Understanding Social Capital in Decentralized Social Platform: An Empirical Study on Friend.tech

Junyu Zhang
junyuzhang2@link.cuhk.edu.cn
The Chinese University of Hong Kong, Shenzhen
Shenzhen, Guangdong, China

Huiyu Wang
huiyuwang@link.cuhk.edu.cn
The Chinese University of Hong Kong, Shenzhen
Shenzhen, Guangdong, China

Wei Cai*
weicaics@uw.edu
University of Washington
Tacoma, Washington, USA

Abstract

This study presents an empirical investigation into social capital formation in decentralized social platforms, focusing on Friend.tech. Following an empirical research framework, we first identify and characterize "3-3 trading behavior," a distinctive reciprocal trading mechanism that has not been observed in other decentralized platforms. This emergent phenomenon arises from the interaction between platform incentives—which structure key-based social and financial interactions—and user-driven strategies that leverage these mechanisms for reciprocal engagement. Building on these observations, we propose a Social Capital Index (SCI) model to quantify user value by integrating social and economic dimensions. Finally, we validate the SCI model using on-chain transaction data and airdrop allocations, demonstrating that it effectively approximates the platform's internal user valuation despite the opaque nature of its reward mechanisms. Our findings provide empirical insights into the interplay between financial incentives and social capital in decentralized ecosystems. This study contributes to the understanding of incentive design, value attribution, and user engagement dynamics in blockchain-based social networks.

Keywords

Friend.tech, Social Capital, 3-3 trading, Social Capital Index

ACM Reference Format:
Junyu Zhang, Huiyu Wang, and Wei Cai. 2025. Understanding Social Capital in Decentralized Social Platform: An Empirical Study on Friend.tech. In *Proceedings of the 17th ACM Web Science Conference 2025 (Websci '25), May 20–24, 2025, New Brunswick, NJ, USA.* ACM, New York, NY, USA, 10 pages. https://doi.org/10.1145/3717867.3717893

1 Introduction

The advent of blockchain technology has ushered in a new era of decentralized platforms, fundamentally altering the landscape of social interactions and value creation in digital ecosystems. Among these innovations, decentralized social platforms have emerged as a frontier for novel user behaviors and economic models. Unlike traditional social platforms that operate under centralized control and data ownership models, decentralized social platforms (DSPs) represent a paradigm shift in digital social interactions. These platforms offer several distinctive advantages:

- **User Data Sovereignty:** Through blockchain's cryptographic mechanisms, users maintain true ownership and control over their data and digital identities
- **Direct Value Capture:** Users can monetize their social capital and influence through tokenization, creating new economic models for content creators and community builders
- **Transparency and Immutability:** All social interactions and transactions are recorded on blockchain, providing verifiable proof of engagement and reputation
- **Community Governance:** Platform decisions and evolution are driven by user consensus rather than corporate interests, fostering genuine decentralization

These fundamental differences from traditional social networks create unique opportunities for studying how social capital forms and operates in trustless, blockchain-enabled environments. Among these innovations, Friend.tech has emerged as a prominent player in this space, exemplifying the potential and challenges of these new social ecosystems through its unique blend of social networking and financial mechanisms.

Since its launch in August 2023, Friend.tech has experienced rapid growth on the Base layer 2 blockchain. The platform has successfully attracted a significant number of users and key opinion leaders (KOLs). Its innovative token economy design introduces a unique concept: users can purchase and trade "keys" that grant access to exclusive social interactions. This creates an ecosystem where social capital becomes directly quantifiable and tradeable.

Users participate in Friend.tech with multiple motivations. These include potential trading profits, social networking opportunities, and anticipation of future airdrop rewards. These motivations have led to the emergence of a distinctive trading pattern known as "3-3 behavior." In this pattern, users reciprocally purchase and hold each other's keys, creating mutual social and financial stakes in their relationships. This behavior has become a defining characteristic of user interactions on the platform.

Our study employs extensive on-chain data mining techniques to examine these platform dynamics. The transparency of blockchain data offers unique research opportunities. We can track and analyze user behaviors, trading patterns, and value creation mechanisms with unprecedented precision. Through quantitative analysis, we explore how the 3-3 trading behavior shapes user engagement and platform evolution. This research provides insights into both the immediate impacts of novel token economic and their broader implications for decentralized social platforms.

*Wei Cai is the corresponding author. Email: weicai@uw.edu.

Websci '25, May 20–24, 2025, New Brunswick, NJ, USA

ACM ISBN 979-8-4007-1483-2/2025/05
https://doi.org/10.1145/3717867.3717893

Our research is guided by the following research questions:

- RQ1: How can the unique 3-3 trading behavior, an emergent phenomenon exclusive to Friend.tech, be quantitatively characterized? How does its prevalence and stability evolve over the platform's lifecycle, and what factors drive its formation and dissolution?
- RQ2: How can a Social Capital Index (SCI) model, integrating both social and economic dimensions, effectively quantify user value in decentralized social platforms?
- RQ3: To what extent can the SCI model predict airdrop allocations, and what limitations and insights does this reveal about decentralized platform incentive mechanisms?

To address these questions, we propose a novel model grounded in social capital theory, adapted to the unique context of blockchain-enabled social interactions. This model incorporates key behavioral features observed on Friend.tech, bridging traditional concepts of social capital with the innovative mechanisms enabled by decentralized technologies.

Our study not only offers a deep dive into the motivations driving user behavior and the formation of community structures on SocialFi platforms but also contributes to the broader understanding of mechanism design in decentralized social media. By analyzing Friend.tech's airdrop distribution through the lens of our model, we demonstrate its predictive power and shed light on the often opaque value allocation processes in these ecosystems.

The insights derived from this research have significant implications for the future development and operation of decentralized social platforms. As the landscape of digital social interaction continues to evolve rapidly, our findings provide valuable guidance for platform designers, policymakers, and users navigating this new frontier of social and economic engagement.

