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Impact of Downvotes on Bot and User Engagement in a Blockchain-Based Social Media Platform

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ABSTRACT

Steemit, a blockchain-based social media (BOSM) platform, allows users to participate in platform governance and earn token rewards through voting. However, some users manipulate votes using bots. On August 27, 2019, Steemit introduced an additional downvote pool for each user to encourage governance of vote manipulation via downvotes. This study employs Regression Discontinuity in Time (RDiT) to empirically analyze the impact of the policy on user and bot behaviors. After the policy, bot upvotes and transfers from users to bots significantly decreased, suggesting effective curbing of vote manipulation, while the delegation of voting power from users to bots did not exhibit significant changes. However, the policy change led to potential side effects. Human users' upvotes and the total number of posts and comments significantly decreased, reflecting a hesitation in content creation and interaction due to increased negative feedback. Additionally, the policy significantly increased reciprocal downvoting, suggesting that some downvotes were used for retaliatory purposes among users. This study is the first to investigate the effects of voting system changes on a BOSM platform, enhancing our understanding of how platform-level design features influence engagement and interactions among humans and bots.

Keywords: Blockchain, online social media, Steemit, downvote, bot, RDiT model.

INTRODUCTION

In the era of mobile internet, online social media platforms (OSM) have rapidly emerged as important channels for users to share knowledge and exchange opinions (Chen *et al.,* 2019). However, traditional social media platforms, like Facebook and Reddit, face numerous challenges alongside their rapid expansion, such as insufficient motivation or contribution from users in generating content and privacy breaches. Moreover, these platforms are highly centralized, with users having no control over the platform management (Sun *et al.,* 2023).

In recent years, the introduction of blockchain technology has provided new ways to address these issues. Blockchain-based online social media (BOSM) platforms utilize decentralized architectures and token incentive mechanisms to encourage users to create and share valuable content while protecting user privacy and intellectual property. Among these platforms, Steemit stands out as a typical representative, attracting significant attention from users and researchers due to its decentralized governance model and unique token economy system (Guidi *et al.,* 2020).

Steemit features a user-participatory governance model and a token incentive mechanism. Leveraging blockchain's decentralized nature, Steemit allows users to directly participate in content governance and reward distribution through voting. Users can use upvotes and downvotes to filter the quality of content in the community and assign appropriate visibility to content, thus achieving quality-based content ranking. Additionally, users receive curator rewards for upvoting posts. Downvoting a post reduces its rewards, but the user casting the downvote does not receive any rewards. As the platform developed, issues of vote manipulation using bots to obtain token rewards emerged within the community (Li & Palanisamy, 2019). Specifically, users could delegate voting power to bot accounts to amplify the voting weight of bot and purchase upvote services from bots to enhance the visibility and rewards of their posts, thereby manipulating votes. This behavior severely affected the fairness and content quality on the platform, undermining the visibility of high-quality content and discouraging content creators.

To address this issue, Steemit introduced the downvote policy through a blockchain hard fork on August 27, 2019, aiming to optimize content quality and fairness by adjusting the voting mechanism. On Steemit, the voting rights available to each user within a specific time frame is limited, referred to as the voting pool. Before the policy change, upvotes and downvotes shared the same voting pool. In this situation, downvotes would occupy upvote voting rights without yielding rewards, thus users lacked the motivation to use downvotes, leading to ineffective content quality governance. After the policy, each user received an additional downvote pool, equivalent to 25% of the original voting pool, calculated separately from the upvote pool. This policy removed the direct cost of downvotes, encouraging community members to utilize downvotes to sanction low-quality content and bot vote manipulation without losing potential upvote rewards.

