Network Analysis and Financial Dynamics of Friend.tech

ISYE 6740

Project Proposal

Team 022

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I. Abstract

Nowadays, understanding the intricacies of online social interactions and financial transactions is crucial. This project delves into Friend.tech, a unique social platform where users engage in both social interactions and token trading. Leveraging data from Friend.tech's API, we explore community structures and financial dynamics within this network. Our study maps out the intricate web of interactions, identifies key influencers and recurring patterns of users. By understanding these elements, we aim to fill the gap in current research on social platforms that integrate token economies, offering practical insights to improve user engagement strategies and enhance platform design. Additionally, our work will shed light on the underlying mechanics of Friend.tech, providing valuable perspectives for both users and developers within the broader context of the rapidly evolving cryptocurrency industry.

II. Background

Over the past ten years, the cryptocurrency world has expanded quickly and changed a lot, making a big impact on the global financial scene. Platforms that integrate social interactions with financial transactions, like Friend.tech, represent the cutting edge of this evolution. Friend.tech, launched in 2023, blends social engagement with token trading, allowing users to buy and sell shares of their social connections. This innovative approach has fostered a vibrant, active community, encouraging sustained user engagement.

Friend.tech is a one-of-a-kind platform that mixes social interactions with token trading. Launched in 2023, it quickly became popular by letting people buy and sell shares of their social connections. This setup not only encourages people to stay engaged but also helps build a lively and active community. Over time, Friend.tech has evolved, incorporating new features and expanding its user base, while continually shaping the way social and financial interactions occur online. According to Dune Analytics the platform has seen significant activity, with total protocol fees amounting to $56M USD (as of July 2024). Friend.tech has seen a huge influx of money, totaling $624,768,935 USD, showing just how financially active the platform is. People have bought shares worth $217,560,360 USD and sold shares worth $228,703,169 USD. With 915,579 unique buyers, it's clear that the platform has widespread appeal and a lot of active users (Dune Analytics, n.d.).

III. Problem Statement

Understanding the dynamics of social platforms like Friend.tech is critical for improving user engagement, identifying key influencers, and optimizing financial transactions. A comprehensive understanding can lead to enhanced user experiences, increased platform loyalty, and better financial performance. However, there is a significant lack of analysis that integrates user behavior and community structures. Our project aims to bridge this gap by conducting an in-depth study of the Friend.tech network. By leveraging data from Friend.tech's API, we will uncover valuable insights about the platform's operations, offering practical implications for strategic growth and success. According to Dune Analytics, Friend.tech has seen substantial activity, with total protocol fees reaching $56M USD to date. This revenue highlights strong user engagement and financial interaction within the platform. Our analysis aims to provide insights that can contribute to the platform's strategic growth and success.

The primary objectives of our project are to construct a comprehensive network model of Friend.tech users, identify distinct user communities, and analyze the influence of key users within the platform. By modeling users as nodes and their financial transactions as edges, we will create a detailed map of the platform's interactions. We will employ clustering algorithms to detect distinct sub-communities, focusing on influencer ownership and portfolio characteristics to understand how different user groups form and interact. Through these objectives, we aim to uncover the underlying dynamics of Friend.tech, offering valuable perspectives for enhancing user engagement strategies and platform design within the broader context of the rapidly evolving cryptocurrency industry.

IV. Literature Review

As digital interactions change, combining social networks and cryptocurrency is becoming a popular topic for research and industry. These reviews focused on the prevailing social networks, cryptocurrency, and how they are coming together on platforms like Friend.tech.

Social networks have really changed how we interact, share information, and connect with others. Studies look at how networks are set up, how people behave online, and how communities form. Granovetter's "strength of weak ties" and Burt's "structural holes" explain how our connections affect sharing information and accessing resources(Ellison, Steinfield, & Lampe, 2007; Boyd & Ellison, 2008).. More recent work examines how social media changes how people interact, share information, and build networks.

Cryptocurrency has transformed finance by using blockchain technology. This invention has made transactions a safer and more transparent trading environment. Bitcoin, which was introduced in 2008, was the first digital currency that set the stage for many more aspiring cryptocurrencies to follow. Many researches had been investigating this new blockchain technology and its economic implications of cryptocurrencies , and how these digital assets are affecting the traditional financial systems (Nakamoto, 2008; Wood, 2014)(Böhme, Christin, Edelman, & Moore, 2015)(Narayanan, Bonneau, Felten, Miller, & Goldfeder, 2016).

Combining social networks and cryptocurrency is a new area, as seen with platforms like Friend.tech. These platforms use users' social connections to create token economies, letting users trade tokens based on their influence and engagement. Research in this area looks at how social interactions and financial transactions work together, covering ideas like social tokens, decentralized finance (DeFi), and token-based incentives (Chen, 2021; Cong, Li, & Wang, 2020). Studies suggest that combining social and financial elements can increase user engagement and create new economic models (Adhami, Giudici, & Martinazzi, 2018). Friend.tech shows how social networks can drive financial innovation, with social tokens blending social influence with monetary value.

The mix of social networks and cryptocurrency is a growing field with many research and innovation opportunities. By studying how these elements interact on platforms like Friend.tech, we can learn more about user behavior, community building, and economic value creation. This review highlights the need for interdisciplinary research to better understand digital economies and their impact on society.

V. Methodology

Data Collection

To analyze the network on Friend.tech, we utilized a Python module specifically designed to interact with the Friend.tech platform (ItsAditya-xyz, n.d.). This module provides various functionalities to retrieve blockchain addresses associated with Twitter usernames, obtain detailed information about users, and identify holders of a particular user's token. From the module, we can achieve 4 main functions which we will be applying throughout the research.

1. Retrieving Addresses from Twitter Usernames: We initiated the process by collecting blockchain addresses associated with specific Twitter usernames. By leveraging the Friend.tech API, we were able to input Twitter usernames and receive corresponding blockchain addresses. This step was crucial for mapping the initial network nodes. For example, by querying the username "HsakaTrades," we retrieved the associated blockchain address. The response, formatted as JSON, was then converted into a structured format for further analysis.

2. Obtaining User Information from Addresses: Once we had the blockchain addresses, the next step was to gather detailed user information linked to these addresses. Using the Friend.tech API, we extracted comprehensive user profiles, which provided insights into the users' activities and their engagement on the platform. This data enriched our understanding of each node within the network.

3. Identifying Token Holders: To map out the connections and interactions within the network, we identified the holders of each user's token. This involved querying the Friend.tech API to list all addresses holding tokens of a specific user. By iterating through these responses, we expanded our network to include all relevant connections. The process involved paginating through the API responses to ensure we captured all token holders, allowing us to build a comprehensive network graph.

