How Information Manipulation on Social Media Influences the NFT Investors' Behavior: A Case Study of Goblintown.Wtf

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***Abstract*—People favor nonfungible token (NFT) because of the attribute to prove digital assets' ownership and promote interactions. Investors are keen to buy and use NFT pictures as social media avatars and participate in online communities around NFT collections. However, information manipulation in the NFT market has led to investors significant losses. Our work explored a way to correspond social media accounts with Ethereum addresses and studied the microstructure of NFT market. Taking Goblintown.wtf as an example, we analyzed the participants, mechanism, and impact of Twitter information manipulation in the market. We found five categories of investors in the NFT market under information manipulation: primary investors, amateur investors, fanatic investors, short-term rational investors, and long-term rational investors. We argue that investors will consume their limited attention more likely when joining NFT online communities. This will lead to more complicated for them to make investment decisions rationally.**

***Index Terms*—Information manipulation, investor behavior, nonfungible token (NFT), social media.**

I. Introduction

THE proposal of ERC-721 gave birth to the nonfungible token (NFT) [1]. Unlike Bitcoin, Ethereum, or other cryptocurrencies, each NFT is unique and can have special traits. People can store digital files in interplanetary file system (IPFS) and link them to NFTs. Hence, the NFT is a solution to prove ownership and protect intellectual property [2]. The common use cases of NFTs include artwork, profile pictures (PFP), passports, videos, etc., which can promote social interactions. The technical–social feature of NFT ignited commercial prosperity in 2021 with the surging price to million US dollars of one NFT and notables' purchases of blue chip collections like CryptoPunks,[1] BAYC,[2] Azuki,[3] etc.

However, NFT investors are at significant financial risk. Dowling [3] found that the NFT market is inefficient, which means manipulating market information on social media can get a windfall profit. In May 2022, Azuki, one of the most desired NFT collections, fell nearly 60% price within a week as a piece of negative news went viral on Twitter [4]. Furthermore, many NFT collections are Ponzi schemes that investors ended up with a worthless "JPEG" [5]. Therefore, we are curious about how information manipulation in social media will influence NFT investors' behavior. While after reviewing related works, we did not find answers to our curiosity.

Hence, we chose Goblintown.wtf[4] (hereafter abbreviated as goblintown), an NFT collection that relied on rumors on Twitter to achieve commercial success as our research subject. Goblintown comprises 10 000 "goblin" NFTs, launched on 20 May 2022. The collection's official website[5] and Twitter page[6] consists of hand-drawn images and confusing gibberish. Moreover, its anonymous team clearly stated that the project has no roadmap, Discord server, and utility. Usually, such a project means a scam. Yet the floor price of a goblintown NFT had skyrocketed to almost $10 000 in just ten days. And the official Twitter account has gained over 120 000 followers. Analysts thought goblintown's success came from rumors about the collection's relationship with blue chip NFTs and notables [6].

Our first research question is: RQ1 *How did the NFT market-relevant information be manipulated in social media?* To answer RQ1, we broke it down into three sub-questions: RQ1.1 *Who participated in the discussion and formed the NFT online community?* RQ1.2 *Whose and which kind of information were more likely to spread?* And RQ1.3 *How did the widely spread information on social media influence the NFT community?* After studying the information manipulation in the NFT market from the social media side, we wanted to analyze from the market side further. So our second research question is: RQ2 *What patterns of investment behaviors did NFT investors have under information manipulation?*

We collected data from Twitter, the Ethereum network, and the correspondence between Twitter accounts and blockchain addresses to answer these questions. We collected goblintown relevant tweets and identified independent accounts. By tra-

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[1]https://opensea.io/collection/cryptopunks
[2]https://opensea.io/collection/boredapeyachtclub
[3]https://opensea.io/collection/azuki
[4]https://opensea.io/collection/goblintownwtf
[5]https://goblintown.wtf/
[6]https://twitter.com/goblintown

versing their avatar pictures, we picked up goblintown fans that used goblintown NFT in their Twitter profile and considered them as goblintown Twitter community members. Then, by deduplicating these members' profile pictures, we identified core members that are most influential and possibly hold at least one goblintown NFT. Moreover, we retrieved transactions and relevant addresses from the goblintown smart contract. Finally, through linking who was using a specific NFT as their avatar and who held the NFT, we obtain correspondences between the above Twitter accounts and Ethereum addresses.

For RQ1, we conducted network visualization, topic framing, and natural language processing (NLP) analysis of our data. Our main finds include: 1) there were four kinds of vital nodes involved in the information spreading on Twitter: the goblintown team, community core members, key opinion leaders (KOLs), and counterfeit projects. The primary sources of the most spreading information were KOLs and counterfeits. The core members and the goblintown team referred to these sources and were information spreaders; 2) the discussion topics in NFT communities were mainly related to rumors and "the fear of missing out" (FOMO) messages; and 3) under information manipulation, the sentiment of all discussion participants became fanatic but then returned to rational. However, the community members maintained the fanatic. For RQ2, we applied network visualization and the K-means algorithm to obtain the answer. Our main finds include: 1) the top goblintown sellers were highly profitable, but hardly participated in discussions and the online community; 2) the top buyers lost more profits when they were more involved in related discussions and became community members; and 3) there were five categories of NFT investors. We described them as primary investors (low-frequency trading, low returns, and low tweets posted), amateur investors (low-frequency trading, low returns, and high tweets posted), fanatic investors (high-frequency trading, low returns, and high tweets posted), and rational investors. Among rational ones, we classified them as short-term rational investors (high-frequency trading, high returns, and low tweets posted), and long-term rational investors (low-frequency trading, high returns, and low tweets posted). Interestingly, the rational investors did not appear when we clustered the NFT community members.

Our findings expanded the investor classification under market information manipulation [7] to the NFT market. We also explained the rational investors' disappearance in the NFT community using behavioral finance theories. Human attention is limited. When investors participate in the NFT community, their attention is consumed by the information sourced from project teams and KOLs. They enthusiastically spread the news and cannot be rational. For investment targets with social attributes like NFT, social media amplifies the effects of information manipulation.

Our main contributions are as follows.

1) We collected data around goblintown and analyzed the NFT market from a micro-view by combining investors' social interactions and blockchain tradings.
2) We analyzed the mechanisms of information manipulation in the NFT market and the role played by the NFT team, community core members, KOLs, and counterfeit projects during the process.
3) We clustered investors into five categories: primary investors, amateur investors, fanatic investors, short-term rational investors, and long-term rational investors, with discussion from a behavioral finance perspective.

II. Related Works

Information manipulation is a widespread phenomenon in financial markets. To drive up stock prices [8], job promotions [9], or salary incomes [10], managers of companies and projects might systematically control the disclosure of internal information or related news. Common methods of information manipulation include direct release rumors, falsification of reports, collusion with third-party media and analysts to release fake statements, etc. [11].

Social media facilitates information spreading and is widely used for market manipulation, such as pushing up stock prices by employing promoters [12] or bots [13] to send lots of stock-related tweets, or mentioning junk bonds in blue chips tweets [14]. Scholars also studied information manipulation on crypto assets. Some focused on the relationship between the features of social media messages and cryptocurrencies' pump and dump [15], [16]. Others explored the influence of tweets from notables and KOLs, like Elon Musk, on token prices [17]. Others considered the role of bots [18] and the interaction between scammers and victims [19]. However, due to the anonymity of blockchain technology, researchers cannot construct an effective link between data on the social media side and the market side, which means it is hard to study some particular investors' behaviors under information manipulation. Hence, these macroscopic works differ little from studies in traditional stock markets.