However, this policy could be a double-edged sword. On one hand, the downvote policy might effectively combat bot vote manipulation, improving content quality; on the other hand, the increased downvotes might inadvertently bring about some side effects. For instance, the increase in negative feedback might lead to content creators' fear of negative evaluation and related social anxiety (Leary, 1983), or inhibit users' intrinsic motivation to contribute knowledge (Chen *et al.,* 2019), making them more cautious about content creation and voting interaction. Furthermore, research has shown that users might downvote for profit or other reasons unrelated to content quality. For instance, many bot accounts are actively downvoting content, and approximately 9% of downvote activities on Steemit potentially being retaliatory (Sun *et al.*, 2023). The added downvotes after policy might become a tool for users to attack each other reciprocally. Therefore, whether the downvote policy negatively affects users' normal content creation and voting behavior remains an important issue to address.
Currently, no research has empirically investigated this significant policy change on BOSM. To fill this research gap, we pose the following research questions:

1. How does the downvote policy affect vote manipulation behavior between humans and bots on the Steemit platform?
2. How does the downvote policy affect users' content creation and voting behavior on the Steemit platform?

This study and implement Regression Discontinuity in Time (RDiT) analysis to reveal the impact of increased downvote availability on the engagement of users and bot on Steemit. Specifically, we first investigate whether the policy can curb vote manipulation, where users delegate voting power to bots and buy upvotes on the platform, as expected. Secondly, we explore whether the policy has side effects that hinder normal user behavior, even leading to malicious downvote abuse. Through this study, we aim to provide an empirical basis for understanding and designing more effective user engagement and content governance mechanisms, offering valuable references for BOSM platform governance.

CONTEXT

Steemit

Steemit (https://steemit.com) is the world's most mature and largest blockchain-based online social media platform, with over 1.6 million users. Steemit not only allows users to act as content creators but also enables them to serve as content curators (Zheng & Boh, 2021). Within the Steemit community, in addition to posting, voting and commenting like on OSN, users can also transfer and delegate cryptocurrencies.

The rewards on Steemit are distributed in the form of tokens, which consist of three types of currencies: Steem, which is the circulating token within the community, can be traded on external markets and circulated within the community, serving as a necessary guarantee for the community's development; Steem Dollar, to ensure the stability of the token's value, Steemit issues this stablecoin, which is pegged to the US dollar, can be exchanged bidirectionally with Steem, and is set to be exchanged with the US dollar at approximately a 1:1 ratio; and Steem Power (SP), which is equivalent to shares in the community, where the more Steem Power a user holds, the greater their influence in the community, such as voting power. Moreover, users can delegate their Steem Power to others to enhance the influence of those accounts (Guidi & Michienzi, 2020).

On the Steemit platform, users can post content and comment on others' content. Other users can evaluate the content through the voting system, including upvotes and downvotes. To incentivize users to create and discover high-quality content, Steemit periodically distributes author rewards to users who post content based on the votes received and curator rewards to users who vote for posts. Each user can vote on a limited number of posts daily, with the voting power determined by the amount of SP they hold—the higher the SP balance, the greater the impact on the post's score. However, Steemit's voting mechanism has been criticized for the inequality in voting power among users (Guidi *et al.,* 2021). Additionally, Steemit includes a reputation system where a user's reputation score increases with more upvotes and decreases with more downvotes.

Each year, Steem generates 9.5% inflation tokens, decreasing by 0.01% every 250,000 blocks until it reaches 0.95%, a process taking approximately 20.5 years. Of the tokens generated through inflation, 75% is allocated to the community's content reward pool, distributed based on each post's reward share (rshare). Within seven days of a post's creation, its rshare accumulates through the votes received. Upvotes increase rshare, while downvotes decrease rshare. In the end, posts compete for currency rewards based on the total rshare received, with the higher the rshare, the higher the rewards (Li & Palanisamy, 2019).

Bots on Steemit

Gudi and Michienzi (2020) identified and categorized bots in the community into curator bots, utility bots, registration bots, money bots, and hunter bots. Since curator bots are the most numerous in the community and directly participate in users' vote manipulation behavior, this study focuses only on curator bots.