2 Related Works

2.1 Decentralized Social Platforms

Before the advent of decentralized social platforms (DSP), the focus was primarily on blockchain-enabled social media, which utilizes blockchain technology to address some of the technical shortcomings of traditional social platforms, combined with a range of unique blockchain incentive mechanisms. For instance, Sari et al. [29] proposes a Blockchain-based news verification system to enhance the credibility of information shared on social media platforms, utilizing an epidemic methodology and a scale-free network model. By implementing Ethereum Smart Contract and various tools, it effectively limits the spread of fake news and improves content quality. A study presents a blockchain protocol for social media networks (BE-SMN) to combat misinformation by modeling it as double-spend attacks and incorporating it into the SIR model. Through numerical analysis on a multi-community network, it demonstrates that BE-SMN effectively mitigates the spread of misinformation compared to baseline networks [24]. Zhan et al. [33] explores the burgeoning field of blockchain-enabled social media, specifically focusing on the case of Pixie, the first fully functional decentralized photo and video sharing network. It presents a conceptual model based on four pillars—technology, governance, incentive design, and organizational structure.

Since many DSPs have been deployed, most research has remained focused on how blockchain technology impacts social platforms. For instance, Guidi [15] provided an overview and analysis of blockchain-based online social media platforms, proposing a new blockchain-based online social network model and detailing the platform's features, services, and common drawbacks. Guidi and Michienzi [16]'s another paper introduced DSP as a novel form of decentralized finance, combining social networks with finance, allowing users to monetize social influence through social tokens, and discussed its prospects, opportunities, and challenges in future social media platforms. In terms of case studies, Den Yeoh et al. [8] examined token prices related to DSP within the StepN game, using FinBERT for sentiment analysis and XGBoost for evaluation. The findings revealed correlations between sentiment scores and token prices, suggesting potential utility for investors in decision-making and highlighting the importance of sentiment analysis in cryptocurrency markets. However, there is still limited research on who participates in DSP, their behavioral patterns, and the structure of the communities they form.

2.2 Social Capital Theory and Its Components

In recent years, the concept of social capital, as proposed by Robert Putnam [26, 27], has attracted significant scholarly attention. Putnam's framework emphasizes three key elements: **social networks**, **trust**, and **reciprocity**, which together form the foundation of social capital. Numerous studies have explored these components in various contexts, providing a comprehensive understanding of how they contribute to societal functioning.

Social Networks: Social capital is often linked to the structure of social networks, which facilitate access to resources and information. Putnam highlights that networks, whether formal or informal, play a critical role in enabling collective action [27]. Researchers like Coleman and Lin have built on this idea, suggesting that both **bonding** (strong ties within close groups) and **bridging** (weaker ties across diverse groups) social capital are essential for fostering collaboration and innovation [7, 14, 23].

Trust: Trust, as a core component of social capital, underpins cooperation and reduces transactional costs. High levels of trust within a community lead to more effective collaboration and increased civic engagement. Studies have found that trust is a critical factor in economic performance and political participation. Trust serves as the glue that holds social networks together, promoting mutual support and cooperation [3, 13, 19, 20].

Expanding on this, Vikash and Kumar [31] propose a framework for assessing trust in social networks, emphasizing its role as a quantifiable and evolving metric. Agreste et al. [1] further analyze trust networks, showing how trust relationships evolve dynamically and influence social interactions over time. These studies highlight the foundational role of trust in shaping social capital, demonstrating that stable and well-connected trust networks contribute significantly to economic and social well-being.

Reciprocity: Reciprocity refers to the mutual exchange of support and favors within a network, where individuals expect their contributions to be returned in the future. This component fosters a sense of obligation and community, reinforcing trust. The reciprocal nature of social capital has been shown to strengthen social cohesion, as individuals are more likely to invest in relationships that offer long-term benefits [27].

Current research underscores the importance of these elements in building resilient and engaged communities. While there are some challenges in measuring social capital consistently across different contexts, the consensus is that networks, trust, and reciprocity collectively contribute to positive societal outcomes, including economic growth, political stability, and social cohesion [7, 23].

2.3 Social Capital in Decentralized Networks

In recent years, the study of social capital within online networks has evolved significantly. Traditional online social networks, such as Facebook, have long been a focus of research due to their ability to foster both bonding and bridging social capital. Bonding social capital involves the strengthening of close-knit groups, while bridging social capital refers to connections across diverse social groups. Studies have highlighted how different types of interactions on platforms like Facebook can lead to varying levels of social capital. Burke et al. demonstrated that passive engagement, such as liking posts, tends to build weaker ties, whereas active engagement, such as commenting and messaging, helps to foster stronger bonds [4, 5]. Similarly, research on trust and reciprocity within these networks has shown that user behavior is shaped largely by the platform's algorithmic structures and the social interactions that arise from these structures [2].

However, the rise of blockchain-based decentralized networks, such as Web3, has introduced new paradigms for social capital formation, enabled by innovative economic mechanisms. Unlike traditional online networks, decentralized systems often use token economies to align user behavior with community goals [32]. These economic incentives allow users to engage in behaviors that contribute to the overall social capital of the network, with tokens representing a form of trust and reciprocity within the system. In this context, Fan et al. explored how Web3 communities structure roles around both altruistic and profit-oriented behaviors, highlighting the complex dynamics introduced by blockchain's transparent and immutable data structure [9].

Trust mechanisms in decentralized environments differ significantly from those in traditional social platforms. Mokhberi et al. [25] explore trust, privacy, and safety factors in peer-to-peer (P2P) markets, emphasizing the challenges of establishing trust in decentralized exchanges where traditional reputation systems are absent. One promising approach is the use of secure inference techniques, such as multiparty homomorphic encryption, which allows users to compute trust scores or analyze reputation without revealing sensitive personal data [6]. This approach enhances user trust in decentralized networks by ensuring that sensitive computations can be performed securely across multiple parties without compromising user privacy. Meanwhile, Lee and Ma [21] introduce a trust-distrust propagation model, which enhances collaborative recommendations by leveraging network trust relationships. Guo et al. [17] further examine multi-faceted trust dimensions in online social networks, demonstrating their importance in decentralized systems where financial incentives are intertwined with social interactions.

The ability to quantitatively model social capital in decentralized networks is greatly enhanced by blockchain's openness, which allows for comprehensive data mining to track user behavior and interactions. As such, blockchain data offers a unique advantage in precisely capturing and modeling social capital in ways that go beyond traditional network platforms [18, 28].