Considering the NFT market, mainstreams focus on using social media data to evaluate the NFT price [20], [21]. The representative one is Kong and Lin [22]. Their work considers the social interaction attribute of NFT and uses the hedonic regression model to value the most famous NFT projects. Their work also proves that NFT has a strong social interaction attribute. But few studies on information manipulation in the NFT market. Dowling found the Decentraland NFT market inefficient and assumed there have information manipulations in NFT markets [3]. Maouchi et al. [23], and Vidal-Tomás [24] found the NFT market is weak to fraudulent actions. Other empirical studies like Tariq and Sifat [25] proved numerous "wash tradings" in NFT markets. However, similar to cryptocurrency studies, existing research on information manipulation in the NFT market still did not leave the traditional financial analysis approach, which only can provide a macro view analysis without revealing comprehensive individual investors' actions.

As described in the introduction, NFT investors purchase NFTs, use NFTs to manifest their identities, and form NFT communities. Vasan et al. [26] revealed that NFTs help artists, institutions, collectors, and curators establish more relations. Colicev [27] points out that NFTs can create a two-way connection between brands and consumers. On social media where passionate about discussing NFT issues (such

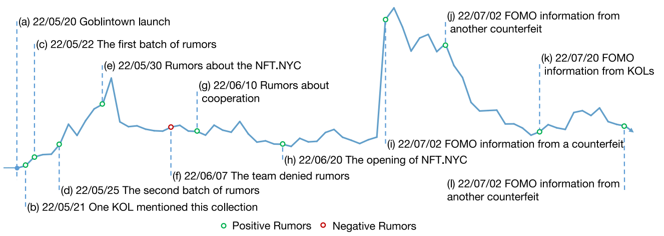


Fig. 1. Timeline of influential information manipulations related to the goblintown collection. The green circles show positive market information, and the red ones show negatives. The shape of the timeline comes from the NFT price.

as Twitter and Discord), it is fashionable for people to use NFT pictures in their profiles and manifest their identities. These behaviors have gathered like-minded people and formed virtual communities around specific NFT collections on social media [28]. Through the study of 18 popular NFT collections, Casale-Brunet et al. [29] reveal that one NFT collection's community can gather more than 10 000 Twitter users, who consistently interact and post thousands of related tweets daily in one year. According to previous studies in the stock and cryptocurrency markets, NFT investors' enthusiasm provides more feasible conditions for information manipulation. Hence, there might have numerous information manipulation in NFT markets. Moreover, due to the social interaction properties, we can link NFT investors' investment actions with their social media identities, which gives us a grab to in-depth study information manipulation and investors' behaviors from a more microview.

III. Information Manipulation of Goblintown.Wtf

As a profile picture (PFP) NFT collection published by an anonymous team and without the roadmap, Discord server, and utility, the most likely fate of goblintown is the NFT price goes to zero and forget by the market. However, rumors and information manipulation on Twitter surged its price. Since its publication on May 20, someone systematically spread rumors and FOMO (the fear of missing out) information about goblintown on Twitter. Fig. 1 presents the influential rumors in chronological order. We follow the US stock market color scheme custom (green means bullish and red means bearish) to set positive market information circles to green and negative market information ones to red. And the shape of the timeline indicates the price change of goblintown NFT.

On May 20 (a), the goblintown collection was officially released in a "free mint" mode, but few investors participated. The situation changed on 21 (b). After a very influential Twitter KOL "mdudas" tweeted that he had minted some goblintown, the collection sold out. Then, a frenzy of information manipulation based on ambiguous news and rumors began. On May 22 (c), numerous tweets suspected that goblintown belonged to NFT's blue-chip team YugaLabs. Many Twitter users believed and flooded into the market. Then by May 25 (d), rumors that goblintown had relations with famous musician Steve Aoki, top crypto artist beeple, 3-D artist Frederic Duquette and rapper Uncle Snoop

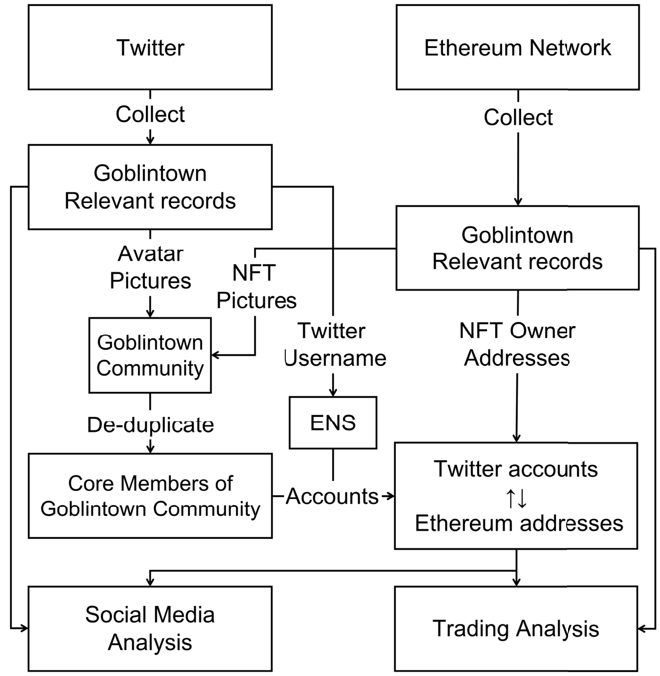


Fig. 2. Data collection process of our work. We collected data from Twitter and Ethereum network to analyze the information manipulation. Moreover, through the goblintown NFT pictures and ENS used by Twitter users, we obtained the correspondence between Twitter accounts and Ethereum addresses, which assisted our in-depth study.

appeared on Twitter. On May 30 (e), Twitter users spread that goblintown would attend the world's most important NFT conference, NFT.NYC. For about 10 days, these rumors pushed the average price of goblintown to $7,837.3, and the team earned over $3.75 million by charging royalties. However, the team officially denied all previous rumors on June 7 (f). And they unilaterally announced on June 10 (g) that they would cooperate with Lee Kum Kee. However, this information did not have a significant impact. On July 2 (i), a counterfeit, "goblinwomen," attracted attention by purchasing a goblintown at an exorbitant price. Many investors who missed goblintown joined the market and pushed the price to the highest. Subsequently, on July 2 (j), 20 (k), and 29 (l), other KOLs and counterfeits released FOMO tweets, which were widely discussed but did not have a big impact on the market.

IV. Data Collection

As shown in Fig. 2, we collected data from Twitter, the Ethereum network, and the correspondence between Twitter accounts and blockchain addresses for our study. Since studying information manipulation in the NFT market is innovative and there are strict retrieval restrictions with Twitter API, we use the representative goblintown as a case study in this work.