Curator bots’ behavior falls into two categories: the first one is users buy votes from bots, where post authors pay tokens to bots through transfers to gain upvotes. The second one is bots automatically vote on posts based on their algorithms. Upvoting for paid users' content is the main voting behavior of robots. Specifically, some users pay STEEM or SBD to one or more bots through transfer operations to enhance their post's visibility and rewards. Since bot accounts typically hold significant voting power (SP), posts upvoted by bots significantly increase in rewards and visibility. Thus, authors not only directly gain author rewards from bot upvotes but also promote their posts within the community, encouraging more user votes and further rewards. For bots, they not only receive the tokens transferred by users but also curator rewards from the upvoted post (Delkhosh *et al.*, 2023). This continuous voting manipulation behavior exacerbates the unequal distribution of community token incentives, reduces the visibility of high-quality content, and severely discourages quality content creators.

However, existing research primarily focuses on users buying votes from bots and overlooks the source of bots' significant voting power. Human interactions with bots extend beyond purchasing votes to delegating SP, which grants bots substantial voting power. This study identifies this voting power delegation behavior, essentially token delegation, where blockchain token owners transfer their voting power represented by tokens to others. Such behavior has become prominent on the blockchain. This mechanism reflects BOSM's decentralized, transparent, and democratic governance model but may also be abused.

Specifically, on the Steemit platform, users can delegate their SP to bot accounts. In return, users receive periodic returns from bots, akin to interest on deposits, with some bots directly offering upvotes as returns. Bots offering delegation services promote their service rules through posts, with the figure below reporting a typical example. For users needing to buy votes, delegating SP to bots not only saves voting time and secures fixed returns but also enhances bots' voting power, amplifying the impact of bot upvotes on their posts. This mutually beneficial delegation mechanism motivates many users to delegate their voting power to bot accounts, amplifying bots' voting weight and indirectly promoting vote buying, thereby disrupting the community’s content visibility and reward distribution.