Moving forward, researchers are encouraged to leverage both the accessibility of blockchain data and the flexibility of social capital theory to create more nuanced user behavior models. While decentralized social platforms have evolved from addressing technical limitations to enabling novel economic mechanisms, and social capital theory has established the fundamental importance of networks, trust, and reciprocity in community development, the research on blockchain-enabled social interactions presents unique opportunities and challenges.

3 Friend.tech Overview

3.1 Introduction To Friend.Tech

Friend.tech is a pioneering decentralized social platform launched in August 2023 on the Base layer 2 blockchain, combining social media and decentralized finance elements. The platform allows users to tokenize their online presence through "Keys" associated with their Twitter profiles, granting access to exclusive chat groups. It employs a bonding curve mechanism for Key pricing, incentivizing early discovery of promising creators. Friend.tech's user-friendly interface, which simplifies Web3 interactions, has contributed to its rapid adoption and popularity.

The platform offers monetization opportunities for creators through Key sales and trading fees, while followers can potentially profit from a creator's growing popularity. Despite its success, with over 920,000 users and substantial trading volume as of September 2024, Friend.tech faces challenges regarding privacy, security, and the long-term sustainability of its business model. Critics argue that the focus on key trading might encourage user turnover rather than stable relationships. Nevertheless, Friend.tech's innovative approach to content monetization and social interaction suggests a promising future in reshaping the intersection of social media and blockchain technology in the Web3 era.

3.2 Economic Mechanism of Key

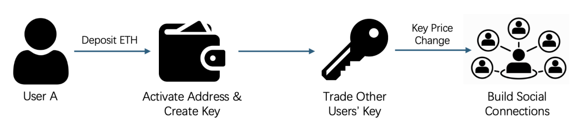

Figure 1: User Social Process in Friend.Tech

As a case study of the decentralized social platform Friend.Tech, it operates on the Layer 2 network Base. Its core concept is to convert user influence into their personal tradable tokens, enabling users to earn income through their social impact. KEY tokens function similarly to paid subscriptions in traditional internet products, granting users access to a friend slot with the purchased individual, facilitating content access and direct interaction. Users can search for and purchase the KEY of users they are interested in. Each user's KEY follows the same price curve, with an unlimited supply. The pricing of a user's KEY is linked to market supply and demand dynamics, where greater user popularity correlates with higher KEY prices. This dynamic interplay fosters a vibrant market ecosystem. We concluded that user social process in Figure 1 and its core mechanism is designed as follows:

- Each user upon registration will receive a cloud-hosted wallet with the transaction address based on the L2 base chain. Additionally, each user will be assigned a default "Key", representing their personal Social Token. Users have their own private chat room.
- Users can establish social relationships by purchasing other users' Keys using ETH. The pricing of all Keys follows the same price curve model: $Price$ = Key Supply$)^2/16,000$, as Figure 2 shown. Supply increases with buying and decreases with selling.
- Purchasing another user's Key grants permission to access their private chat room.
- A 10% transaction fee is charged for each buying and selling transaction, with half of it collected as a protocol fee by Friend.Tech, and the other half given directly to the Key issuer as income.
- Friend.Tech distributes points weekly based on user activity on the platform, which may represent airdrop quotas, a unique introduction mechanism in Web3.

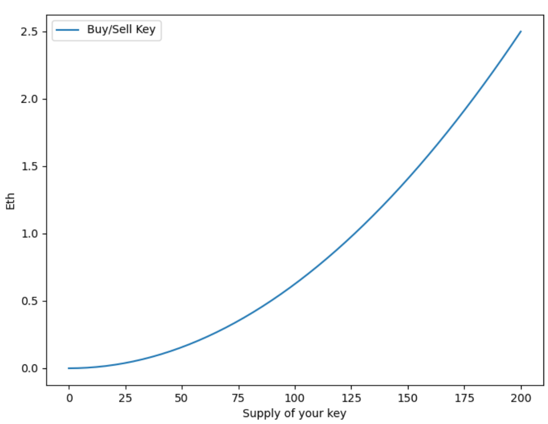

Figure 2: Pricing Model for Key in Friend.Tech

3.3 Airdrop of Token $ Friend

In May 2024, Friend.tech, a decentralized social media platform built on Base, conducted a highly anticipated airdrop of its native FRIEND token, with the airdrop rule as a black box, coinciding with the launch of its version 2 protocol. The event, which took place on May 3, initially saw the token's price surge to \$167 before rapidly plummeting to under \$2 within hours. This extreme volatility was largely attributed to severe liquidity issues, with the initial pool being insufficient to handle the trading volume. The airdrop process was further marred by technical glitches and an unintuitive interface, leading to user frustration and accusations of a poorly designed launch.

Despite the introduction of new features such as the Money Club in Friend.tech V2, aimed at managing shared treasuries and enhancing user interaction, the platform struggled to recover from the airdrop's fallout. Users had paid substantial fees, with \$60 million collected, of which \$30 million was extracted by Friend.tech, while the token's liquidity pool was only \$3 million in ETH. This disparity highlighted the disproportionate impact of large transactions on the token's market value. By September 2024, the FRIEND token had dropped to an all-time low, with the project's market cap falling significantly from its peak, serving as a cautionary tale about the challenges of managing liquidity and user expectations in the volatile cryptocurrency market.