A. Social Media Data

Goblintown does not have a Discord server, and its official and main discussions occurred on Twitter. We employed

Twitter Academic Research API[7] to retrieve the social media data relevant to goblintown. Because the first relevant tweet appeared on 17 May 2022, all our data range from 17 May 2022, to 31 July 2022. Using "goblintown" as the keyword, we retrieved related discussion data. As English is the predominant communication language in the crypto industry, we only collected relevant tweets posted in English. We also removed the suspended accounts' tweets. Finally, we collected 491 643 tweets from Twitter. These data include usernames, texts, timestamps, types (originality/retweet/quote/reply), and reference relations (if one tweet was not original, the reference relation means which tweet it was retweeting/quoting/replying to). We identified 136 758 independent users from these tweets. We also collected all these participating users' follower numbers, Twitter profile pictures, and when they started to use these avatars.

B. Ethereum Network Data

Using the same span (May 17 to July 31), we collected transaction data from the smart contract of goblintown NFT through Etherscan.[8] These data include addresses of both sides of the transactions, block timestamps, the value being transacted in ETH (the token of Ethereum) and US dollar value, and related NFTs' ids. After deleting incomplete transactions and de-duplication, we collected 29 887 transactions and 14 543 relevant investors' addresses. From these data, we obtained 4509 wallet addresses holding goblintwon NFTs and NFTs distribution (which goblintown NFTs were held by a specific address) on 31 July 2022. Then we retrieved the picture linked to each goblintwon NFT from the collection page on Opensea.

C. Twitter-Ethereum Correspondence Relation

We totally obtained 3549 correspondences between Twitter accounts and Ethereum addresses to study the manipulation of NFT market information on social media. First, we focused on users who adopted goblintown as their Twitter avatars. Using OpenCV[9] suite in python, we compared profile pictures retrieved in Section IV-A and NFT pictures retrieved in Section IV-B. This process helped us to identify 3587 accounts as goblintown fans that used NFTs from the collection in their Twitter profile. Because using an NFT as the avatar is a way to manifest one's social media identity and gather other like-mind people, we looked at these 3587 users as the goblintown community on Twitter. However, people can download NFT images as their avatars to participate in the community even if they do not own the NFTs. Hence, we found Twitter accounts that used the same NFT picture and only retained the account with the most followers as the owner for each reused NFT. By de-duplication, we identified 1417 goblintown core Twitter community members that are most influential on social media and possibly held at least one goblintown NFT. Meanwhile, through these NFT pictures, we determined these core members' Ethereum addresses.

In addition, we attempted to obtain more correspondence relations through Ethereum Name Service (ENS). An ENS generally begins with human-recognizable words and ends with ".eth" (such as goblinking.eth) [30]. As the short domain name of an Ethereum address, many Twitter users like to use the ENS as their Twitter usernames, which is also a social behavior to show their identity in the crypto area [31]. Since reversing the users' ENS names can reveal their Ethereum addresses and vice versa, we used ENS API[10] to process ENS names in Twitter usernames and trading addresses we obtained in Section IV-A. We identified another 2132 correspondences between Twitter accounts and Ethereum addresses.

V. Methodology

This section first presents how we conducted the network visualization analysis of tweets and transactions related to the goblintown NFT collection. Second, it describes our framing and NLP analysis of the change in topic frames and sentiment of discussions on Twitter. Last, we introduce how to apply the K-means method to capture user clusters from profits, transaction frequency, and posted goblintown tweets.

A. Network Visualization Analysis

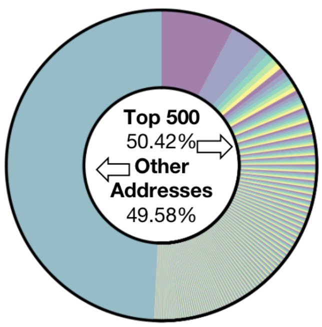
As described in Section IV, we obtained the reference relation of goblintown tweets. Moreover, we had transaction data from the collection. After cleaning and preprocessing, these data were subjected to network visualization analysis. Based on graph theories, network visualization can describe human behaviors and reveal complex relations among crowds and market [32], [33]. When conducting this method to analyze a complex network, people are visualized as nodes, and relationships or interactions between them as edges.

We employed Gephi (0.9.7)[11] to conduct the network visualization. After inputting time-series data, Gephi can visualize networks and reveal trends and stories behind them, widely used in network research [34]. For the Twitter data in RQ1, Twitter accounts are the nodes in visualization. And to simplify the research process, accounts' received references (retweets/quotes/replies) from others are equally displayed as edges. While for the trading data in RQ2, each goblintown NFT trader is the node in visual results. And the transaction relations are shown as edges. We used directed graph mode to visualize the network because Twitter and NFT markets both follow the asymmetrical principle: On Twitter, one account's tweets may be retweeted but not necessary for this account to retweet back (it is the same for NFT transactions). Finally, we used the default parameters of the "Force Atlas 2" and "Fruchterman Reingold" modes to lay out our networks.

B. Word Cloud, Topic Framing and NLP Analysis

We pre-processed the collected tweet texts in Python with NLTK suite[12] to lowercase capitals and to remove stop words,

[7]https://developer.twitter.com/en/docs/twitter-api
[8]https://etherscan.io/
[9]https://github.com/opencv/opencv
[10]https://docs.ens.domains/contract-api-reference/subgraphdata/entities
[11]https://gephi.org/
[12]https://www.nltk.org/



	Address	Distribution%
Top 1	0x62a...a0f	7.73
Top 2	0x83c...ba2	3.56
Top 3	0x002...eb5	0.96
Top 4	0xc0c...328	0.76
Top 5	0xf89...280	0.64
Top 6	0x4ff...290	0.58
Top 7	0xf97...412	0.57
Top 8	0x0f5...c12	0.50
Top 9	0x5a7...860	0.47
Top 10	0x483...27d	0.43

Fig. 3. Distribution of 4509 owners of the goblintown collection. There was a head aggregation in the NFTs distribution, but it was insignificant.

punctuation, etc. For RQ1.2, we first employed a python suite wordcloud [13] to obtain an overview of goblintown related discussions. Then, to reveal specific topics, we introduced semantic network analysis provided by KH Coder [35], an open-access quantitative content analysis tool, to perform the framing study of tweet texts. This method avoids the subjective influence of human coders [36] and is widely used in text topics study of online discourses. We used the first 100 frequently co-occurring keywords in monthly tweets of goblintown to cluster frames and kept the minimum spanning tree. Keywords were located based on the Fruchterman and Reingold algorithms. The words in each frame reveal a theme. And correlations between keywords are calculated by the Jaccard coefficient and linked by edges.

To study RQ1.3, we used another NLP suite, TextBlob,[14] to obtain each pre-precessed tweet's sentiment polarity and objectivity. We conducted sentiment analysis over 3 months. To facilitate the qualitative comparisons, we defined the sentiment percentage $SP = \frac{Num.S}{Num.T}$ %. In this equation, *Num.S* means the number of tweets with one kind of polarity (positive/neutral/negative) or subjectivity (subjectivity/neutral/objectivity) property. And *Num.T* means the total number of tweets in the same period. We can determine people's sentimental variation by comparing the monthly change in the percentage of tweets' polarity and objectivity.

