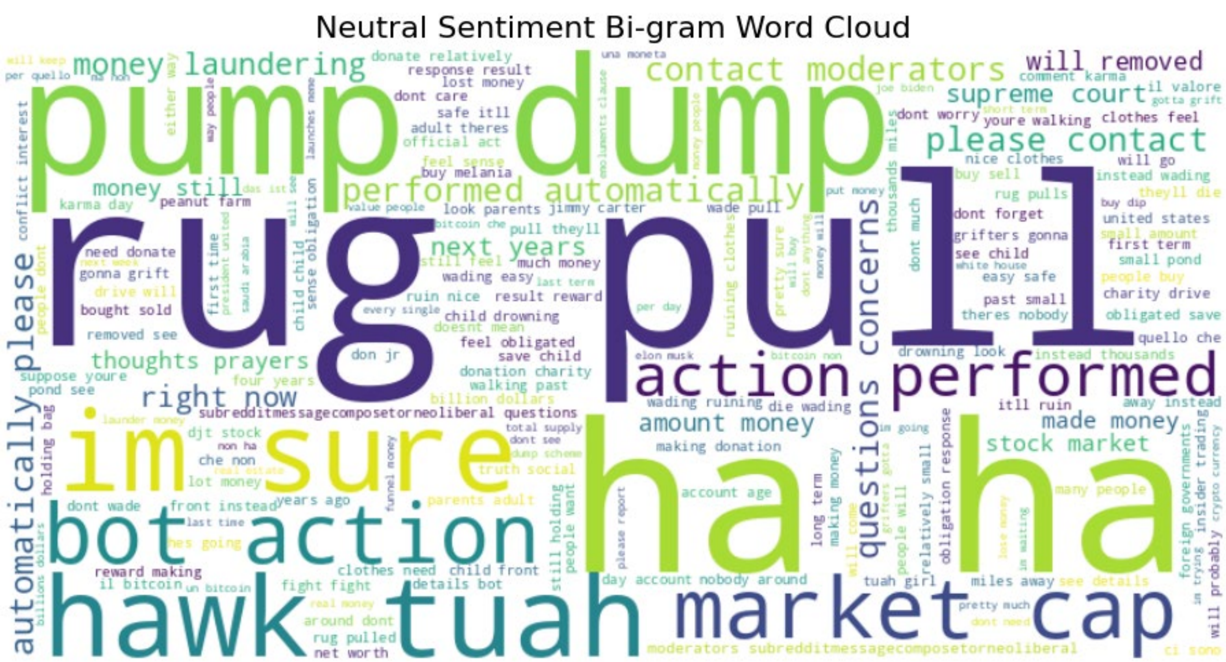

Figure A2. Neutral Sentiment Bi-gram Word Cloud

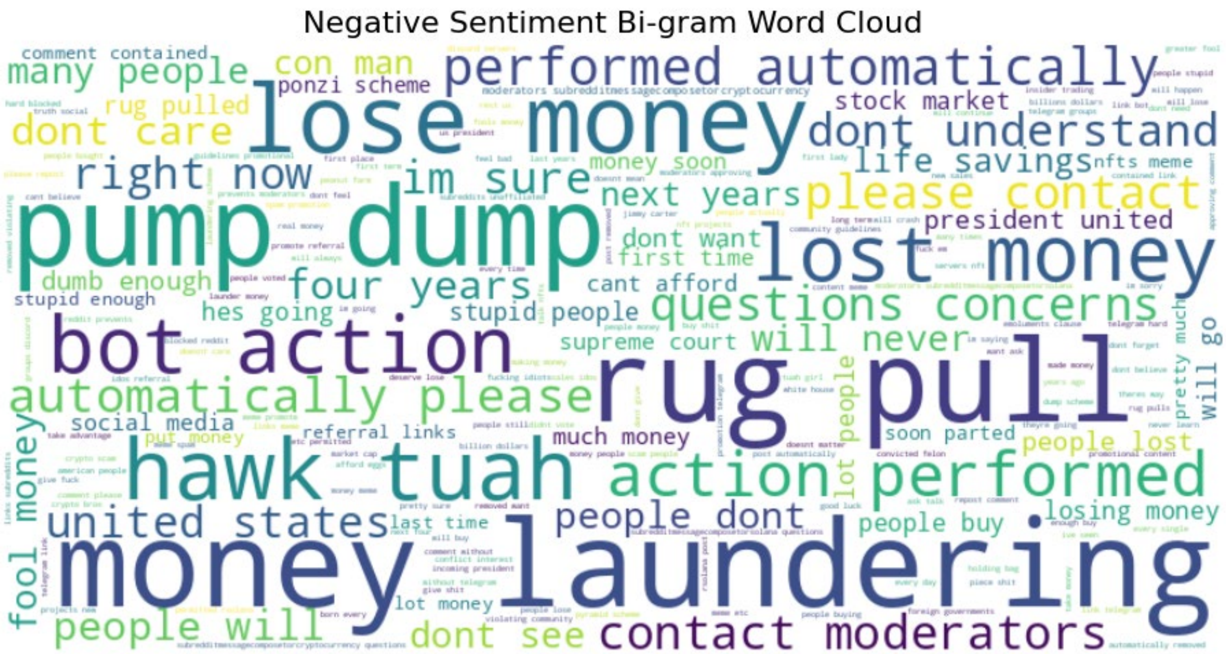