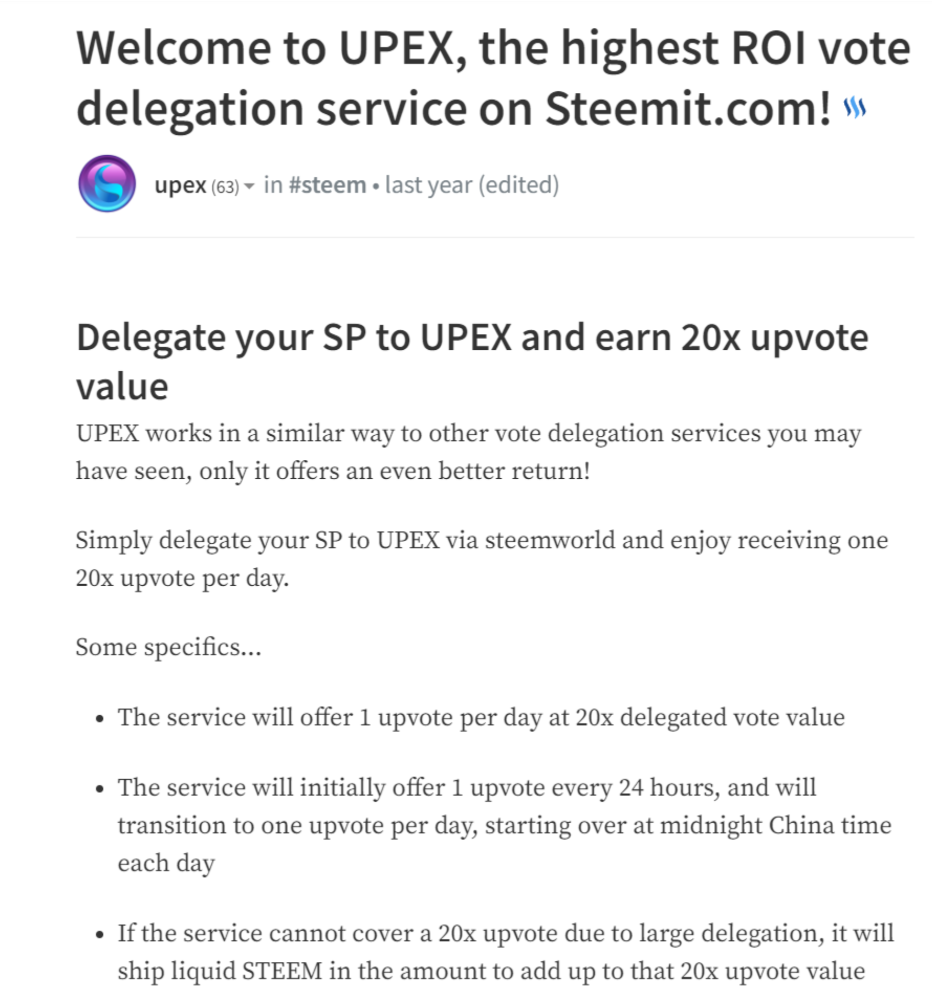

Figure 1: A Bot Delegation Service

LITERATURE REVIEW

Our work involves related literature on two primary themes. The first is peer evaluation systems in online social media (OSN) platforms, and the second is issues within blockchain-based social media (BOSM), especially regarding bots.

Peer Evaluation Systems in OSN

The first stream of literature relevant to our research involves peer evaluation systems in OSN platforms, mainly in the form of voting systems. Participants increasingly use online communities to access and share information and collaborate on problem-solving. However, one key issue is how to design peer evaluation systems that encourage sufficient and sustained knowledge contributions. Currently, many online communities like Reddit use voting systems with upvotes and downvotes to rank posts and comments.

To evaluate the effectiveness of voting systems, extensive research has been conducted on various voting behaviors. The primary issue with voting systems in online communities is vote manipulation (Carman *et al.*, 2018). Vote manipulation refers to users using bots or other accounts to upvote posts or comments to enhance their ranking, or to downvote posts or comments similar to their own to gain a relative advantage in competing content. Additionally, in some online platform designs, there is a significant disparity in voting power among users. Zhang *et al.* (2019) studied vote manipulation behavior on platforms like Quora and Zhihu, finding that some super-users with substantial voting power manipulate rankings for profit through malicious voting (upvoting or downvoting). To counter vote manipulation, Reddit implemented defensive measures, including shadow banning to block spam bots (Carman *et al.*, 2018). Bian *et al.* (2008) designed a social media ranking framework incorporating user interactions and content relevance, improving robustness against common forms of vote manipulation attacks. Steemit employs a voting system similar to OSM, and given the presence of curator bots and its decentralized nature, vote manipulation is easier to achieve, potentially causing greater harm to the community. Therefore, our research focuses on the impact of the downvote policy on vote manipulation between humans and bots on Steemit.

Another closely related literature stream focuses on how content evaluation by voting systems affects user engagement behavior. Most of the current studies focus on the impact of upvotes on user participation in OSN. For instance, Burtch *et al.* (2022) found that positive recognition in the form of peer awards led to longer and more frequent content generation on Reddit. However, understanding the impact of negative feedback like downvotes on user engagement is limited and lacks consensus. In existing studies, Chen *et al.* (2019) demonstrated that receiving downvotes significantly reduces the ongoing knowledge contribution of community participants. Zhu *et al.* (2023) noted that compared to receiving no feedback, receiving negative feedback can increase the quantity and quality of user comments. This shows that users strive to improve content quality to avoid receiving downvotes again. Finally, Davis *et al.* (2021) found that content downvoted on Reddit received higher engagement than content that received upvotes.