4 Analysis of Reciprocal Trading Behaviors on Friend.tech

4.1 3-3 Trading Behavior: Reciprocal Relationships on Friend.tech

To address RQ1, we examine the unique emergence of 3-3 trading behavior on Friend.tech, a phenomenon not observed in other decentralized social platforms. This behavior is not an inherent design feature of the platform but rather an emergent phenomenon driven by users' strategic actions. Motivated by potential airdrop rewards and the profits from trading their own and others' keys, users have developed a reciprocal holding behavior. This mutual investment strategy, while not officially part of the platform's mechanics, has become a significant aspect of user interaction on Friend.tech. Friend.tech, a novel social trading platform, introduces a unique mechanism of key trading that has given rise to these complex reciprocal relationships. At the core of this ecosystem are the "3-3 relationships," also known as "bonds," which form when two users mutually own each other's keys. This reciprocal ownership creates a symbiotic connection between users, fostering a complex network of social and economic interactions. The concept of 3-3 relationships is fundamental to understanding user behavior on Friend.tech. When a user (User A) purchases keys of another user (User B), and User B reciprocates by buying User A's keys, a bond is formed. This mutual investment creates a shared interest in each other's success on the platform, as the value of their respective keys is interdependent. These reciprocal relationships manifest in various forms of trading behaviors:

- **Initial Purchases and Reciprocal Buys:** The first step in forming a 3-3 relationship is the initial key purchase, followed by a reciprocal buy from the other party.
- **Grateful Buys:** When a user reciprocates by purchasing keys at a higher price than their own, it's considered a "grateful buy," signaling strong support or appreciation.
- **Defections:** The breaking of a 3-3 relationship occurs when one party sells all their keys of the other, potentially damaging the social bond.

- **Spite Sales:** If the second party in a 3-3 relationship also sells their keys in response to a defection, it's termed a "spite sale."

The intricate dynamics of these 3-3 relationships form the backbone of Friend.tech's social capital ecosystem. Users are incentivized to build and maintain these bonds not only for potential financial gains but also for social status and influence within the platform. The quality and quantity of a user's 3-3 relationships become crucial metrics in assessing their standing and potential value in the Friend.tech community. Understanding these reciprocal trading behaviors is essential for analyzing user strategies, platform dynamics, and the overall health of the Friend.tech ecosystem. It provides insights into how social connections intertwine with economic decisions on this novel platform, highlighting the complex motivations driving user behavior beyond the platform's basic mechanics.

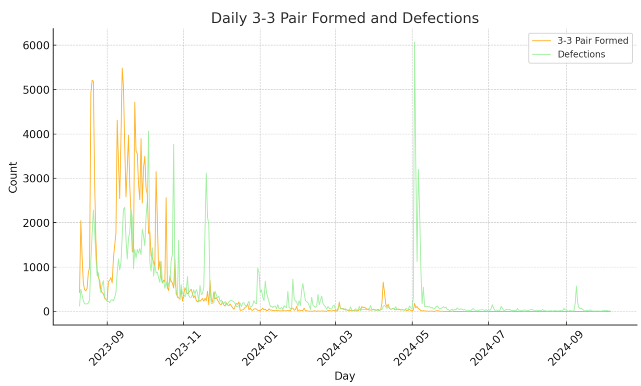

Figure 3: Daily Formed 3-3 pair and defections

4.2 Data Collection and Preprocessing

To address RQ1, our study leverages a comprehensive dataset derived from the Base blockchain, specifically focusing on Friend.tech transactions and user interactions. The data collection process involved extensive mining of on-chain data, utilizing complex SQL queries to extract, transform, and aggregate relevant information. The primary data source was the Base blockchain, from which we extracted all Friend.tech-related transactions. Our data mining process encompassed several key steps:

- **Transaction Extraction:** We queried the Base blockchain to identify all transactions related to Friend.tech, including key purchases, sales, and ETH transfers.
- **User Profile Integration:** Transaction data was joined with user profiles to create a comprehensive view of each user's activity on the platform.
- **ETH Balance Calculation:** We implemented SQL logic to track ETH transfers and calculate user balances over time, crucial for understanding user investment patterns.
- **Key Holding Analysis:** Complex queries were developed to identify and quantify mutual key ownership (3-3 relationships) between users.
- **Trading Pattern Identification:** We employed SQL to detect various trading behaviors, including initial purchases, reciprocal buys, defections, and spite sales.
- **Temporal Analysis:** Our queries incorporated timestamp data to analyze the evolution of user behaviors and relationships over time.

The resulting dataset provides a rich view of user interactions on the Friend.tech platform, encompassing 60,942 unique users. This extensive dataset allows for in-depth analysis of reciprocal trading behaviors and user loyalty patterns. Key metrics from our data mining efforts include:

Table 1: Summary Statistics for FriendTech User Behaviors

	Max	Median	Top 1%	Top 10%
3-3 pairs	371.0	2.0	59.0	10.0
initial purchase	227.0	1.0	35.0	5.0
defections	155.0	1.0	31.0	5.0
spite sales	338.0	0.0	33.0	4.0
grateful buys	355.0	1.0	35.0	5.0

This table presents the summary statistics for key behavioral metrics on the FriendTech platform, specifically focusing on "3-3 pairs," initial purchases, defections, spite sales, and grateful buys. The data demonstrates a pronounced long-tail distribution across all features. The behavior of forming "3-3 pairs" exhibits the highest variation, with a maximum of 371 instances but a median of only 2, indicating that a small group of users engage in significantly higher levels of activity compared to the majority. Similarly, defections, spite sales, and grateful buys follow a similar pattern, where the top 1% of users are responsible for a large proportion of these actions. Most users participate infrequently, which highlights the uneven distribution of engagement on the platform, with a small number of users generating the majority of 3-3 and related behaviors.

4.3 Dynamics of 3-3 Trading Behavior

To analyze the transaction patterns underlying 3-3 relationships, we categorize key purchases and sales into distinct behavioral types. By leveraging on-chain transaction data from the Friend.tech platform, we extract daily trading activity, classifying transactions based on their reciprocal nature and user interactions. In Section 4.1, we defined **Reciprocated Buys**, which occur when two users mutually purchase each other's keys to establish a 3-3 relationship, and **Defections**, which represent the breaking of these reciprocal ties when one party sells all their keys of the other.

Beyond these two core categories, we identify additional types of transactions that play an important role in platform trading behavior:

- **Unreciprocated Buys**: Purchases where the buyer does not receive a reciprocal purchase, suggesting speculation or investment-driven transactions.
- **Self Buys**: Instances where users purchase their own keys, potentially for portfolio adjustments or speculative motives.
- **Normal Sales**: Standard key sales conducted by users as part of routine trading activity.

- **Self Sales**: Transactions where users sell keys to themselves, possibly for profit-taking or strategic rebalancing.