Figure A3. Negative Sentiment Bi-gram Word Cloud

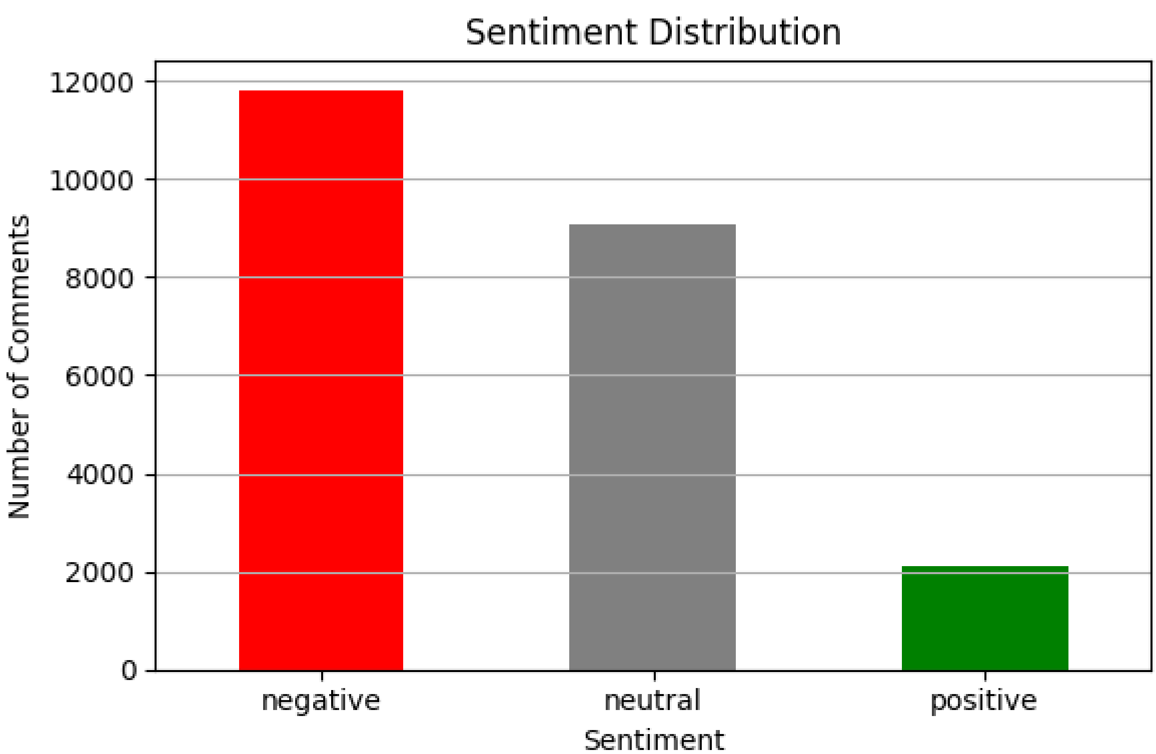

Figure A4. Overall Sentiment Distribution (Positive/Neutral/Negative)