C. Investor Clustering

In the analysis of RQ2, we used the K-means algorithm to study the NFT market investors' behavior. As an unsupervised machine learning method, the K-means clusters data by calculating the minimal sum of the squared distance between points and their nearest cluster centers [37]. This method is simple, direct, and does not need multiple random initializations, which is suitable for multiple dimensions clustering. We applied sklearn suite[15] in Python to conduct the clustering. Each goblintown NFT investor's transaction frequency, profits (revenue subtracts cost), and posted tweets numbers act as the input. Finally, we visualized the clustering results in a 3-dimensional coordinate.

[13]https://github.com/amueller/word_cloud
[14]https://textblob.readthedocs.io/
[15]https://scikit-learn.org/

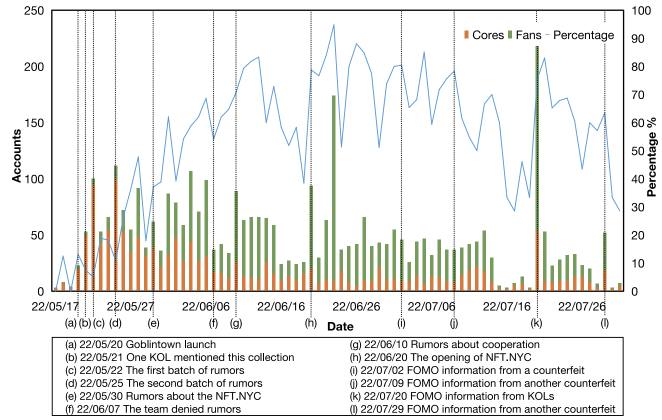


Fig. 4. Rumors influenced core members and fans to join the goblintown community. Fans were more susceptible to market rumors compared to cores.

VI. Result and Analysis

A. Goblintown Community

As we introduced above, users who participated in goblintown discussions and used relevant NFT as their Twitter profile pictures are members of the goblintown community. Using goblintown avatars, they disclose their identity on social media and build a virtual community for communication and interaction. However, not all members of the goblintown community are holders of goblintown NFT. We defined those Twitter community members who held goblintown NFT as core members. Correspondingly, community members who just downloaded the NFT images and did not have ownership were goblintown fans.

We first looked at the goblintown NFT owners. Fig. 3 shows the distribution of 4509 owners of the 10 000 goblintown NFTs. The top 500 addresses held 50.42% of the overall collection, and the remaining addresses contained 49.58%. The figure also shows the distribution of the Top ten addresses. There was an aggregation phenomenon in the distribution, but it was insignificant. Hence, the whole collection is not occupied by a few giant whales, and our study of investor behavior based on goblintown is feasible. Considering members of the goblintown community we identified, they represent 31.43% of all investors involved in the transaction, and held 5526 NFTs of the collection, occupying 55.26% of the total supply. Hence, the goblintown Twitter community is influential on social media and essential to the goblintown NFT market.

As shown in Fig. 4, we counted the date that core members and fans joined the goblintown community. By comparing the joining situation of these two types of community members with important marketing information about the goblintown collection spread via Twitter, we found that both core members and fans were susceptible to market news. Although only rumors, many Twitter users joined the goblintown community when positive market information emerged [such as (c), (d), and (e)]. Comparatively, when negative market information appeared, the number of new members decreased [such as (f)]. Moreover, the percentage line of new community fans relative to all new community members reveals that positive market

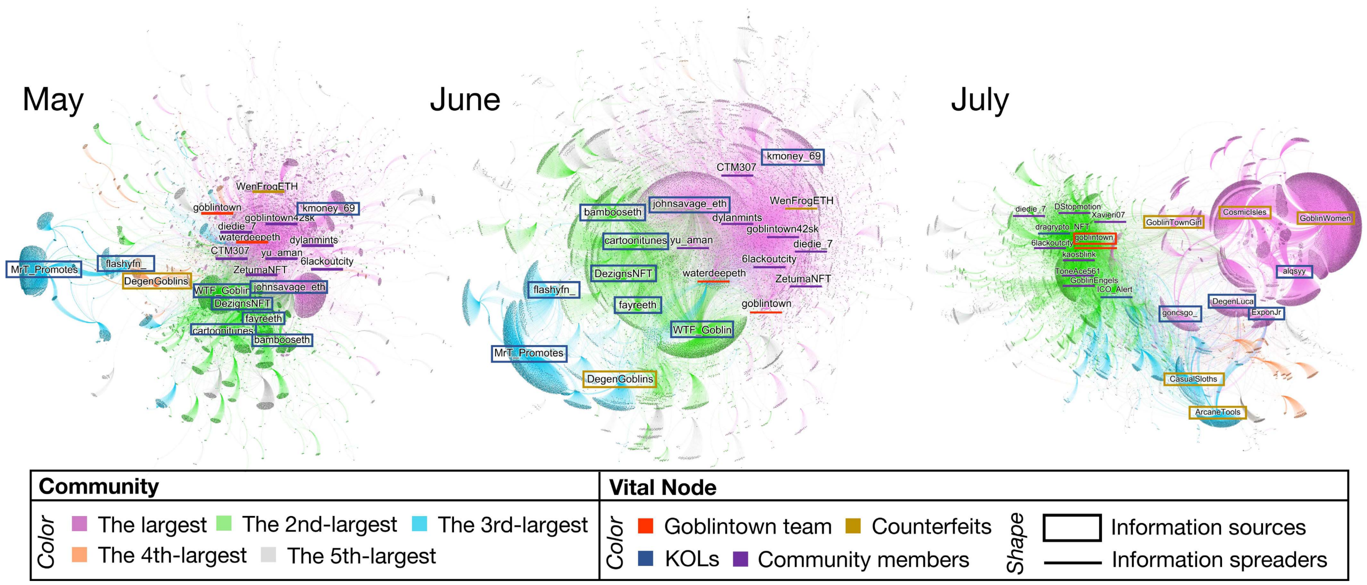


Fig. 5. Subgraphs separately visualize the spreading network of goblintown discussions on Twitter in May, June, and July. Each network was composed of five main communities. Five colors indicate these communities. The nodes in the same community had closer reference relations. Four vital roles were involved in goblintown market information manipulation: goblintown team, counterfeits, KOLs, and community members. The colors show their roles. The labels reveal these vital nodes' Twitter accounts. And the annotation shapes present their spreading function.

TABLE I
STATISTICAL DESCRIPTION OF THESE THREE NETWORKS

	Avg. Degree	Diameter	Avg. Path	Modularity	Clustering Coeff.
May	1.59	15	4.87	0.58	0.02
June	1.59	15	4.87	0.58	0.02
July	1.51	14	5.68	0.56	0.02

rumors in the early stage mainly attracted core members. Subsequently, new members were dominated by fans who only downloaded goblintown NFT pictures as their avatars.

B. Four Vital Roles of Information Manipulation on Twitter

In Fig. 5, three subgraphs separately visualize the spreading network of goblintown relevant information on Twitter in May, June, and July. Nodes present Twitter accounts, while edges mean the reference (retweet/quote/reply) interactions between them. Table I shows the statistical description of these three networks. According to the table, the spreading networks on Twitter have almost the same graphic features over 3 months. Every user interacted with more than one other user and was connected by some vital nodes to create communities in network visualizations. These communities are respectively represented in light purple, green, blue, orange, and gray, according to their percentage orders in the network visualization. Nodes belonging to a community had closer information interactions.