Network Construction

In order to visualize the network of token holders on the Friend.tech platform, we began by collecting data on ten prominent Twitter users and their corresponding key holders. This data collection process involved several steps to ensure a comprehensive and accurate representation of the network. We started by defining a list of ten influential Twitter users, whose token holdings would serve as the central nodes in our network analysis. The selected users were: "Cobie," "blknoiz06," "0xRacerAlt," "HsakaTrades," "KyleSamani," "TrustlessState," "tarunchitra," "twobitidiot," "R89Capital," and "ljin18" (CoinTracking, 2023). In subsequent analysis, we include more influencers as defined by the "Crypto Twitter" community as influential.

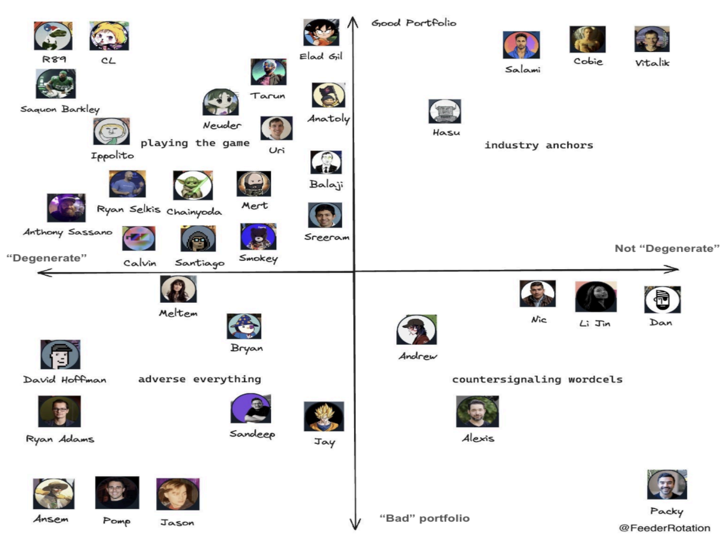

Figure 1: Crypto Twitter sentiment towards various influencers. "Degenerate" here is a term used colloquially in the community to indicate controversiality and high risk-appetite (FeederRotation, 2024).

For each Twitter user, we retrieved the blockchain addresses associated with their usernames using the Friend.tech platform's API. This process involved obtaining a JSON response containing the relevant address information, which was then converted into a structured format for easier manipulation and integration into our broader dataset. Once the addresses were obtained, we proceeded to identify the token holders for each address. This involved iteratively querying the Friend.tech API to gather a comprehensive list of all token holders associated with each address. The collected data was structured into a DataFrame, with columns representing the holder's address, the central user's address, and the central user's Twitter username. The data for all ten Twitter users was concatenated into a single DataFrame, providing a consolidated view of the entire network. This comprehensive dataset included detailed information about each user and their token holders, forming the basis for our network visualization. To represent the network graphically, we plotted the connections between users, where nodes represented individual users and edges indicated token holdings. The thickness of the edges corresponded to the balance of tokens held, providing a visual cue for the strength of each connection. This network graph, as shown in Figure 2, effectively illustrated the intricate web of interactions and financial connections among the users on Friend.tech.

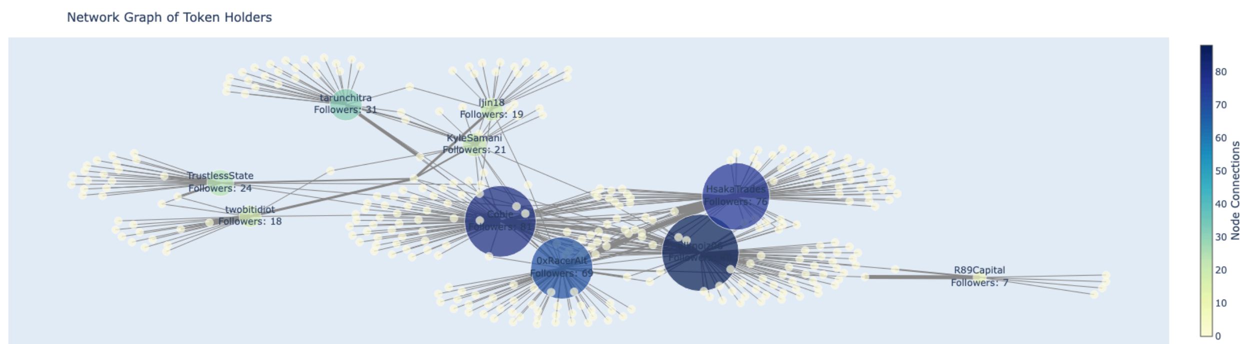

Figure 2: Network Graph of Token Holders

To gain deeper insights, we further expanded the network by including an additional layer of key holders. This secondary expansion involved analyzing the key holders of the initial ten influential users. The expanded network included 434 key holders, accounting for duplicates since a single individual could hold tokens from multiple leaders. Given the increased complexity of the expanded network, we employed a three-dimensional visualization technique to better capture the intricate relationships and connections. The 3D network graph, as shown in Figure 3, provided a more comprehensive view of the token holder interactions, highlighting the dense interconnections and the centrality of key influencers. It also allows interactive features for views to better understand the relationships.

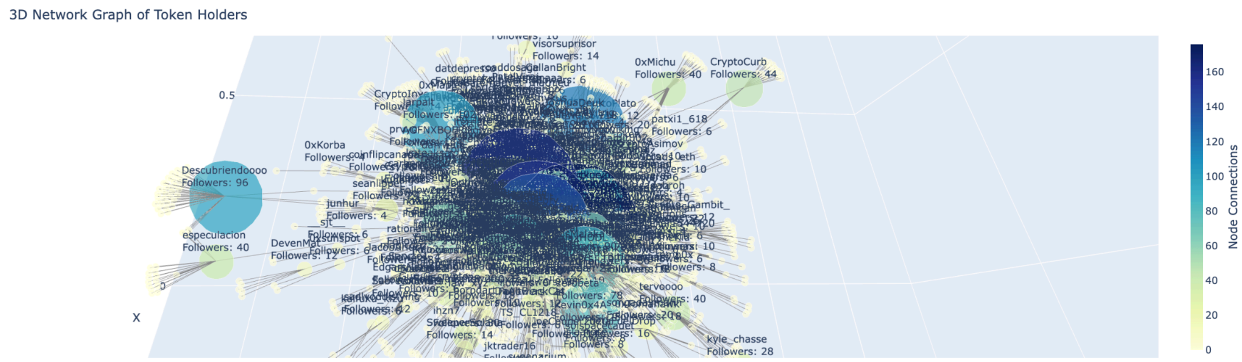

Figure 3: 3D Network Graph of Token Holders

<u>Key Distributor Analysis</u>

Our analysis of key distributors on the Friend.tech platform provides valuable insights into user engagement and the distribution of tokens. The average holder count stands at approximately 9, suggesting that most users have a moderate number of holders, typically ranging between 3 to 11, with some exceptions reaching up to 120 holders. The holding count exhibits considerable variability, with an average of around 42.5, influenced by a few users holding a significantly large number of tokens, with maximum counts reaching 7871. The follower count also shows substantial variation, with an average of about 573, and some users having as many as 69732 followers, indicating notable disparities in user influence. Lastly, the following count averages around 88, indicating that users generally follow fewer accounts than their follower count, though some follow up to 14056 accounts.