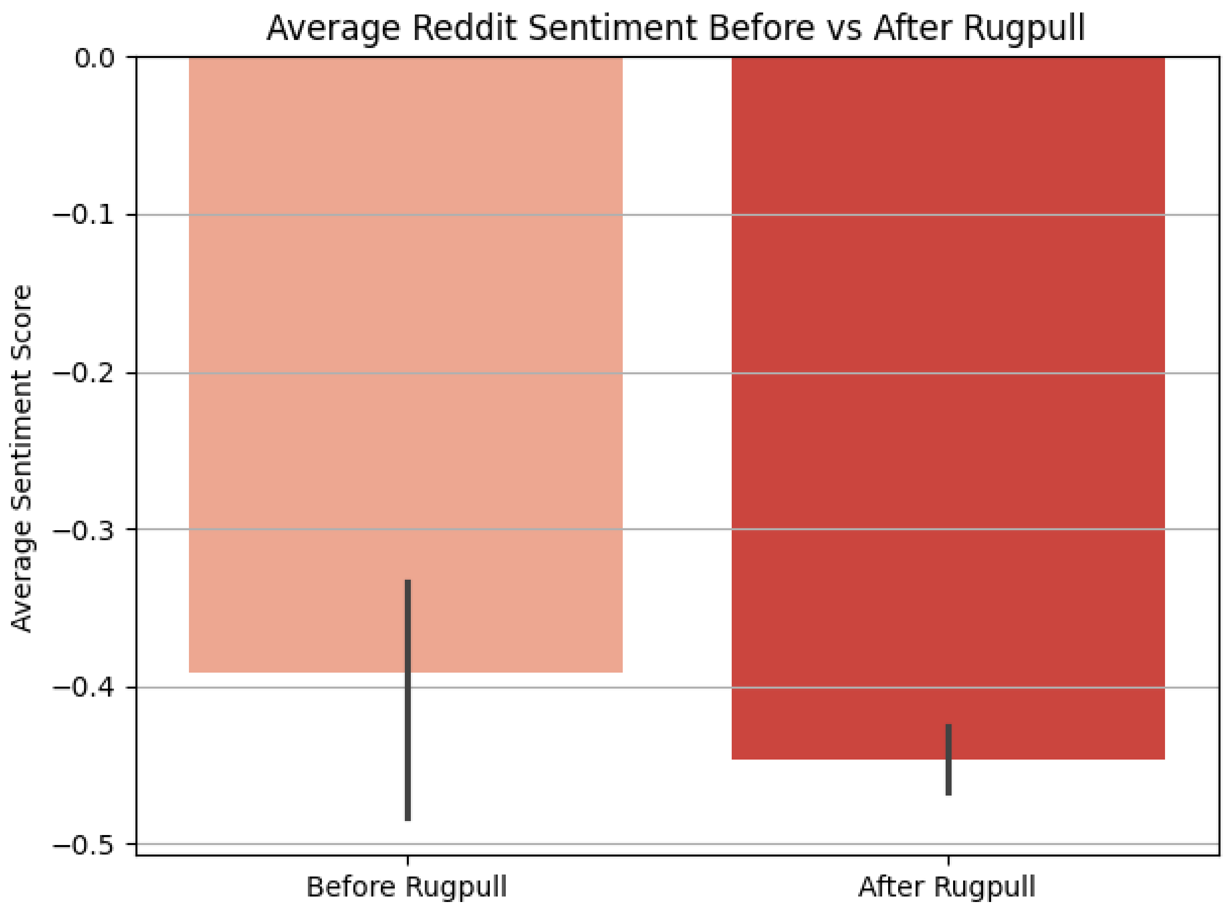

Figure A5. Average Sentiment Before vs. After Rugpull (Bar Chart)

References

Krause, David, Beyond the Hype: A Meme Coin Reality Check for Retail Investors (July 11, 2024). Available at SSRN: https://ssrn.com/abstract=4891841 or http://dx.doi.org/10.2139/ssrn.4891841