We found four vital roles were involved in goblintown market information manipulation on Twitter and indicated them in different color annotations: goblintown team (red), counterfeit projects (dark yellow), KOLs (dark blue), and goblintown community members (purple). In addition, we identified the top ten information sources and spreaders in the three information spreading networks by calculating the in-degree and out-degree of each node, distinguished by rectangle and

TABLE II
TRANSACTIONS OF VITAL SOURCES IN 3 MONTHS

Twitter Account	Role	Address	Transaction	Holding Num
goblintown	Goblintown team	0x62a...a0f	Y	817
CosmicIsles ArcaneTools GoblinWomen CasualSloths GoblinTownGirl	Counterfeits	-	-	-
DegenGoblins	KOLs	0xea2...b1a	N	0
johnsavage_eth		0x8D8...15d	N	0
WTF_Goblin		0xea0...343	Y	35
MrT_Promotes		0xACc...c89	N	0
kmoney_69		0xbb6...BF2	Y	0
bambooseth		0xBD1...4b1	N	0
flashyfn_		0x4cb...241	N	0
cartoonitunes		0x428...b88	N	0
DezignsNFT		0x4a6...659	N	0
fayreeth		0x8a8...2EA	N	0
alqsyy		0x76d...d11	N	0
DegenLuca		0xbd1...26b	N	0
goncsgo_		0x0a3...e1b	N	0
ExponJr		0xa3b...7cb	N	0

We ignored counterfeit projects' addresses and indicated them as "-".

line. The rectangle indicates the node is an information source, meaning many Twitter users referred to tweets posted by the node. The node with a line below means it referred to many tweets and is an information spreader. Moreover, by combining these Twitter sources and spreaders with the Ethernet addresses we identified, we knew whether these nodes participated in goblintown transactions and held the collection. The data was shown in Tables II and III. We ignored counterfeits' situations since their smart contracts would not participate in goblintown NFT transactions and represented them as "-". Additionally, "Y"/"N" means whether the address participated in transactions, and "?" means we did not find the corresponding address.

According to the network visualization analysis, when the market performed well (May, June), the primary sources of

This article has been accepted for inclusion in a future issue of this journal. Content is final as presented, with the exception of pagination.

TABLE III
TRANSACTIONS OF VITAL SPREADERS IN 3 MONTHS

Twitter Account	Role	Address	Transaction	Holding Num
goblintown	Goblintown team	0x62a...a0f	Y	817
waterdeepeth		0xbBe...762	Y	15
WenFrogETH	Counterfeits	-	-	-
dragrypto_NFT	KOLs	0x8f3...da2	Y	2
ICO_Alert		?	?	?
6lackoutcity	Goblintown community	0x8C8...814	Y	1
DStopmotion		0x62A...4e3	Y	0
diedie_7		0x950...55c	Y	1
Xavieri07		0x607...04c	Y	2
GoblinEngels		0xb31...227	Y	1
kaosblink		0xA98...650	Y	1
goblintown42sk		0xdBE...bAf	Y	1
dylanmints		0x57a...619	Y	0
yu_aman		0xf58...648	Y	0
ZetumaNFT		0xAdD...df7	Y	1
CTM307		0xD5a...beB	Y	1
ToneAce561		0x948...280	Y	1

1. "?" means we did not find the corresponding Ethereum address.
2. We ignored counterfeit projects' addresses and indicated them as "-".

information were the KOLs. Goblintown Twitter community members and the team played the role of the spreader. At this time, the goblintown team and community members were the largest part of the network. They spread the information revealed from the second largest component, KOLs. When the market was underperforming, KOLs, counterfeit projects, and the goblintown team were the primary sources of information. Community members and the goblintown team were the main spreaders. Meanwhile, counterfeits and KOLs became the main component of the network. And the team perhaps wanted to reverse the market downturn, playing the dual role of information source and spreader at this time. Concerning transactions, we also found that although KOLs were the main source of information, they hardly participated in goblintown trading or held the collection. Vital community members in these networks were the opposite, but their holdings were tiny. For this phenomenon, we speculate that KOLs might be directly rewarded by project teams just as third-party media and analysts in the stock market. Thus, they did not need to participate in risky NFT transactions. Comparatively, community members become spreaders because of fanatic emotion rather than economic motivation.

C. Features of the Most Spread Information

Then we wanted to know what information would most likely be spread during the information manipulation on Twitter. Hence, we analyzed all these tweet texts we collected. The word cloud of the top 100 words (the center goblin of Fig. 6) reveals the general overview of the most spread information. The surrounding frames display the most popular topics in goblintown tweets. These topics are related to the collection's publication mode "free mint," the rumors of goblintown's ambiguous relation with some blue chips "larvae" and "BAYC" and notables "beeple." Some vital KOLs like "alqsyy" and their common market operation methods "giveaway" are also in these frames. Moreover, discussion participants spread topics relevant to the goblintown NFT community, like "goblinfollowgoblin," "friends," and "vibe." However, there is also much FOMO information. People talked

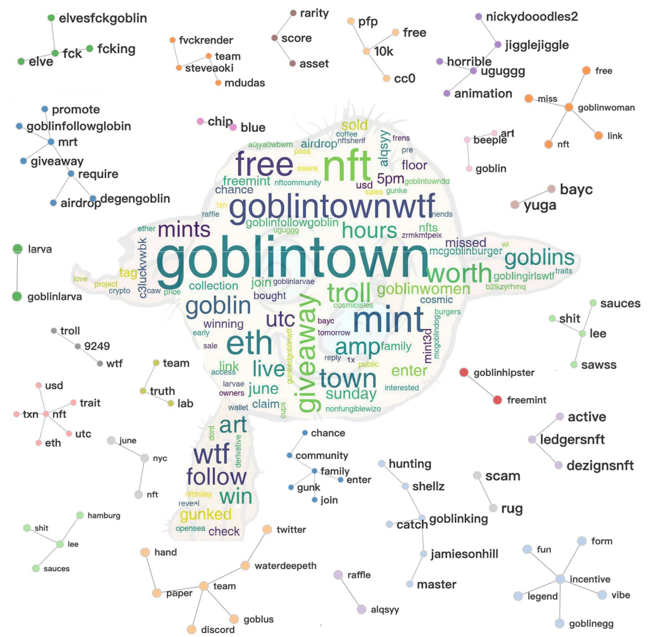


Fig. 6. Word cloud of the top 100 words in all tweets reveals the general overview of goblintown tweets. And the surrounding frames clustered from each month's top 100 co-occurrence words indicate the most spreading topics.

about the exorbitant price of goblintown NFT #9249. While some counterfeits, like "goblinwomen" lured investors not to miss another chance to be rich. So we saw an intriguing situation: people were actively building a virtual community around goblintown, but the information in this community was mainly rumors and FOMO.

D. Twitter Users' Reactions Under Information Manipulation

We applied sentiment analysis to study Twitter users' reactions to information manipulation. Fig. 7 shows the polarity and subjectivity changes between the NFT community and all discussion participants in 3 months. Twitter discussion participants and the goblintown community emerged with more positive and subjective discourses in June since they were immersed in numerous positive market rumors. The higher red and brown dotted lines indicate the situation was more significant in the community than in all participants. Then, neutral polarity and objective subjectivity tweets increased among all discussion participants in July. However, the community sentiment changed little. The phenomenon indicates that information manipulation had achieved a "good" result in the NFT community. It also shows that investing assets with strong social attributes, such as NFT, might change people's rational principles. And this kind of investment target fits well with the information manipulation on social media platforms.