Meanwhile, Many social media platforms like Facebook are reluctant to implement downvote options because it may reduce the loyalty of members and destroy the community atmosphere. Therefore, systems allowing users to downvote peers' content may also represent significant risks. Platforms like Amazon have removed this option from their review systems. For such policy changes, Yoo *et al.* (2022) studied the impact of removing the downvote option on user online content generation on Asia’s largest restaurant review platform. The policy change aimed to prevent abuse like retaliatory downvotes. The results showed that after removing the downvote option, the total number of community posts and replies significantly increased without leading to more negative emotions in replies. Our research focuses on the opposite impact, exploring how increased downvote availability affects content creation and voting behavior on platforms like Steemit. By comparing these research scenarios, we can gain a more comprehensive understanding of how downvote mechanisms as an evaluation tool influence online community dynamics, contributing to broader discussions on digital platform content evaluation systems.

Issues in BOSM

Extensive research has focused on various issues arising from the mechanism design of BOSM. For instance, while the immutability of content on decentralized social media can enhance credibility by making users' information history more transparent, it also makes removing malicious content difficult as it is stored on the blockchain (Guidi *et al.*, 2020). Since any user can disseminate content without central control, it may lead to the generation of spam content, prompting users to leave the network (Zheng & Boh, 2021). Thus, decentralized social media faces certain content moderation challenges. In response, the Steemit platform introduced the downvote policy, attempting to use more downvotes to suppress malicious and low-quality content.

More importantly, since blockchain-based social media like Steemit incentivizes high-quality content contributions through reward mechanisms, significant research has examined whether these incentives achieve the intended outcomes. Kim and Chung (2018) pointed out that although BOSM emphasizes decentralization, inequality among users can undermine this vision, particularly in the distribution of economic rewards. Thelwall (2018) studied the characteristics and rewards of Steemit posts, finding that posts focusing on interpersonal communication received higher rewards than information-rich high-quality content posts. This may lead users to focus more on networking rather than high-quality content creation.

Under this reward system, another efficient way for community users to profit is by using bots. After users purchase upvotes from bots for their posts, the posts receive significant exposure regardless of their quality, hindering the discovery of genuinely high-quality content (Guidi *et al.*, 2020). This could be more severe than creating malicious content itself. Li and Palanisamy (2019) analyzed the operations of 1.12 million users on Steemit over two years, proving issues like bot abuse of the upvote function, with over 16% of tokens sent to suspected bot accounts, and discovered the existence of bot supply networks. Guidi and Michienzi (2020) found that bots on Steemit are significantly more active than human users, holding a large share of cryptocurrency transfers on the platform.

Furthermore, scholars analyzing blockchain systems have pointed out the drawbacks of the technology leading to power concentration, with the existence of bots on Steemit potentially exacerbating this inequality. Blockchain-based platforms like Steemit typically rely on token-weighted voting ("τ-weighted") for content management and on-chain governance. This design is based on the principle that users holding significant tokens are most motivated to increase the platform's overall value. However, Tsoukalas and Falk (2020) found this theory unreliable, as τ-weighted often hinders genuine voting and weakens the platform's predictive capabilities, with platform accuracy decreasing as the number of genuine users and token holdings become decentralized. In Steemit, where users can delegate voting power to bots, these negative impacts may be more severe. For instance, if a user with significant SP upvotes a post, users with less SP find it difficult to downvote it (Guidi *et al.*, 2020). If a bot with significant SP vetoes other posts, it can seriously impact the community's content ecosystem. For example, on the BOSM platform DTube, which adopts the same voting rules as Steemit, users have reported using high-voting-power bots to veto content they dislike, and suppressed users reported this automated voting as downvote abuse (Nagappa, 2023). After the downvote policy, these abuses may become more rampant. Finally, the delegation of voting power on BOSM may also lead to power abuse and even security issues. Huang *et al.* (2020) found that numerous bots on the eosio blockchain were used for malicious and fraudulent purposes, with 5541 accounts identified for power abuse.