The Friend.tech platform's user engagement analysis, as illustrated in the plots, reveals a diverse range of influence and engagement among its users. The top 10 users by holder count are led by 'valeande' with 120 holders, followed by 'CryptoYieldInfo' and 'blknoiz06' with 89 and 87 holders, respectively. This indicates that a select few users have significantly higher engagement compared to the average. In terms of follower count, 'blknoiz06' stands out with a staggering 69732 followers, this is unsurprising given Ansem (blknoiz06) role in onboarding retail users into the Solana ecosystem, contributing notably to total on-chain volumes. Followed by 'cryptojamie7' and 'NftRabbi' with 65882 and 60630 followers, highlighting their substantial reach and influence within the community. These plots collectively illustrate the varied levels of user popularity and influence on Friend.tech, with a few users dominating in terms of holders, followers, and expected returns, indicating their prominent position within the network. Please refer to Figure 4-5.

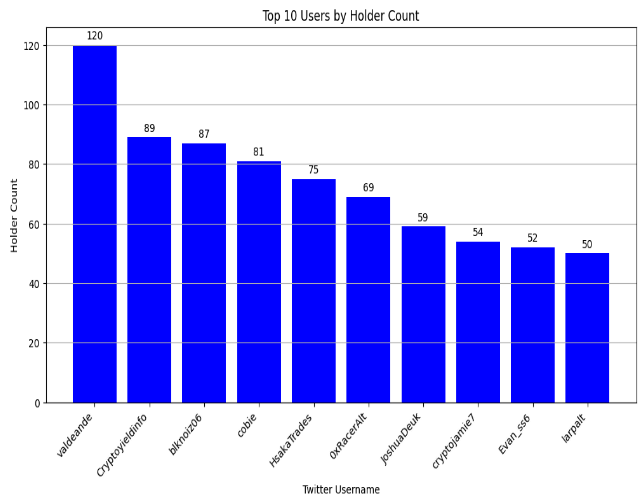

Figure 4: Top 10 Users by Holder Count

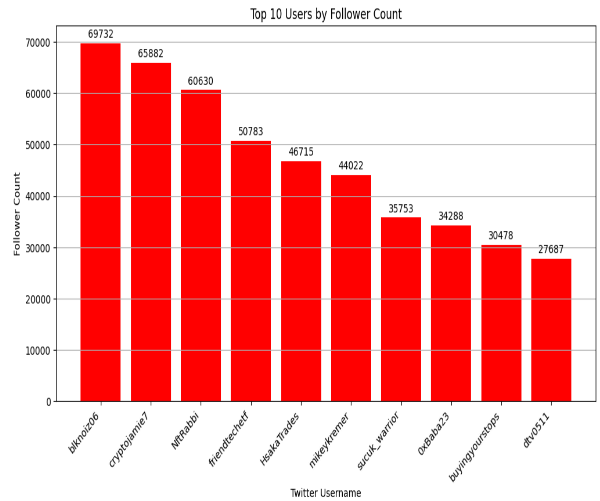

Figure 5: Top 10 Users by Follower Count

Key Holder Analysis

In order to understand the dynamics of user engagement and token distribution on the Friend.tech platform, we performed a key holder analysis. Our key holder analysis of the Friend.tech platform reveals significant insights into user engagement and network dynamics. The average holder count is 6.84, indicating that most users have a modest number of holders, typically ranging from 3 to 8, with a few outliers having up to 120 holders. The holding count, which averages 27.08, shows high variability due to a few users holding a large number of tokens, skewing the distribution with counts as high as 7871. Follower count also varies widely, with a mean of 263.85 and some users having up to 69734 followers, highlighting significant differences in user influence. Finally, the average following count is 59.73, showing that users generally follow fewer accounts than they are followed by, although some follow as many as 14856 accounts.

The key holder analysis is further enriched by examining the top users based on their holding and following counts. The first plot highlights the top 10 users by holding count, with 'xiaopangpang99' leading significantly with 7871 holdings, followed by 'inyourvalls' with 4241, and 'gems_ft' with 3246. This illustrates a concentration of token holdings among a few users as shown in Figure 6. The second plot shows the top 10 users by following count, where 'RyanMoeller88' stands out with 14856 accounts followed by 'xiaopangpang99' with 7887, and 'trade4btc' with 5556 as shown in Figure 7. These plots demonstrate the diversity in user engagement on the platform, with certain users exhibiting extensive influence and activity by holding many tokens and following numerous accounts. This dual analysis of holding and following counts provides a comprehensive view of the active and influential users within the Friend.tech network.