E. Investors Behaviors

From the market side to consider information manipulation, we studied its influence through investors' transaction frequencies and profits. The transaction frequency reflects the trading decisions made by investors after making subjective

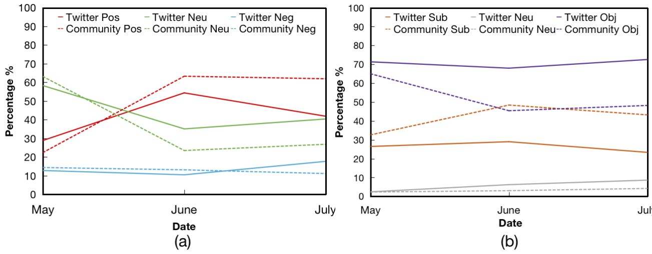


Fig. 7. Sentiment analysis between the goblintown NFT community and all goblintown discussion participants in 3 months: (a) polarity aspect, (b) subjectivity aspect. Solid lines: all Twitter discussion participants. Dashed lines: goblintown community members.

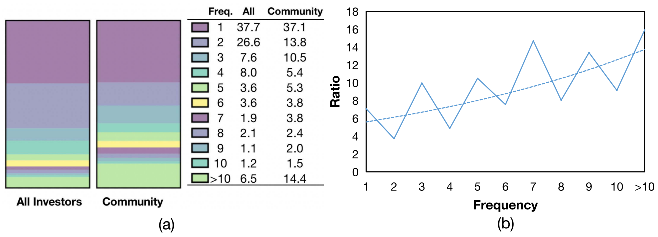


Fig. 8. (a) Transaction frequency distributions between all goblintown NFT investors and the community core members we identified. (b) Ratio of different transaction frequency distributions in these two investor groups.

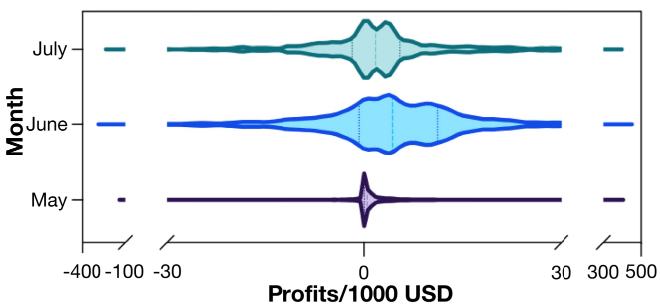


Fig. 9. Distribution of goblintown NFT investors' profits in May, June, and July. It reveals that most investors almost did not gain profits, while a few investors had extremely high gains/losses.

judgments about the market information they are exposed to. The profit can test the result of investors' decisions.

The transaction frequency distribution of all investors and our identified core members of the goblintown NFT community are shown in Fig. 8(a). The largest part of investors made only one trade (37.7% and 37.1%). The majority of investors only participated in less than ten trades (93.5% and 85.6%). However, as the frequency increases, the percentages of corresponding investors among the community core members increase more than in all investors [Fig. 8(b)]. Hence, the analysis of transaction frequency reveals that the core member of the goblintown community tended to be involved more in this collection's trading. Then, we used violin plots to show the distribution of investors' profits who participated in the goblintown NFT trades in May, June, and July (Fig. 9). Most investors distributed in a range of $(-30, 30)$ thousand USD with a mean value of around 0. However, a very tiny number of investors had extremely high gains/losses.

We also visualized the transactions network to find vital traders (Fig. 10), where nodes represent goblintown NFT investors and edges represent selling/buying goblintown NFT

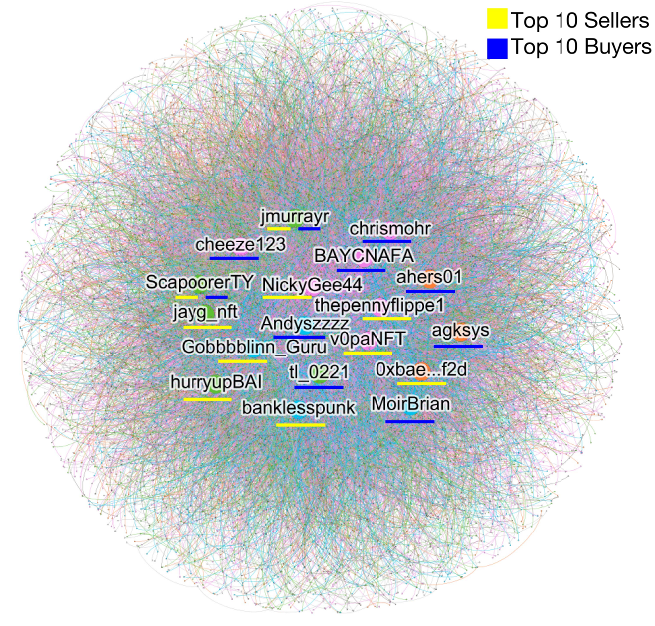


Fig. 10. Visualization of the goblintown NFT transactions network. Nodes represent traders and edges represent transactions. The color of the indicator lines shows the identity of the top ten sellers/buyers.

among them. We counted features of the network as follows: average degree 1.93, diameter 26, average path 7.82, modularity 0.58, and clustering coefficient 0.007. The statistical description reveals that each trader averagely had about two transactions with others, and nodes can be divided into several larger communities. However, it is difficult to draw clear network structures. Hence, we chose the "Fruchterman Reingold" mode to lay out the visualization. And based on the in-/out- degree of each node, we calculated the top etn sellers and buyers. As Table IV shows that only one top seller we did not identify its Twitter account-Ethereum address correspondence. Hence, we used the abbreviation of its address as the label and "?" in its tweets amounts. Except this, the table shows these vital investors' Twitter and trading situations. We found those top sellers who neither posted goblintown tweets nor held goblintown NFTs gained positive profits. Moreover, most profiting sellers were nonentity on Twitter. They do not have many followers and participate in few social interactions. Conversely, sellers being active in the relevant Twitter discussion and having goblintown NFTs lost a lot. The same phenomenon occurred among the top buyers.