Nonetheless, academic understanding of the interaction mechanisms between bots and users on Steemit remains limited. This study is the first to focus on SP delegation between humans and bots on BOSM, considering it a factor in vote manipulation behavior on Steemit and examining its dynamic changes following the downvote policy. Additionally, existing research analyzing user behavior on Steemit is based on the old voting model before the policy implementation (Sun *et al.,* 2023), failing to fully reflect post-policy user behavior changes. Our study aims to fill these gaps in the literature. We plan to use the RDiT estimation method to explore the impact of the downvote policy on vote manipulation behavior and user creation and voting behavior on Steemit. The conclusions of this study will provide a more comprehensive perspective on the content evaluation mechanisms and user engagement behavior on blockchain social media platforms.

HYPOTHESES DEVELOPMENT

The downvote policy, by increasing the availability of downvotes for each user, directly leads to an increase in downvotes on the platform. When downvotes become a cost-free governance tool, users will more frequently use downvotes to participate in content review and community governance to enhance the quality of community content. Moreover, downvotes on Steemit not only affect the visibility of content but also directly impact the author's economic rewards. Since rewards are distributed from a shared reward pool, downvotes reduce the rewards of downvoted content, indirectly increasing the reward opportunities for other content that is not downvoted. Therefore, this mechanism incentivizes users to use downvotes more frequently after the policy change, not only for content quality control but also to improve their own reward distribution.

Following the policy change, there was a significant increase in downvote activities on Steemit, such as the "New Steem" campaign initiated by large accounts like OCDB, urging users to downvote posts upvoted by bots. Furthermore, the transparency of content on the blockchain allows users to track all behaviors of other users, including signs of bot voting, making it easier for users to use the new downvote pool to combat low-quality content. Therefore, we focus on the impact of this increase in downvotes on the following variables.

Firstly, the downvote policy directly targets vote manipulation behavior between humans and bots, which will significantly affect bot voting activities. As previously mentioned, bots on Steemit mainly upvote posts in exchange for payment from users. However, after the policy implementation, these posts purchased for upvotes will be directly suppressed by numerous downvotes, significantly reducing the rewards and visibility of these posts. According to Rational Choice Theory, humans make decisions based on the principle of maximizing personal benefits. Therefore, since the profitability of purchasing upvotes decreases and may bring reputational damage, we believe that the motivation of community members who have long been paying bots for upvotes will diminish, leading to a reduction in direct transfer to bots and, consequently, a decrease in the upvotes provided by bots. In this scenario, the reduced demand for bots results in lower revenues, thereby affecting the sustainability of bot services. Due to insufficient profitability, the returns provided by bots to users for delegations will also decrease, which may similarly reduce users' motivation to use delegation services.

Hence, We expect that the increase in downvotes following the policy change will lead to a decrease in the number of bot upvotes on the platform. Notably, we consider users' transfers and delegation of voting power to bots as potential influencing mechanisms. Moreover, since the effectiveness and profitability of bot services are undermined, we anticipate that users' transfers and delegation behaviors to bots will similarly decrease under the same logic. Based on the above explanations, we propose the following hypotheses:

Hypothesis 1 (H1): The increase in downvotes will reduce the total upvotes given by bots.
Hypothesis 2 (H2): The increase in downvotes will reduce the total number of transfers from human users to bots.
Hypothesis 3 (H3): The increase in downvotes will reduce the total number of delegations from human users to bots.

Next, we consider the policy's potential impact on human upvote behavior from two aspects. Motivation theory suggests that individuals participate in online communities driven by both intrinsic motivation and extrinsic motivation (Deci & Ryan *et al.*, 2013). Intrinsic motivation refers to engaging in an activity for its inherent enjoyment or satisfaction, while extrinsic motivation stems from external factors like rewards, recognition, or punishment.