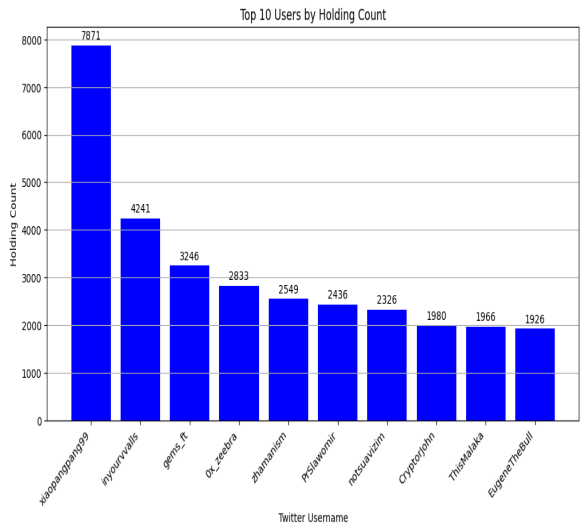

Figure 6: Top 10 Users by Holder Count

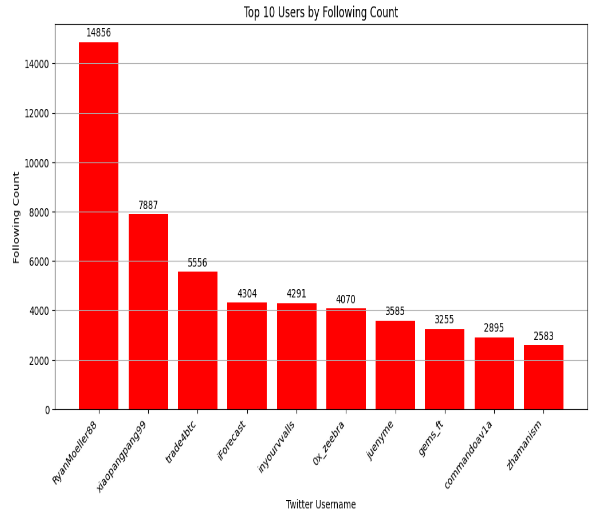

Figure 7: Top 10 Users by Following Count

Community Detection

In our further analysis, we aimed to understand the community structures within the network by performing community detection and clustering. This process involved several key steps to identify and visualize the relationships and connections among the key holders of influential industry leaders on the Friend.tech platform. We selected 50 prominent industry leaders by their Twitter usernames and analyzed the connections among their key holders (Influencer Marketing Hub, n.d.). This selection was based on the assumption that these leaders would have significant influence and connectivity within the network. The dataset included approximately 600 key holders associated with these 50 leaders.

To categorize the network into distinct communities, we applied the k-means clustering algorithm. K-means clustering is a widely used method that partitions the data into a specified number of clusters, minimizing the variance within each cluster. In our analysis, we opted for three clusters (k=3) based on preliminary assessments of the data's structure and to maintain simplicity. To prepare for the clustering, we ensured that we transformed the dataset and created subsequent columns with binary indicators (0 or 1) representing whether each key holder possessed keys from a particular owner address. A value of 1 indicated ownership of the keys from that owner address, while a value of 0 indicated no ownership. After applying the k-means clustering algorithm, the results indicated the presence of three distinct clusters:

Cluster 0: 307 key holders
Cluster 1: 87 key holders
Cluster 2: 55 key holders

These clusters were determined based on the key ownership patterns among the key holders. Specifically, the clustering algorithm grouped together key holders with similar ownership profiles, effectively highlighting communities with shared interests or connections to specific industry leaders. To visualize these clusters, we created an interactive network graph. Each node represented a key holder, and edges indicated connections based on key ownership. The nodes were color-coded according to their assigned cluster, providing a clear visual representation of the community structure within the network. The interactive network graph, as shown in Figure 8, illustrates the three clusters with distinct colors.

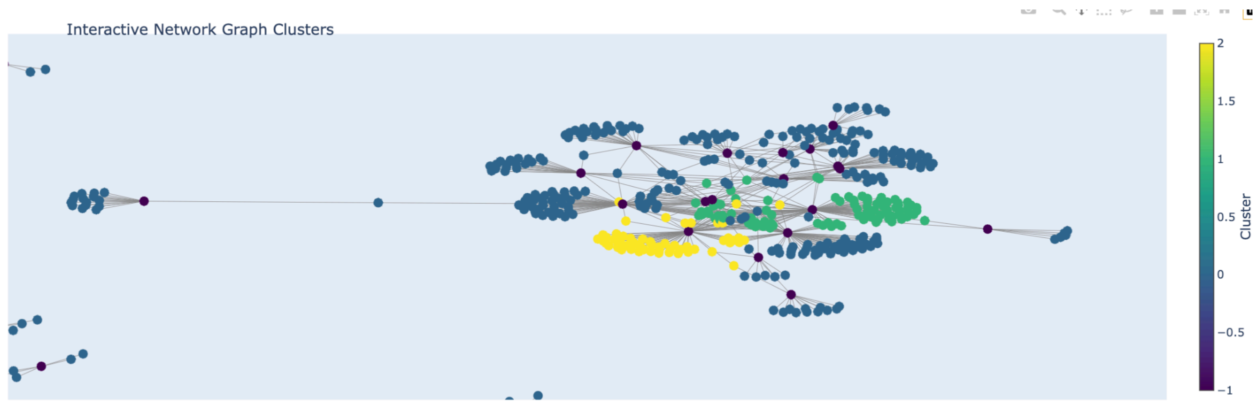

Figure 8: Interactive Network Graph Clusters

This visualization enabled us to observe the distribution and relationships among the key holders more effectively. It highlighted the central nodes and the density of connections within each cluster, providing insights into the community dynamics and the influence of different industry leaders.

Cluster Analysis

Cluster analysis reveals distinct patterns across three clusters. Cluster 0 is the largest, containing 306 records, followed by Cluster 1 with 87 records, and Cluster 2 with 55 records. In terms of social metrics, Cluster 0 has the highest averages for both holder count (~9) and holding count (~68), as well as follower count (~760) and following count (~102). This suggests Cluster 0 is characterized by high engagement and significant social interactions. Cluster 1 shows lower averages in holder count (~6) and holding count (~22), with follower and following counts averaging around 618 and 61, respectively, indicating moderate engagement. Cluster 2, while the smallest, has a similar holder count (~9) but a lower holding count (~19) and the lowest social metrics with follower and following counts averaging 276 and 39, respectively.

The plot visualizes the distribution of various metrics across the three identified clusters. It features a histogram with color-coded bars representing different metrics such as holder count, holding count, follower count, and following count. The x-axis displays the values of these metrics, while the y-axis shows their frequency within each cluster. The plot is divided into three sections, one for each cluster, enabling a clear comparison of how each metric varies across clusters. Transparency in the bars allows overlapping distributions to be easily observed, highlighting the differences and similarities in engagement and financial activities among the clusters.