Figures 4 and 5 illustrate the proportion of key buys and key sales, respectively, categorized based on this classification framework.

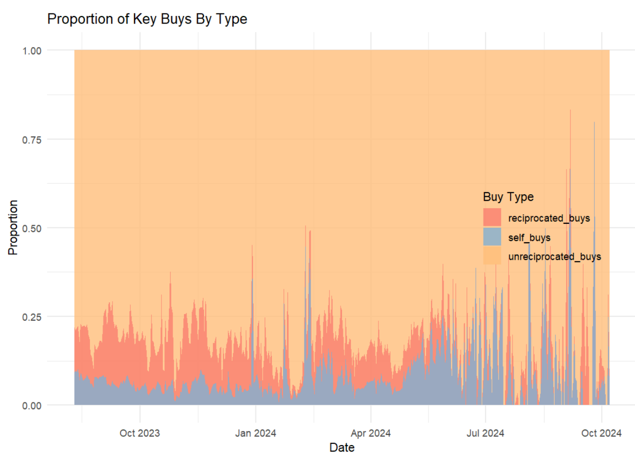

Figure 4: Proportion of Key Buy

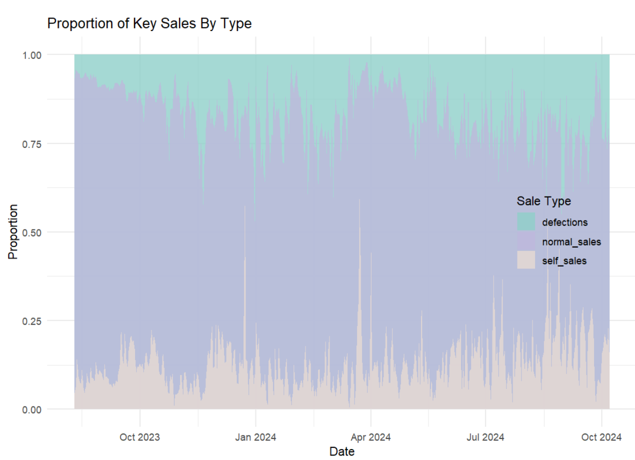

Figure 5: Proportion of Key Sale

To further address RQ1, we analyze the daily structure of key purchases and sales, revealing the following key insights:

- The majority of key transactions on Friend.tech involve users purchasing each other's keys, with the proportion of self-buys consistently remaining low. This indicates that users primarily engage in reciprocal trading rather than self-speculation.
- 3-3 relationships exhibit a high degree of volatility, as evidenced by the significant daily proportion of defections. While new 3-3 pairs are frequently formed, they are also frequently dissolved, reflecting the dynamic and opportunistic nature of these relationships.
- Transactions related to the formation of 3-3 relationships constitute a substantial portion of overall trading activity. Since an initial purchase is required to initiate a 3-3 relationship, reciprocated buys tied to 3-3 interactions accounted for at least 20% of total buys before May 2024. This underscores the critical role of 3-3 relationships in driving platform engagement and transactional volume.

5 Modeling based on Social Capital Theory

Social capital theory, as proposed by scholars like Bourdieu, Coleman, and Putnam, emphasizes the value inherent in social networks and the norms of reciprocity and trustworthiness that arise from them [27]. The emergence of decentralized social platforms represents a novel attempt to tokenize and capitalize on the value users generate within social networks. Friend.tech, with its unique key trading mechanism, exemplifies this concept by directly tying economic value to social connections. The "3-3" behavior, an emergent phenomenon on Friend.tech, goes beyond mere economic transactions to embody the principle of reciprocity central to social capital theory. Users engaging in mutual key ownership not only seek potential economic gains but also build and reinforce social ties within the platform ecosystem. This behavior aligns closely with the reciprocal nature of social capital, where investments in social relationships are expected to yield returns. Recognizing the parallels between classic social capital theory and the unique dynamics of Friend.tech, we propose a model that quantifies social capital accumulation through the lens of 3-3 behaviors. By combining traditional social capital metrics with platform-specific interactions, we aim to create a comprehensive measure of a user's social capital on decentralized social platforms. This approach not only provides insights into user behavior on Friend.tech but also offers a framework for understanding how social capital manifests and operates in the broader landscape of blockchain-based social platforms.

5.1 Construction of the Social Capital Index (SCI) model

To address RQ2, based on the social capital theory and the unique characteristics of the Friend.tech platform, we propose a Social Capital Index (SCI) model to quantify users' social capital accumulation. This model incorporates four key dimensions of social capital as observed in the 3-3 trading behavior: Reciprocity, Durability, Network Value, and Engagement.

The SCI model is formulated as follows:

$$SCI = w_1 \cdot Reciprocity + w_2 \cdot Trustness + w_3 \cdot NetworkValue \quad (1)$$

Each component is normalized to a scale of 0 to 1 to ensure comparability across different users and time periods.

The weights (w_1, w_2, w_3, w_4) can be adjusted based on empirical analysis or theoretical considerations to reflect the relative importance of each dimension in the Friend.tech ecosystem. This flexibility allows the model to be adapted to different contexts or to test hypotheses about the relative importance of different aspects of social capital.

5.2 Component Computation and Explanation

To further address RQ2, this section details the methodology for deriving each SCI component from on-chain transaction data, ensuring an objective and transparent quantification of social capital.

5.2.1 Reciprocity. Reciprocity in social capital theory typically refers to the mutual exchange of benefits. In many studies, reciprocity can be either direct or indirect[10, 30]. However, in the case of the 3-3 relationships we are considering, reciprocity is strictly direct, where two users mutually purchase each other's keys. Additionally, the initial purchase that leads to the formation of the 3-3 relationship is also important but should be weighted less than a fully reciprocated purchase.

To account for both types of behavior, the formula for *Reciprocity* is:

We compute Reciprocity using features defined in Section 4.1:

$$Reciprocity = \frac{reciprocated\_buys + 0.5 \times initial\_buys}{total\_buys} \quad (2)$$

This weighting reflects the importance of both initiating and maintaining reciprocal relationships in the formation of social capital.