From the perspective of intrinsic motivation, according to the theory of psychological ownership, management scholars have found that psychological ownership positively influences organizations. When employees feel a high level of psychological ownership towards an organization, they are more likely to contribute positively to its development and take on more responsibilities (Pierce *et al.*, 2001). The decentralized nature of BOSM relies on users' autonomy in community governance, and as participation and interaction increase, members' sense of belonging also enhances (Zheng & Boh, 2021). Therefore, it can be hypothesized that Steemit users possess a high level of psychological ownership. The downvote policy incentivizes these users to more actively engage in content quality control, which may manifest not only in downvotes but also in upvotes. Human users may use more upvotes to support valuable content to promote community development, maintain balance, or offset the negative atmosphere brought by the increased downvotes.

From the perspective of extrinsic motivation, since BOSM provides economic incentives, Steemit's content rewards are distributed based on each post's reward share (rshare), and posts compete to share currency rewards (Li & Palanisamy, 2019). If the platform adds extra downvotes, it would offset some of the benefits of upvotes, prompting human users to cast more upvotes to counterbalance this reduction in earnings.

Lastly, due to the increased availability of downvotes, we hypothesize that human users may become more cautious when posting content, which might reflect in higher-quality content, as high-quality content is less likely to receive downvotes. Therefore, in an environment where overall content quality improves, human users may cast more upvotes.

Hypothesis 4 (H4): The increase in downvotes will increase the total upvotes given by human users.

We then examine the policy's impact on human content creation behavior, since robots in the community generally do not participate in posting activities. Specifically, we focus on the impact of the policy on human posting and commenting behaviors.

Firstly, Chen *et al.* (2019) demonstrated, based on motivation theory, that punishment or negative feedback weakens intrinsic motivation, reducing participants' knowledge contributions in online communities. Since downvotes are directly related to negative evaluations and criticism, they might induce fear. According to the Fear of Negative Evaluation (FNE) model, FNE or fear of failure refers to an individual's concern or distress over the possibility of being negatively evaluated by others. Due to FNE, individuals may seek others' approval and avoid the possibility of negative evaluation (Leary, 1983).

In a BOSM that provides downvotes, commenters may feel fear or social anxiety due to negative evaluations. Following the introduction of the downvote policy, there have been reports of many users experiencing unexplained downvote attacks, making them feel frustrated. To avoid receiving negative evaluations, users might reduce their posting and commenting activities, which could also encourage them to spend more time and effort on creating their posts or comments. Lastly, since downvotes reduce the author's reputation, to mitigate reputation loss, users might initially reduce their participation levels. Regardless of the consideration, we anticipate a reduction in users' content creation activities after the policy change.

Hypothesis 5 (H5): The increase in downvotes will reduce the total posts and comments of human users.

We also focus on the behavior of users who previously bought votes from bots. These users primarily profit from the author rewards gained through bot upvotes. However, after the policy introduction, content from these users, previously benefiting from purchased upvotes, will be the primary target of downvotes. Therefore, we expect these users' original profit model through collaboration with bots to be significantly affected. Investigating their content creation behavior after losing bot assistance is an intriguing question.

Research on the motivations behind participation in Online Social Networks (OSN) indicates that individuals contribute to enhance their professional reputation (Chen *et al.*, 2019). As users who buy votes are primarily targeted by downvotes, they suffer significant reputation loss. When downvotes damage their online reputation, they may increase their contributions of knowledge to mend their public image. However, in BOSM platform, where economic incentives prevail, we believe this scenario is unlikely. Users who buy votes are speculators within the community, utilizing bots primarily for profit maximization rather than genuinely contributing high-quality content. Therefore, on Steemit, we consider the reactions of these long-term bot-using users from the perspective of algorithmic agents.