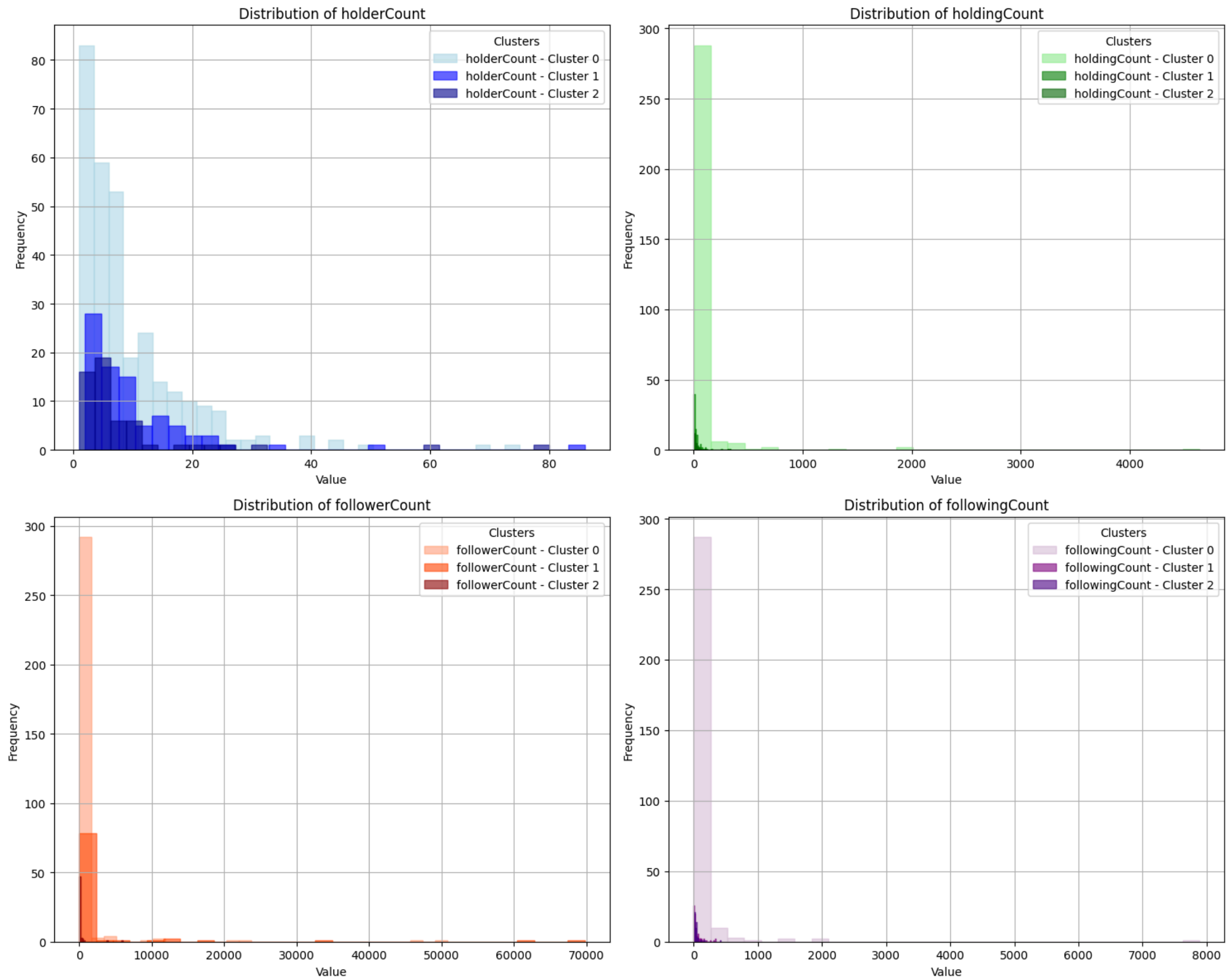

Figure 9: Distribution of Metrics by Cluster

Financial Analysis

We began by calculating the descriptive statistics for the buy and sell prices, both before and after fees. The average buy price is 0.011328 ETH, slightly higher than the average sell price of 0.010156 ETH. After accounting for fees, the mean buy price increases to 0.011894 ETH, while the mean sell price decreases to 0.009648 ETH. This indicates the impact of transaction fees on the overall price. The standard deviation for buy prices is 0.031897 ETH, and for sell prices, it is 0.030923 ETH. This suggests a relatively high variation in the prices, reflecting the dynamic nature of the market on Friend.tech. The minimum buy price observed is 0.000063 ETH, with the maximum reaching 0.930250 ETH. Similarly, the sell prices range from 0 ETH to 0.915063 ETH. This wide range highlights the diversity of transactions occurring on the platform.

The scatter plots below visualize the distribution of buy and sell prices, both before and after fees. Each point represents an individual transaction, plotted against its index to show the variation across the dataset. The scatter plots illustrated that most buy and sell transactions occurred at prices below 0.1 ETH, with some outliers reaching higher values up to 0.6 ETH for buy prices and 0.915063 ETH for sell prices. The distributions for prices after fees followed similar patterns, with buy prices slightly higher and sell prices slightly lower due to the impact of transaction fees.

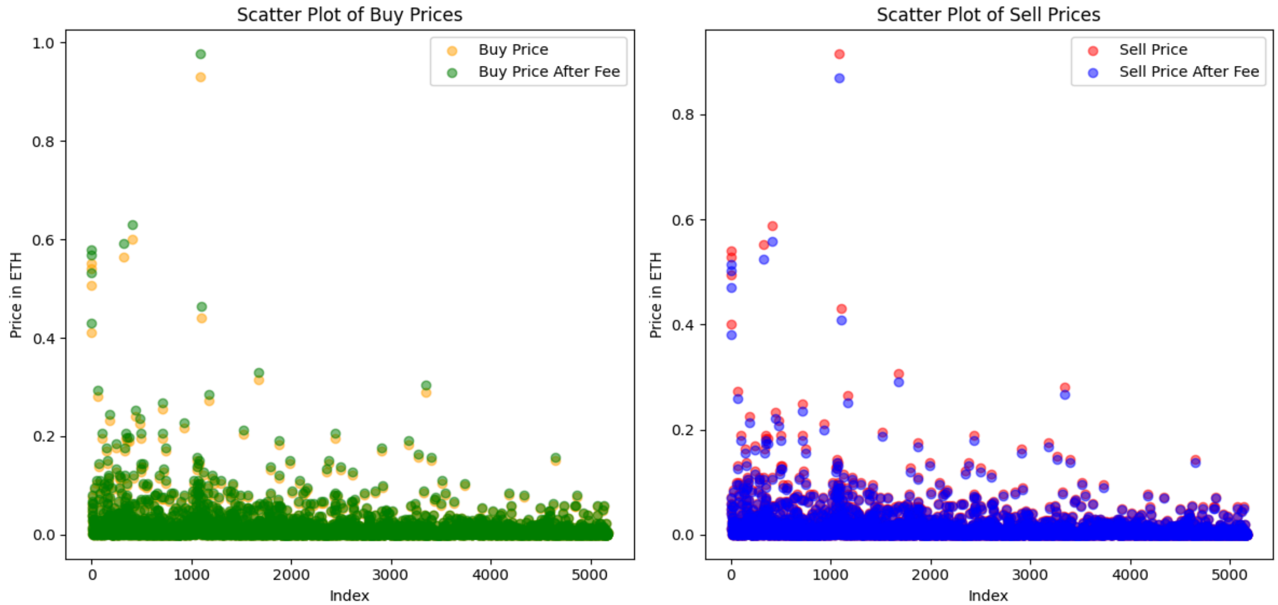

Figure 10: Scatter Plots for Buy Prices and Sell Prices

<u>User Activities</u>

To further understand user behavior on the Friend.tech platform, we analyzed user activity based on the last online timestamps. This analysis involved examining user activity by month and by hour, providing insights into when users are most active on the platform.