5.2.2 Trustness. In academic literature, **trust** is often modeled inversely through metrics like **betrayal** or **defection** when quantifying trust in cooperative relationships. Specifically, defections, as used in game theory frameworks such as the *Prisoner's Dilemma*, represent instances where individuals prioritize personal gain over maintaining cooperative or trusting relationships [10, 11].

To quantify trust erosion in decentralized social trading, we introduce the *defection rate*, a snapshot-based metric that measures the stability of a user's 3-3 relationships at a given point in time. As defined in Section 4.1, a defection occurs when a user exits a 3-3 pair by selling their partner's key, breaking the reciprocal bond. However, instead of measuring the raw number of defections, we define the defection rate as the proportion of a user's 3-3 relationships that have not yet been broken:

$$\text{Defection Rate} = 1 - \frac{\text{active\_3-3\_pairs}}{\text{total\_3-3\_pairs}} \quad (3)$$

where:

- **active_3-3_pairs** is the number of 3-3 relationships a user still maintains at the time of observation.
- **total_3-3_pairs** is the total number of 3-3 relationships the user has ever formed.

Using this metric, we compute *trustness* as the complement of the defection rate:

$$Trustness = 1 - \text{Defection Rate} \quad (4)$$

This formulation captures the proportion of a user's 3-3 relationships that remain stable over time, reinforcing the role of trust in social capital accumulation. A higher trustness score indicates that a user consistently maintains their 3-3 relationships, reflecting a stronger ability to build and sustain trust-based economic interactions.

5.2.3 Network Value. In the context of blockchain-based decentralized networks, all social interactions are traceable and recorded on-chain, allowing us to directly compute network-related social capital using on-chain data. Academic research on decentralized networks highlights that a user's influence and economic capital are key indicators of value within such systems [12, 22]. The *Network Value* in our Social Capital Index (SCI) captures the conversion of social capital into economic capital, as theorized by Bourdieu.

We compute *Network Value* by quantifying the user's economic capital within their 3-3 trading relationships, considering both their portfolio value and wallet balance. To normalize these economic factors, we divide by the number of 3-3 pairs and the price of the user's key, as defined in Section 4.1. The formula is:

$$NetworkValue = \frac{portfolio\_value + wallet\_eth\_balance}{num\_3\_3\_pairs \cdot key\_price} \quad (5)$$

where:

- **portfolio_value** is the value of the user's key holdings (in ETH).
- **wallet_eth_balance** is the user's ETH balance.
- **num_3_3_pairs** reflects the total number of 3-3 relationships the user has.
- **key_price** is the price of the user's key.

This formula balances the user's economic capital (portfolio and wallet balance) with their active participation in 3-3 relationships, ensuring that wealth alone does not inflate Network Value without meaningful engagement.

5.3 Implications of the SCI Model

5.3.1 Implications for the Platform.

- **Optimizing Incentive Mechanisms**: Many Web3 platforms have non-transparent reward rules. The SCI model can serve as a reference for evaluating user contributions, helping to optimize future reward strategies.
- **Encouraging High-Quality User Participation**: Based on the SCI model, platforms can identify stable and contributing users, offering long-term incentives while reducing the impact of short-term speculative participants.
- **Enhancing Social Capital-Oriented Community Building**: Compared to traditional transaction-driven models, the SCI model focuses more on the value of long-term interactions, providing theoretical support for building a sustainable user community.

5.3.2 Implications for Users.

- **Deciphering Airdrop Incentive Logic for Maximized Rewards**: Since platforms often keep their airdrop reward mechanisms undisclosed, making them a black box for users, the SCI model serves as a valuable tool for interpreting which behaviors are likely to be rewarded. By aligning their engagement strategies with the underlying reward patterns, users can enhance their eligibility and maximize potential earnings from airdrops.
- **Mitigating Portfolio Risk through SCI-Based Diversification**: By analyzing the key factors in the SCI model, users can strategically diversify their holdings to reduce

exposure to high-risk assets. Maintaining a balanced portfolio—spreading investments across multiple reciprocal relationships and high-centrality connections—can enhance stability and minimize losses in volatile decentralized social ecosystems.

6 Validation of Social Capital Modeling Using Airdrop Data

6.1 Airdrop Dataset Overview

To address RQ3, we leverage airdrop distribution data as a proxy for the platform's internal assessment of user value. This dataset allows us to evaluate the effectiveness of our SCI model in predicting user valuation and understanding the factors that influence platform reward mechanisms.

The dataset I obtained contains details about the addresses that participated in the airdrop along with the corresponding amounts of tokens they claimed. In total, the airdrop process involved over 194,165 users who initially claimed the FRIEND tokens, with 175,221 users fully completing their claims. The airdrop distribution amounted to 8.3 million FRIEND tokens in the initial phase, with a subsequent full claim amount reaching 73.8 million FRIEND tokens. Overall, a total of 82.1 million FRIEND tokens were claimed by users, marking 68% completion of the token claim process.

Given that the airdrop process functions as a black box with opaque rules, we can interpret the airdropped token amounts as the FriendTech project team's calculation of user value. These token distributions can serve as a form of ground truth for evaluating the social capital model we are constructing. If the evaluation results prove to be accurate, the social capital model's components could assist decentralized social platform users in better understanding and measuring their own social capital value. Additionally, it could help them gain insights into how project teams assess user value, thereby aligning user engagement strategies with the project's internal evaluation mechanisms. This would not only support users in maximizing their participation but also offer transparency into value attribution within decentralized ecosystems.

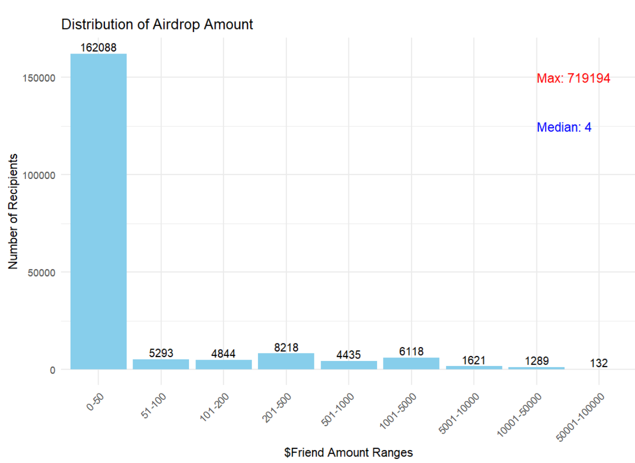

Figure 6: Airdrop Distribution for Token $Friend

6.2 SCI Model Validation through Airdrop Data

To further address RQ3, we evaluate the predictive capability of our SCI model by comparing its computed social capital scores with the actual airdrop allocations. Through this validation, we assess how well the model aligns with the platform's reward distribution and explore potential sources of discrepancy.