F. Five Kinds of NFT Investors

To further study the investment pattern in the NFT market under information manipulation, we performed K-means clustering on 3549 goblintown NFT investors whose Twitter accounts we had identified. Moreover, since the 1417 community core members are vital for the NFT collection, we also studied their performances. Considering trading frequency, profits, and the posted amount of goblintown tweets, we summarized five categories. We described them as primary investors (cluster 0), amateur investors (cluster 1), fanatic investors (cluster 2), short-term rational investors (cluster 3), and

TABLE IV
TWITTER AND TRADING SITUATION OF TOP TEN SELLERS/BUYERS

	Twitter Account	Role	Address	Tweet	Holding Num	Profit /1000USD		Twitter Account	Role	Address	Tweet	Holding Num	Profit /1000 USD
Seller	?	?	0xbae...f2d	?	0	166.3	Buyer	jmurrayr	Nonentity	0xcd2...dec	0	0	103.2
	v0paNFT	Nonentity	0x232...e88	1	0	101.9		tl_0221	Nonentity	0x1ad...c58	0	0	193.7
	thepennyflippe1	Nonentity	0x14d...46d	0	0	160.8		ahers01	Goblintown community	0xc0c...328	45	80	-120.6
	jayg_nft	KOLs	0x637...129	0	0	84.9		cheeze123	Nonentity	0xbc7...7e5	0	0	172.3
	jmurrayr	Nonentity	0xcd2...dec	0	0	103.2		chrismohr	Nonentity	0xec7...96c	0	0	118.8
	banklesspunk	Nonentity	0x6c8...4dc	1	0	66.6		BAYCNAFA	Goblintown community	0x002...eb5	8	102	-337.1
	hurryupBAI	Nonentity	0x823...d42	1	0	51.8		Andyszzzz	Nonentity	0x99a...62d	0	0	-1.8
	Gobbbblinn_Guru	Nonentity	0xa42...64a	0	0	448.9		agksys	Nonentity	0xa07...f86	3	3	-45.6
	NickyGee44	KOLs	0x3b5...429	16	9	-305.9		MoirBrian	Goblintown community	0x685...ba7	2	44	-152.3
	ScapoorerTY	Nonentity	0xe86...583	0	0	111.9		ScapoorerTY	Nonentity	0xe86...583	0	0	111.9

1. "?" means we did not find the corresponding Twitter account.
2. Nonentity means the Twitter account has little influence (few followers and tweets).

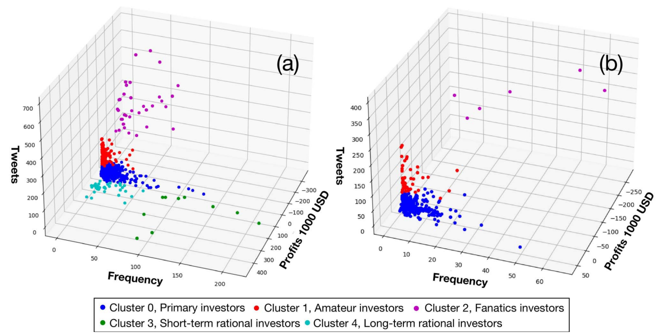


Fig. 11. Clustering of (a) all identified goblintown NFT investors and (b) core members of the community. There totally have five categories of investors in the goblintown NFT market.

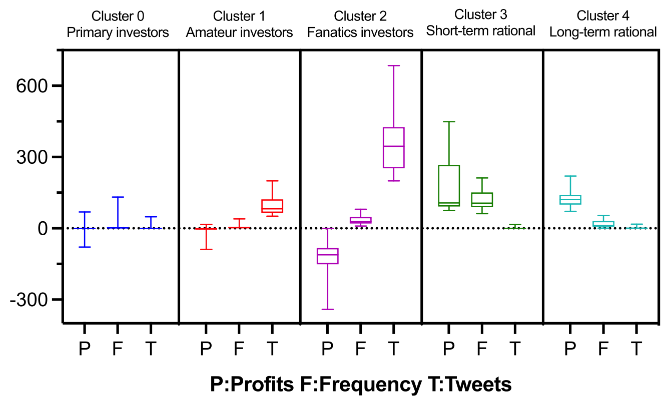


Fig. 12. Comparing profits, transaction frequency, and posted tweets between five kinds of goblintown NFT investors.

long-term rational investors (cluster 4). Fig. 11(a) and (b) separately show the clustering result of identified investors and community core members. And Fig. 12 displays the distributions of their profits, transaction frequency, and numbers of posted goblintown tweets.

Primary investors (cluster 0) refer to the investors who transacted NFT a few times, gained/lost a few profits, and were lightly involved in the Twitter discussions. Primary investors occupied the majority in the market (94.8% in identified investors and 93.7% in community core members). Considering the analysis in Section VI-E, their investment performed at the average level. And since they were not deeply involved in NFT social interactions, they represent the most common investors attracted by the social attributes of NFTs and the information on Twitter. Although each primary investor was not involved in many transactions, their enormous population can still provide significant profits for information manipulators.

Amateur investors (cluster 1) refer to the investors deeper involved in the NFT community but did not have many transactions nor gains/losses. They occupied 2.8% of identified investors and 5.3% of core members. Amateurs had similar performance with primary investors (cluster 0) in NFT trading profits and frequency. But they are second only to the fanatics (cluster 2) in their enthusiasm for tweeting. In other words, they were more like to participate in the NFT community than primary investors. But they might not have as much money or were infatuated as fanatics. Some vital information spreaders mentioned in Table III belong in this category.

Fanatics investors (cluster 2) refer to the investor most enthusiastic in posting goblintown tweets and engaging in NFT communities. They were also active in goblintown transactions. However, their deep involvement did not provide a matched reward. There were 0.9% and 0.8% fanatics in identified goblintown investors and community members. Fanatic investors are the category with the worst losses and included almost all vital individual information spreaders.

Short-term rational investors (cluster 3) refer to the investors involved in numerous transactions and gained lots of profits, but they were almost not involved in NFT discussions. They occupied 0.3% of all investors and did not present in the core community members. We also found that these investors did not retain any goblintown NFTs after the purchase. For example, one of the top sellers, "Gobbbblinn_Guru" (0xa42...64a), was involved in 92 transactions, earned \$448.9k, but did not post related tweets nor hold goblintown NFT. Because of their highest trading frequency, they were likelier to make decisions rationally based on market price changes. Also, no retaining of investment targets indicates that they were focused on short-term interests.

Long-term rational investors (cluster 4) refer to the investors involved in a few transactions and discussions but gained lots. This category occupied 0.9% of all identified investors. Like short-term rational ones (cluster 3), they were also almost not involved in NFT discussions and disappeared from the community. Such as 0xdca...339, whose Twitter is "Mwis_NFT" with few followers and tweets, did not participate in the goblintown-related discussions nor change