The bar chart of user activity by month shows a high user activity in the months leading up to July, with a peak in July itself. This is expected, as the data was collected in July, capturing the most recent activity as we used last online time as the measurement. Still, there are a considerable number of users who've not been active since earlier this year, corresponding with the recent rally in crypto. As shown in figure 11, more users are quite active on the platform.

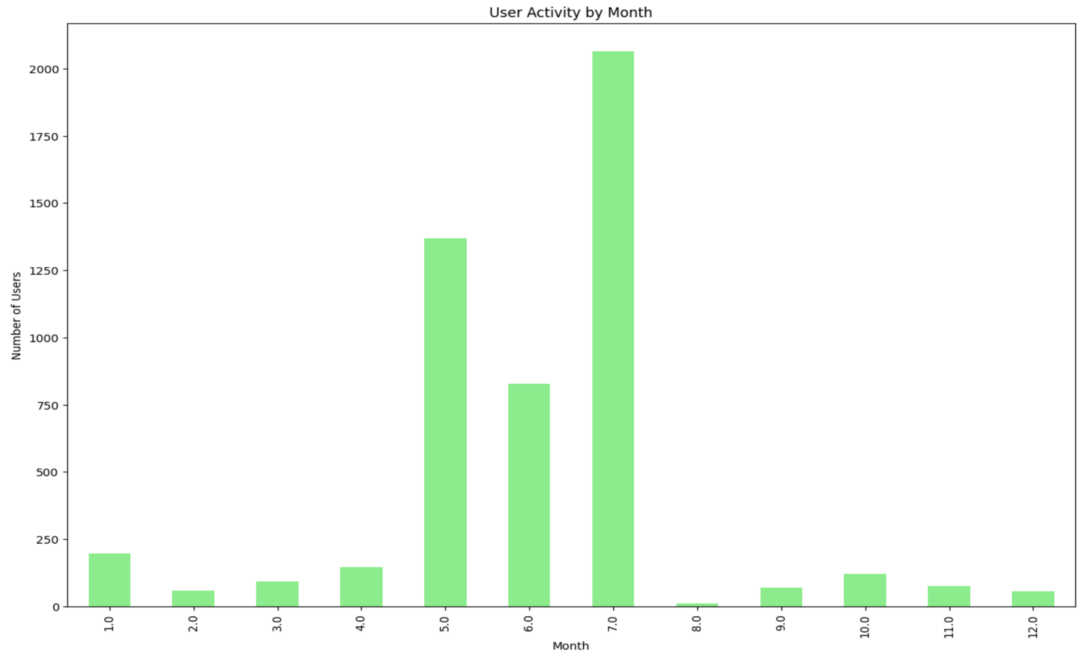

Figure 11: Scatter Plots for Buy Prices and Sell Prices

Superimposed on the user activity distribution are the line plots for average buy and sell prices by hour. These plots show the fluctuation in transaction prices throughout the day. The average buy and sell prices exhibit notable peaks and troughs, reflecting the dynamic nature of the market. Both buy and sell prices peak around 2:00, 6:00, and 18:00 hours, suggesting that these times coincide with increased trading activity. The highest peak occurs around 18:00 hours, aligning with the peak in user activity. This indicates a potential correlation between high user engagement and increased trading activity. The average prices dip around 4:00, 7:00, and 12:00 hours, which may correspond to lower trading activity during these times. The troughs in prices suggest periods of reduced market activity.

The combined analysis of user activity and financial transactions on Friend.tech reveals significant insights into market behavior and user engagement. The peaks in user activity, which occur primarily in the late afternoon and early evening, align with higher average buy and sell prices, suggesting that increased user engagement drives up trading activity and transaction prices. The fluctuations in average prices throughout the day reflect the dynamic nature of the market, with certain times being more favorable for trading. This correlation between user activity and transaction prices indicates that strategic timing of transactions during peak activity periods can maximize potential gains for users. Additionally, platform developers can use this information to tailor features and services to enhance user engagement during these high-activity times, ultimately contributing to the platform's growth and success. Understanding these patterns provides a comprehensive overview of how user behavior influences financial dynamics on Friend.tech.

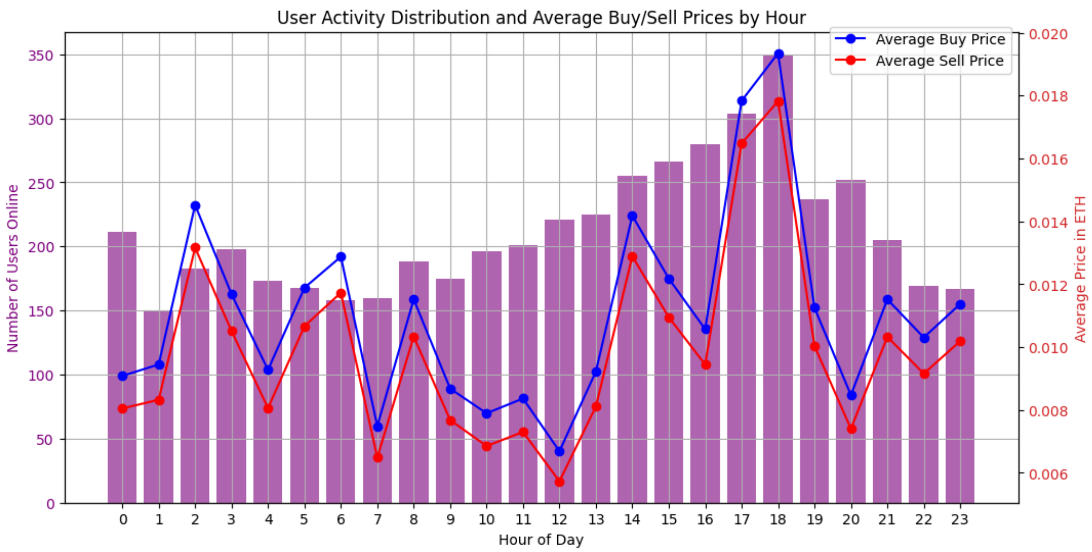

Figure12: User Activity Distribution and Average Buy/Sell Prices by Hour

<u>Total Expected Return</u>

To estimate the potential financial outcomes on the Friend.tech platform, we calculated the total expected return for each influencer. This metric is derived by multiplying the influencer's share supply, representing the total number of keys they possess, by the display price of these keys. The formula used for this calculation is as follows. By applying this calculation, we were able to determine the overall expected return from distributing all keys for each influencer.

$$Total\ Expected\ Return\ = Share\ Supply\ \times Display\ Price$$

The results of this calculation were then plotted to visualize the relationship between the buy price of keys (in ETH) and the total expected return. The scatter plot, shown in Figure 13, depicts this relationship, highlighting how higher buy prices correspond to greater expected returns.