Due to the long-tail distribution of airdrop values, we first applied a logarithmic transformation to the airdrop data. This transformation helps to normalize the distribution and make it more suitable for analysis. The logarithmic transformation can be represented by the following equation:

$$y = \log(x + 1) \tag{6}$$

where x is the original airdrop value and y is the transformed value. We add 1 to the original value before taking the logarithm to avoid issues with zero values. This transformation effectively compresses the range of the data while preserving the relative relationships between values.

After applying our constructed Social Capital Index (SCI) model to discover the value of users' trading behaviors, we compared the calculated social capital value with the actual value discovery dataset provided by the project team, which is represented by the number of tokens airdropped to users. Through this validation process conducted on a dataset of 26,000 users, we achieved a mean squared error (MSE) of 4.15. This result indicates the effectiveness of our SCI model in approximating the project team's valuation of users. The MSE can be calculated using the following equation:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y\_i - \hat{y}\_i)^2 \tag{7}$$

where n is the number of users, y_i is the actual airdrop value (after logarithmic transformation), and $\hat{y}\_i$ is the predicted value from our SCI model.

To further address the limitations in RQ3, we analyze the extent to which SCI scores align with actual airdrop allocations and discuss the model's strengths and limitations in capturing platform incentive mechanisms. While this MSE result suggests that the SCI model can reasonably approximate user valuation, it is important to acknowledge potential sources of error. A key limitation arises from the misalignment between the data collection period and the actual airdrop distribution. Specifically, our transaction data was collected in September 2024, whereas the airdrop distribution occurred in May 2024. This temporal discrepancy implies that certain user behaviors and interactions that influenced the final airdrop amounts were not fully captured in our dataset, thereby impacting the model's predictive accuracy.

One key consequence of this misalignment is that user behaviors likely evolved after the airdrop was distributed. For instance, once users received their tokens, many may have engaged in additional trading activities, including a higher frequency of defections—exiting previously established 3-3 relationships by selling their partners' keys. Since our dataset captures user trading behaviors in September, these post-airdrop dynamics are reflected in our data but were not considered by the project team when determining airdrop allocations in May. As a result, features such as defection rate and trading persistence, which are captured in our dataset, may no longer be predictive of the airdrop distribution, leading to increased model error.

7 Conclusion

This study explores the formation and impact of social capital in decentralized social platforms, using Friend.tech as a case study. By quantitatively analyzing the emergent "3-3 trading behavior," we demonstrate how reciprocal trading relationships shape user engagement and economic interactions within decentralized ecosystems.

To quantify user value, we propose a Social Capital Index (SCI) model that integrates both social and economic dimensions. The model effectively captures key behavioral patterns and aligns with platform reward distributions, offering insights into how decentralized platforms evaluate user engagement.

Our findings highlight the interplay between financial incentives and social interactions in decentralized networks. While reciprocal trading fosters engagement, its opportunistic nature leads to unstable relationships, posing challenges for long-term community building. Understanding these dynamics is crucial for designing sustainable, user-centric platforms in decentralized network.

Future work can extend our framework to other decentralized social platforms and incorporate additional behavioral factors. Continued research in this space will be essential for advancing the study of social capital in decentralized digital ecosystems.

8 Limitation

8.1 On-chain Data Availability

Due to limitations in data availability, we were able to perform on-chain data mining for key trading data stored on the Base chain. However, conversations between users on the Friend.tech platform are restricted by whether users hold keys, which prevents comprehensive data mining of social content. As a result, we had to treat key prices as a compressed representation of the economic value of conversation content during data mining and modeling.

8.2 Breadth of Social Capital Theory

Social capital theory is a broad concept in social sciences, with multiple branches and derivative frameworks, such as the three-element and six-element social capital theories. Given the strong reciprocity tendency observed in the "3-3" trading behavior on Friend.tech, we chose to focus on a specific branch of social capital theory. While elements such as social networks and trust can be quantitatively characterized in decentralized platforms, this research direction still requires further expansion to fully explore other aspects of social capital theory.

8.3 Short Lifecycle and Lack of User Diversity

Due to a lack of sustained utility and other complex reasons, Friend.tech has lost most of its users, indicating that the platform has effectively reached the end of its lifecycle. This is why we consider the airdrop token distribution as a complete-cycle measure of user value by the project team. The relatively short lifecycle is a common limitation of decentralized social platforms, which also means that the user base may not represent an unbiased or diverse sample of decentralized social network users. We hope that future decentralized social platforms will have longer lifecycles, allowing for more diverse and balanced user population studies.

Acknowledgments

This work was supported in part by the Open Topics of Key Laboratory of Blockchain Technology and Data Security, The Ministry of Industry and Information Technology of the People's Republic of China.