Krause, David, The $TRUMP Meme Coin: Genius, Greed, or Grift? (January 20, 2025). Available at SSRN: https://ssrn.com/abstract=5104413 or http://dx.doi.org/10.2139/ssrn.5104413

Krause, David, The $TRUMP Meme Coin: A Cryptocurrency Revolution or a Political Gimmick? (January 23, 2025). Available at SSRN: https://ssrn.com/abstract=5109409 or http://dx.doi.org/10.2139/ssrn.5109409

Krause, David, Are Meme Coins and NFTs Cultural Assets or Securities? Implications of Trump's Digital Asset Reclassification (January 27, 2025). Available at SSRN: https://ssrn.com/abstract=5113077 or http://dx.doi.org/10.2139/ssrn.5113077

Krause, David, Risks of Investing in Meme Coins: A Case Study of the $TRUMP Coin (February 05, 2025). Available at SSRN: https://ssrn.com/abstract=5126056 or http://dx.doi.org/10.2139/ssrn.5126056

Ludwig, Eric T., Sentiment-Based Option Pricing for Meme Coins. Available at SSRN: https://ssrn.com/abstract=5131168 or http://dx.doi.org/10.2139/ssrn.5131168

Krause, David, The LIBRA and $TRUMP Political Meme Coins: Exploring Financial Risks and Threats to Democratic Integrity (February 17, 2025). Available at SSRN: https://ssrn.com/abstract=5141805 or http://dx.doi.org/10.2139/ssrn.5141805

Prabhu, Tejesh, and Nagaraja Nagaraja. "Forecasting of Price Returns of Meme Coins." Srusti Management Review, vol. 16, no. 2, 2023, pp. 127–132.

Appendix A

Include here the 1st page of the Turnitin Report.

Every supervisor has his/her own Turnitin account. If not then the supervisors are requested to get the account from Library as soon as possible.

9% Overall Similarity

The combined total of all matches, including overlapping sources, for each database.

Match Groups

- **16** Not Cited or Quoted 9%
  Matches with neither in-text citation nor quotation marks
- **0** Missing Quotations 0%
  Matches that are still very similar to source material
- **0** Missing Citation 0%
  Matches that have quotation marks, but no in-text citation
- **0** Cited and Quoted 0%
  Matches with in-text citation present, but no quotation marks

Top Sources

7%	Internet sources
1%	Publications
8%	Submitted works (Student Papers)

Integrity Flags

0 Integrity Flags for Review

No suspicious text manipulations found.

Our system's algorithms look deeply at a document for any inconsistencies that would set it apart from a normal submission. If we notice something strange, we flag it for you to review.

A Flag is not necessarily an indicator of a problem. However, we'd recommend you focus your attention there for further review.

0% detected as AI

The percentage indicates the combined amount of likely AI-generated text as well as likely AI-generated text that was also likely AI-paraphrased.

Caution: Review required.

It is essential to understand the limitations of AI detection before making decisions about a student's work. We encourage you to learn more about Turnitin's AI detection capabilities before using the tool.

Detection Groups

0 AI-generated only **0%**
Likely AI-generated text from a large-language model.

0 AI-generated text that was AI-paraphrased **0%**
Likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

Disclaimer
Our AI writing assessment is designed to help educators identify text that might be prepared by a generative AI tool. Our AI writing assessment may not always be accurate (it may misidentify writing that is likely AI generated as AI generated and AI paraphrased or likely AI generated and AI paraphrased writing as only AI generated) so it should not be used as the sole basis for adverse actions against a student. It takes further scrutiny and human judgment in conjunction with an organization's application of its specific academic policies to determine whether any academic misconduct has occurred.

Frequently Asked Questions

How should I interpret Turnitin's AI writing percentage and false positives?
The percentage shown in the AI writing report is the amount of qualifying text within the submission that Turnitin's AI writing detection model determines was either likely AI-generated text from a large-language model or likely AI-generated text that was likely revised using an AI-paraphrase tool or word spinner.

False positives (incorrectly flagging human-written text as AI-generated) are a possibility in AI models.