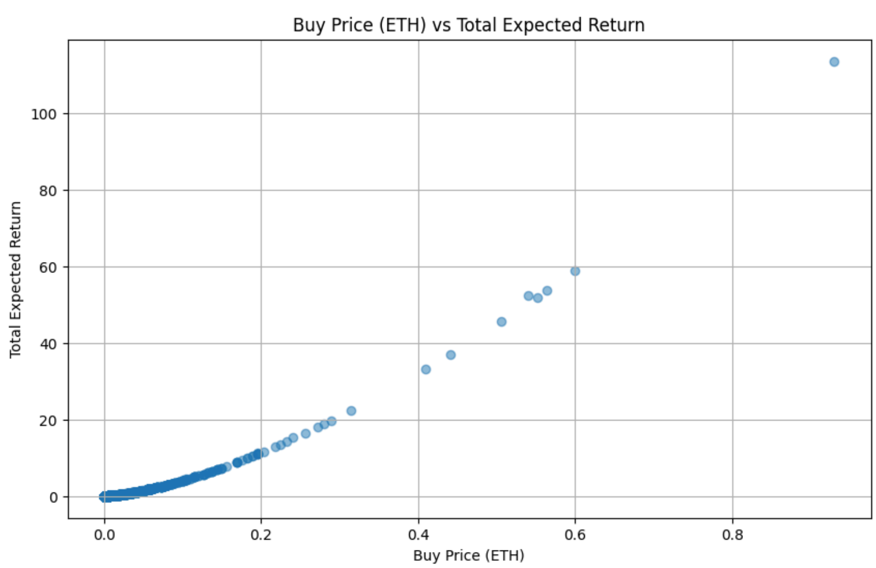

Figure 13: Buy Price (ETH) vs. Total Expected Return

The plot illustrates a clear positive correlation between the buy price and the total expected return. As the buy price increases, the total expected return also rises, indicating that influencers with higher key prices have the potential for substantial financial returns from distributing their keys. This analysis provides valuable insights into the economic potential for influencers on Friend.tech, emphasizing the significance of key pricing in determining overall financial outcomes.

Price-Based Segmentation

To gain deeper insights into the characteristics of users based on their share prices, we performed a price-based segmentation analysis. This analysis categorizes users into different tiers based on their buy and sell prices and examines their attributes such as follower count, holder count, holding count, and balance.

We divided users into four tiers based on their buy prices: Low, Medium-Low, Medium-High, and High. The segmentation analysis reveals distinct patterns among users in different buy price tiers

	buy_price_tier	followerCount	holderCount	holdingCount	balance
0	Low	28.882392	2.463787	14.196678	1.096774
1	Medium-Low	52.682060	4.313499	20.769094	1.200000
2	Medium-High	185.279070	6.764441	29.741935	1.000000
3	High	865.266898	15.178510	47.015598	1.166667

Figure 14: Descriptive Statistics of Price-based Segmentation

Users in the higher buy price tiers tend to have a significantly higher follower count. For example, the High buy price tier has an average follower count of 865.27, indicating that higher-priced users are more influential on the platform. The holder count increases with the buy price tiers, reflecting greater interest and investment in higher-priced users. Users in the High buy price tier have an average holder count of 15.18. Similar trends are observed in the holding count, with higher buy price tiers showing increased holding counts. This suggests that users in higher buy price tiers have more tokens distributed among their holders. The balance metric, representing the financial stability of users, also shows an upward trend with higher buy price tiers. The High buy price tier has a balance of 1.17, indicating better financial health.

Holder Count and Holding Count Tier Analysis

We performed segmentation based on the number of holders and the number of holdings. This analysis aimed to categorize users into different tiers and examine their attributes such as display price, buy price, and sell price.

We categorized users into three tiers based on their holder counts: Low, Medium, and High. The table below summarizes the key characteristics of each tier. Users with higher holder counts tend to have significantly higher prices across all metrics. For example, users in the High holder count tier have an average display price of 0.030480 ETH, a buy price of 0.030467 ETH, and a sell price of 0.028147 ETH. This indicates that users with more holders are perceived as more valuable.

	holder_count_tier	displayPrice	buy_price_eth	sell_price_eth
0	Low	0.001651	0.001650	0.001208
1	Medium	0.005030	0.005028	0.004090
2	High	0.030480	0.030467	0.028147

Figure 15: Descriptive Statistics of Holder Count Tier

Similarly, we segmented users based on their holding counts into Low, Medium, and High tiers. A similar trend is observed in the holding count analysis, where higher holding counts correspond to higher prices. Users in the High holding count tier have an average display price of 0.022629 ETH, a buy price of 0.022625 ETH, and a sell price of 0.020835 ETH. This suggests that users with more extensive holdings are also perceived as more valuable.

	holding_count_tier	displayPrice	buy_price_eth	sell_price_eth
0	Low	0.004877	0.004874	0.004141
1	Medium	0.008085	0.008077	0.006979
2	High	0.022629	0.022625	0.020835

Figure 16: Descriptive Statistics of Holding Count Tier

These analyses provide a nuanced understanding of how the number of holders and holdings influences user valuation on the Friend.tech platform. By recognizing these patterns, the platform can better understand the factors that contribute to user value and develop strategies to enhance user engagement and financial outcomes.

Correlation Analysis

To understand the relationship between share prices and social metrics on the Friend.tech platform, we conducted a comprehensive correlation analysis. This analysis examined the correlation between share prices (both buy and sell) and various social metrics such as follower count, holder count, holding count, and following count.

We calculated the correlation coefficients between the share prices and the social metrics to measure the strength and direction of these relationships. The results are visualized in the heatmap shown in Figure 17, which provides a detailed view of the correlation matrix.