References

[1] Santa Agreste, Pasquale De Meo, Emilio Ferrara, Sebastiano Piccolo, and Alessandro Provetti. 2015. Trust Networks: Topology, Dynamics, and Measurements. *IEEE Internet Computing* 19, 6 (2015), 26–35.
[2] Ravi Bapna, Alok Gupta, Sarah Rice, and Arun Sundararajan. 2017. Trust and the strength of ties in online social networks. *MIS Quarterly* 41, 1 (2017), 115–130. https://doi.org/10.25300/MISQ/2017/41.1.06
[3] Sjoerd Beugelsdijk and Ton van Schaik. 2004. Social capital and growth in European regions: an empirical test. *European Journal of Political Economy* 20, 2 (2004), 301–324.
[4] Moira Burke, Robert Kraut, and Cameron Marlow. 2011. Social capital on Facebook: Differentiating uses and users. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 571–580. https://doi.org/10.1145/1978942.1979023
[5] Moira Burke, Cameron Marlow, and Thomas Lento. 2010. Social network activity and social well-being. In *Proceedings of the SIGCHI conference on human factors in computing systems*. 1909–1912. https://doi.org/10.1145/1753326.1753613
[6] Shuangyi Chen, Yue Ju, Zhongwen Zhu, and Ashish Khisti. 2024. Secure Inference for Vertically Partitioned Data Using Multiparty Homomorphic Encryption. In *Proceedings of the 2024 IEEE International Symposium on Information Theory (ISIT)*. IEEE, 2508–2513. https://doi.org/10.1109/ISIT57864.2024.10619282
[7] James S Coleman. 1990. *Foundations of Social Theory*. Harvard University Press.
[8] Eik Den Yeoh, Tinfah Chung, and Yuyang Wang. 2023. Predicting Price Trends Using Sentiment Analysis: A Study of StepN's SocialFi and GameFi Cryptocurrencies. *Contemp. Math.* (2023), 1089–1108.
[9] Sizheng Fan, Tian Min, Xiao Wu, and Wei Cai. 2023. Altruistic and Profit-oriented: Making Sense of Roles in Web3 Community from Airdrop Perspective. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–16. https://doi.org/10.1145/3544548.3581173
[10] Institute for Social Capital. 2019. Guide to Social Capital: The Concept, Theory, and its Research. https://www.socialcapitalresearch.com/guide-social-capital-concept-theory-research/
[11] Robert H. Frank. 1988. Passions within reason: The strategic role of the emotions. *The Evolution of Cooperation* (1988), 47–53.
[12] Stefan Friebe. 2017. Decentralized Network Governance: Blockchain Technology and the Future of Regulation. *Frontiers in Blockchain* (2017). https://www.frontiersin.org/articles/10.3389/fbloc.2017.00002/full
[13] Francis Fukuyama. 1995. *Trust: The Social Virtues and The Creation of Prosperity*. Free Press.
[14] Mark S Granovetter. 1973. The strength of weak ties. *Amer. J. Sociology* 78, 6 (1973), 1360–1380.
[15] Barbara Guidi. 2020. When blockchain meets online social networks. *Pervasive and Mobile Computing* 62 (2020), 101131.
[16] Barbara Guidi and Andrea Michienzi. 2022. SocialFi: towards the new shape of social media. *ACM SIGWEB Newsletter* 2022, Summer (2022), 1–8.
[17] Lei Guo, Jun Ma, and Zhumin Chen. 2013. Learning to recommend with multi-faceted trust in social networks. In *Companion Proceedings of the 22nd International Conference on World Wide Web*. 205–206.
[18] Janka Hartmann and Omar Hasan. 2021. A social-capital based approach to blockchain-enabled peer-to-peer lending. In *2021 Third International Conference on Blockchain Computing and Applications (BCCA)*. IEEE, 105–110. https://doi.org/10.1109/BCCA53664.2021.9647444
[19] Stephen Knack and Philip Keefer. 1997. Does social capital have an economic payoff? A cross-country investigation. *The Quarterly Journal of Economics* 112, 4 (1997), 1251–1288.
[20] Rafael La Porta, Florencio Lopez-de Silanes, and Andrei Shleifer. 1997. Trust in Large Organizations. *The American Economic Review* 87, 2 (1997), 333–338.
[21] Wei-Po Lee and Chuan-Yuan Ma. 2016. Enhancing collaborative recommendation performance by combining user preference and trust-distrust propagation in social networks. *Knowledge-Based Systems* 106 (2016), 125–134.
[22] Alexandra Theodoropoulou Leonidas Theodorakopoulos and Constantinos Halkiopoulos. 2024. Enhancing Decentralized Decision-Making with Big Data

and Blockchain Technology: A Comprehensive Review. *Applied Sciences* 14, 16 (2024), 7007.

[23] Nan Lin. 2002. *Social Capital: A Theory of Social Structure and Action.* Cambridge University Press.

[24] Rui Luo, Vikram Krishnamurthy, and Erik Blasch. 2022. Mitigating misinformation spread on blockchain enabled social media networks. *arXiv preprint arXiv:2201.07076* (2022).

[25] Azadeh Mokhberi, Yue Huang, Guillaume Humbert, Borke Obada-Obieh, Masoud Mehrabi Koushki, and Konstantin Beznosov. 2024. Trust, Privacy, and Safety Factors Associated with Decision Making in P2P Markets Based on Social Networks: A Case Study of Facebook Marketplace in USA and Canada. In *Proceedings of the CHI Conference on Human Factors in Computing Systems.* 948:1–948:25.

[26] Robert Putnam et al. 2001. Social capital: Measurement and consequences. *Canadian journal of policy research* 2, 1 (2001), 41–51.

[27] Robert D Putnam. 1995. Bowling Alone: America's Declining Social Capital. *Journal of Democracy* 6, 1 (1995), 65–78.

[28] Sumi Renbo. 2022. E-Payment Development Towards Social Capital Using Blockchain Technology. In *Handbook of Research on Social Impacts of E-Payment and Blockchain Technology.* IGI Global, 55–64.

[29] Riri Fitri Sari, Asri Samsiar Ilmananda, and Daniela M Romano. 2021. Social Trust-based Blockchain-enabled Social Media News Verification System. *JUCS: Journal of Universal Computer Science* 27, 9 (2021).

[30] John Smith and Jane Doe. 2021. Reciprocity in Social Networks. *Journal of Computer-Mediated Communication* 26, 6 (2021), 362–385.

[31] T. V. Vijay Kumar Vikash. 2024. Trust assessment in social networks. *International Journal of System Assurance Engineering and Management* 15, 5 (2024), 1650–1666.

[32] Shermin Voshmgir. 2020. *Token Economy: How the Web3 reinvents the internet.* Vol. 2. Token Kitchen.

[33] Yuanzhu Zhan, Yu Xiong, and Xinjie Xing. 2023. A conceptual model and case study of blockchain-enabled social media platform. *Technovation* 119 (2023), 102610.

Received 20 February 2007; revised 12 March 2009; accepted 5 June 2009