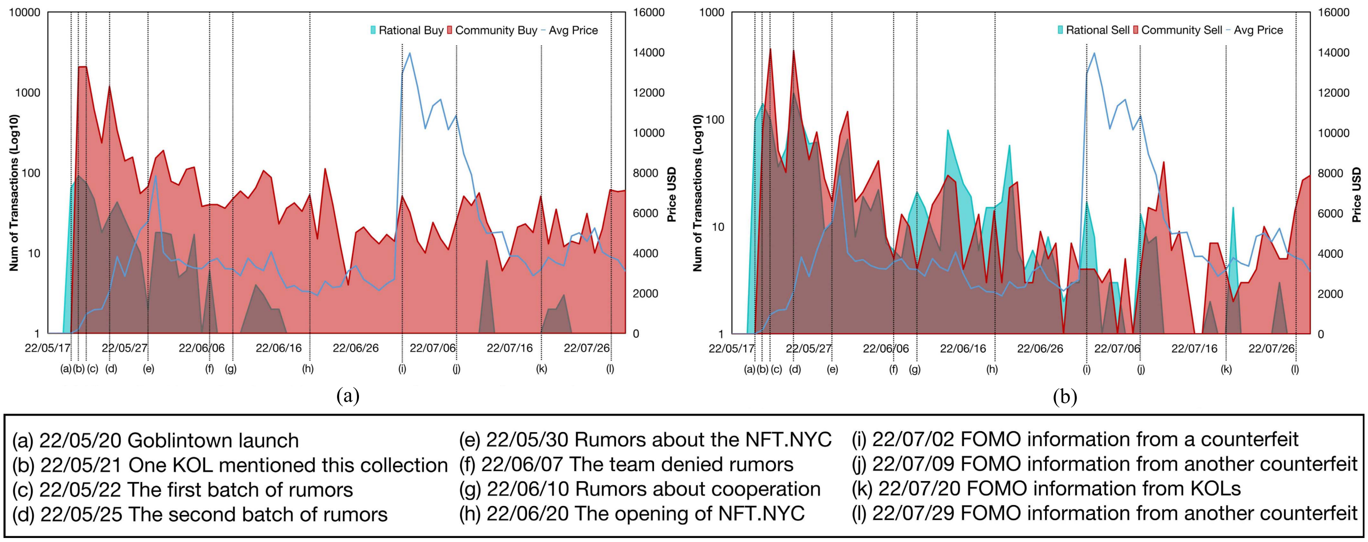


Fig. 13. Different performances of daily transactions among rational investors (clusters 3 and 4) and goblintown NFT core members. (a) Buy situation of rational investors and community members. (b) Sell situation of rational investors and community members.

avatar. This investor only had four transactions of goblintown NFT but gained more than $125k. Compared with short-term rational ones (Cluster 3), the holding period of long-term investors is longer.

After describing the five kinds of investors we clustered, it is reasonable to analyze which one's investment strategy is better briefly. First, we believe investors should actively participate in NFT trading as it has the potential to deliver high returns. Second, as an investment target, most people expect a corresponding return after paying time and principal in NFT investments. Therefore, rational investors' strategies are helpful since they averagely obtain much higher profits than other investors.

G. Rational Investors VS NFT Community Investors

The above analysis found that rational investors (clusters 3, 4) were absent in the goblintown NFT community. This phenomenon led us to study further. First, we compared the daily transactions among the rational investors and goblintown core members. Fig. 13(a) reveals that rational investors began purchasing goblintown before the rumors spread. At that time, the community had not been formed. Then positive rumors more significantly led community members to purchase. When counterfeit information spread, such as (i) and (l), community members also bought in goblintown. Comparatively, rational investors did not as sensitive to information. Their purchase behaviors correlated more to the price change, like at (d). They even did not react to the opening of NYC.NFT (h), and rational investors nearly did not purchase after that. Regarding negative information, like the team denied previous rumors (f), rational investors chose to purchase while community members hesitated. Subgraph (b) reveals that after the initial spreads of rumors, rational investors more intensively sold when good news appeared, like (g) and (h). Similarly, rational investors earlier used the impacts of counterfeits' FOMO information to sell NFTs. In sum, the rational investors participated earlier and performed more strategically in the goblintown collection. They were more likely to address positive rumors as selling opportunities and were bold to buy when facing negative rumors.

We also wondered whether the different investment behaviors between NFT community members and rational investors were specific to goblintown. Hence, we studied all NFT collections' transactions among these two groups. Fig. 14 reveals rational investors preferred to involve in more NFT collections and to trade more frequently. Except for the possibility of having more capital, it is likely because rational investors treat buying NFT as an investment. They retained fewer NFTs after purchase than community members, combined with higher profits. The results are similar to goblintown case, which suggests that community members were intoxicated by NFT rumors spreading on social media. But rational investors kept away from NFT communities and treated NFTs as investment targets, which bought them higher returns.

VII. Discussion

The rational man hypothesis holds that an investor will perform a cost-benefit analysis to determine whether a decision is correct. However, the investment behaviors of goblintown community members did not fit this hypothesis. These investors were avid in Twitter NFT communities, trusting manipulated information and ignoring their losses. In fact, the influence of social network communication on markets has hundreds of history [38], and research in this area is most notable in behavioral finance, which incorporates psychological theories into financial analysis.

Behavioral finance researchers argue that making decisions involves investors' attention allocation. Research on the stock market proved that because investors' attention is limited, the brain will automatically ignore most information when confronted with excess news [39]. In addition, our brain has a self-protection mechanism, which means investors do not readily believe received market information. However,

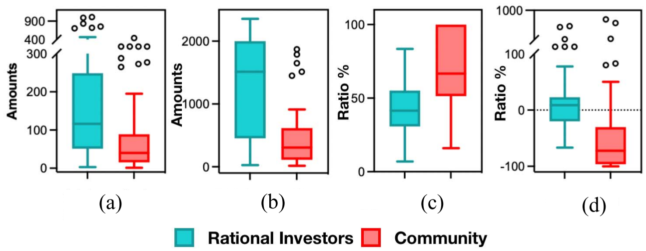


Fig. 14. Differences of NFT investments between long-term rational investors and goblintown core members. (a) Number of collections invested. (b) Amounts of transactions. (c) Retained ratio of NFTs after purchase. (d) Profits rate.

if similar information repeatedly appears, they will turn to gullibility and hardly change their perceptions [39], [40]. The emergence of social media has strengthened this phenomenon. Our research on NFT market investors is consistent with these studies. When investors are attracted by NFTs and participate in the virtual community, they will be surrounded by buzz on social media, which will interfere with their rational investment decisions. At the same time, NFT's social interaction attributes are not previously found in stocks, real estate, cryptocurrencies, etc. NFTs naturally have a stronger fit with social media, facilitating information manipulation. When some community members shift their perceptions due to repeated exposure to rumors, they quickly turn into rumor spreaders. So we saw those highly profitable rational NFT investors had nearly not engaged in the NFT community and Twitter discussions at all.

A different way of attention allocation determines the different patterns of investment behaviors. Hong and Stein [7] first divided investors under information manipulation into news watchers and momentum traders. News watchers make predictions about stocks' values and guide their investments based on the information they receive from the social network, but they ignore price trends. Momentum traders focus only on price movements and ignore other news. Subsequent scholars built on this foundation by proposing many classifications and definitions of investors, such as arbitrageurs, noise traders, etc. We distinguished profits, trading frequency, and social media interactions more carefully. Our two kinds of rational investors expand the concept of momentum traders. And amateur and fanatic investors refine the news watchers. Hence, our work extends behavioral finance theories to the NFT market.

VIII. Limitation and Conclusion

This work analyzed the NFT market by combining investors' social media and blockchain trading behaviors. This method is based on the unique feature of NFT and allows studying investors' behaviors from a more micro perspective than traditional stock or cryptocurrency markets. During the process, we investigated the mechanisms of information manipulation in the NFT market and four roles (goblintown team, counterfeit projects, KOLs, and goblintown community members). We described five kinds of NFT market investors: primary investors, amateur investors, fanatic investors, short-term rational investors, and long-term rational investors. Through behavioral finance theories, we explained their behavioral patterns.

Even though our work innovated in the study of information manipulation, there are still some limitations. We studied only one NFT collection and excluded non-English social media data. Additionally, our data only covered a three-month period. However, since many NFT collections have a short life cycle in the emerging NFT market, where English is the main communication language, it is reasonable for us to use goblintown as the first step of our study. In future work, we plan to extend our relationship database between investors' social accounts and blockchain addresses through other NFT collections. After that, we can develop automatic tools to identify the roles in NFT market information manipulation.

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