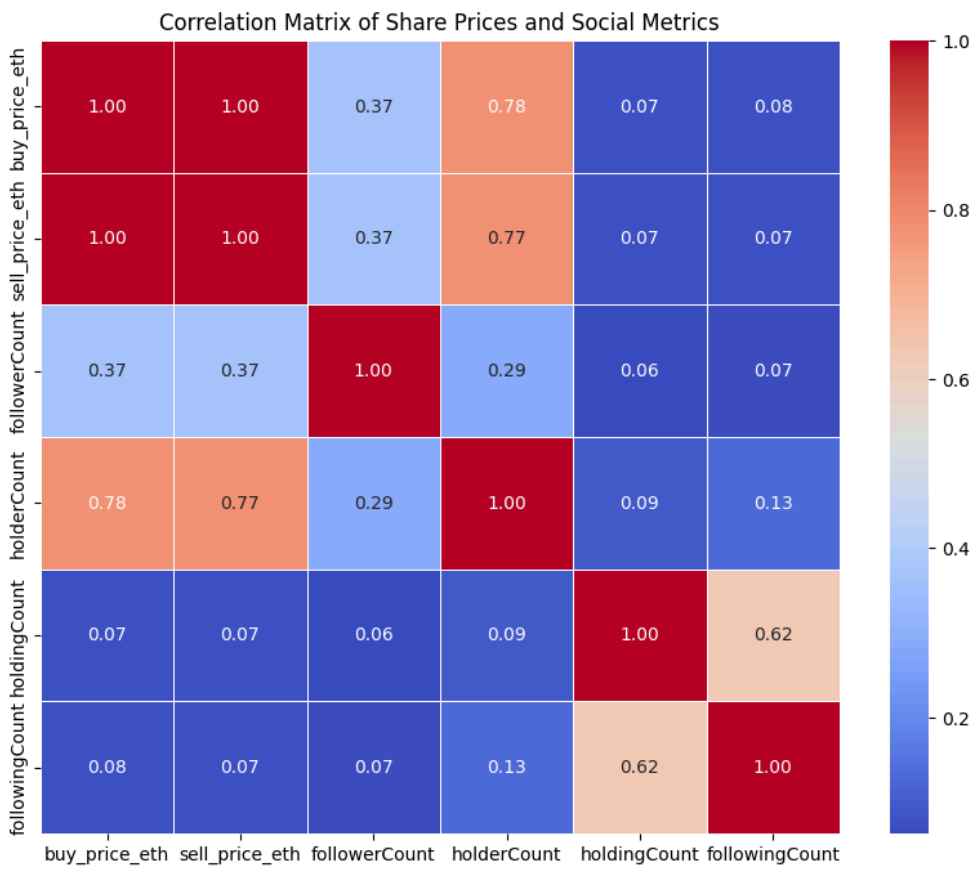

Figure 17. Correlation Matrix of Share Prices and Social Metrics

- **Share Prices and Follower Count:** The correlation between buy price and follower count is 0.37, indicating a moderate positive relationship. This suggests that more popular users, as indicated by their follower count, tend to have higher share prices. Similarly, the sell price also shows a correlation of 0.37 with follower count.
- **Share Prices and Holder Count:** There is a strong positive correlation between buy price and holder count (0.78), and a similar correlation for sell price (0.77). This indicates that users with a higher number of holders tend to have significantly higher share prices.
- **Share Prices and Holding Count:** The correlation between share prices and holding count is relatively low (0.07 for buy price and 0.06 for sell price), suggesting a weak relationship.
- **Share Prices and Following Count:** The correlation between share prices and following count is very low (0.07 for buy price and 0.07 for sell price), indicating that the number of users a person follows does not have a significant impact on their share prices.
- **Interrelationships Among Social Metrics:** The heatmap also shows the interrelationships among the social metrics themselves. For example, holder count and holding count have a moderate positive correlation (0.29), and holding count and following count have a strong positive correlation (0.62).

The correlation analysis provides valuable insights into how social metrics relate to share prices on the Friend.tech platform. The moderate to strong correlations between follower count, holder count, and share prices highlight the importance of user popularity and engagement in determining financial value. These insights can help platform users and developers optimize strategies for user engagement and pricing, enhancing the overall user experience and economic dynamics on Friend.tech.

VI. Conclusion

Our comprehensive analysis of the Friend.tech platform, leveraging data from its API and employing various analytical methods, has yielded significant insights into the social and financial dynamics of this unique social network. We first plotted the network construction and completed our dataset collection. By examining the interactions of 50 prominent industry leaders and approximately 600 key holders, we were able to identify three distinct clusters using k-means clustering. Cluster 0 emerged as the largest and most active group, comprising 307 key holders, with the highest engagement metrics: an average holder count of 9, holding count of 68, follower count of 760, and following count of 102. Cluster 1, with 87 key holders, demonstrated moderate engagement and financial metrics, while Cluster 2, the smallest cluster with 55 key holders, showcased notable financial metrics despite lower social engagement levels. Our key holder analysis revealed an average holder count of 6.84 and a holding count of 27.08, indicating significant variability and highlighting the diverse engagement levels on the platform.

Our price-based segmentation and correlation analysis underscored the strong relationship between share prices and social metrics. Notably, higher buy price tiers were correlated with greater follower counts (average of 865.27 in the high tier) and holder counts (average of 15.18 in the high tier). Strong positive correlations were also observed between share prices and holder counts (0.78 for buy price), emphasizing the impact of user popularity on financial value.

In summary, our study provides valuable insights into the community structures, user engagement, and financial dynamics on Friend.tech. These findings offer practical implications for enhancing user engagement strategies and optimizing platform design, thereby contributing to the platform's growth and success. Understanding these dynamics is crucial for both platform developers and users in navigating the rapidly evolving landscape of social networks integrated with token economies.

VII. Limitation and Future Studies

Our study faced certain limitations, primarily due to API restrictions that limited access to specific features and data points on the Friend.tech platform. These restrictions constrained our ability to gather more comprehensive and granular data, which could have provided deeper insights into user behavior and network dynamics. Additionally, the dataset used in our analysis was relatively small and focused on a subset of prominent users and key holders, which may not fully represent the broader user base of Friend.tech.

Future studies can address these limitations by incorporating larger and more diverse datasets to capture a wider range of user interactions and financial activities. Expanding the scope of data collection and analysis will enable a more detailed understanding of the platform's dynamics. Furthermore, future research could explore the impact of emerging features and functionalities on user engagement and financial outcomes, providing a more holistic view of the evolving landscape of social networks integrated with token economies.

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