Curator bots can be seen as automated intelligent tools for vote promotion, with vote-buying users' use of bots on Steemit viewed as a form of algorithmic agency, algorithmic agency-generated information helps users process information more effectively and encourages participation. (Delkhosh *et al.*, 2023). Many crowdfunding platforms have begun using bot advisors to help lenders optimize P2P lending investment performance. Ge *et al.* (2021) empirically studied how investors use bot advisors and how this usage impacts investment performance, finding that if humans trust bots and do not excessively interfere, better investment results are achieved. Fügener *et al.* (2022) studied human-AI collaboration in image classification tasks, discovering that humans' disadvantages compared to bots lie in their weaker understanding of their own abilities and strengths, making them more inclined to cooperate with machines.

For Steemit users' willingness to trust bots and engage in algorithmic agency behavior, academia describes this as algorithm appreciation. Algorithm appreciation refers to the tendency of individuals to prefer and adhere to algorithmic advice over human advice when they know the suggestion comes from an algorithm (Logg *et al.*, 2019). Due to the advantages of bots in efficiency, profitability, and sustainability, we believe that vote-buying users might have developed algorithm appreciation and a certain degree of dependence on bots during continuous vote purchasing. Therefore, after the policy introduction, these vote-buying users, lacking bot support, might feel at a loss. Moreover, as the original profit model through content creation may no longer be viable, the reduction in earnings might discourage their content creation enthusiasm. Based on the above explanations, we propose the following hypothesis:

Hypothesis 6 (H6): The increase in downvotes will reduce the total posts and comments of vote-buying users.

Finally, we investigate whether the additional downvotes might be abused by focusing on retaliatory voting behavior on BOSM platforms. Malicious attacks and cyberbullying in online communities have been widely studied and showed that negative feedback like downvotes might trigger malicious behavior. Yoo *et al.* (2022) found retaliatory downvotes on Asia's largest restaurant review platform, prompting the platform to remove the downvote option. Furthermore, the scale of online conflict behavior can easily escalate. Datta and Adar (2019) found that most conflicts (77.2%) on Reddit are reciprocal, using subreddit downvotes to identify community conflicts, as users receiving negative feedback might not have violated norms or produced low-quality content but might be due to the community's hostile stance.

While platform users can use the additional downvote pool to participate in content review and community governance, these extra downvotes might become tools for users to attack each other reciprocally. Sun *et al.* (2023) identified retaliatory downvote behavior on Steemit, where two users downvote each other, influenced by conflicts in their replies or reciprocal downvoting. They also observed bots being used to repeatedly downvote the same account. We predict that after the downvote policy, the increased negative feedback in the community may lead to more malicious downvote behavior, such as retaliatory voting among users. Thus, we propose the following hypothesis:

Hypothesis 7 (H7): The increase in downvotes will increase the total number of reciprocal downvotes on the platform.

DATA AND MODEL CONSTRUCTION

Bot Data

Existing research often identifies bot accounts by analyzing voting and transfer records among users, assuming accounts that sell votes are bots (Delkhosh *et al.*, 2023). However, this method has limitations. Due to the prevalence of vote-buying and group voting behavior on Steemit, it is challenging to determine whether accounts selling votes are human users or bots. To accurately compile a complete list of curator bots, we implemented the following methods:

1. We examined the reference literature on bot accounts listed in Guidi and Michienzi's study (2020), including the "Bots" entry summarized on Steem Center and a post on Steemit that statistically identifies bots. We checked all related posts and links under these bot entries, including the "List of Bots" entry and the "Curator bots" entry.

2. We searched for keywords related to bots on Steemit, such as #bidbot, #upvote, #bid, #bot, and #bots, reviewing 182 posts related to curator bots and compiling the bot accounts mentioned in these posts.

3. We found 54 curator bots under the #introduceyourself topic posts, where these bots described their operational rules and promoted their services.

4. We checked 1,084 post comments on Steemit and identified bot accounts generating automated comments, as bots tend to leave similarly formatted comments under posts they vote on. Below is a typical example of a bot comment.

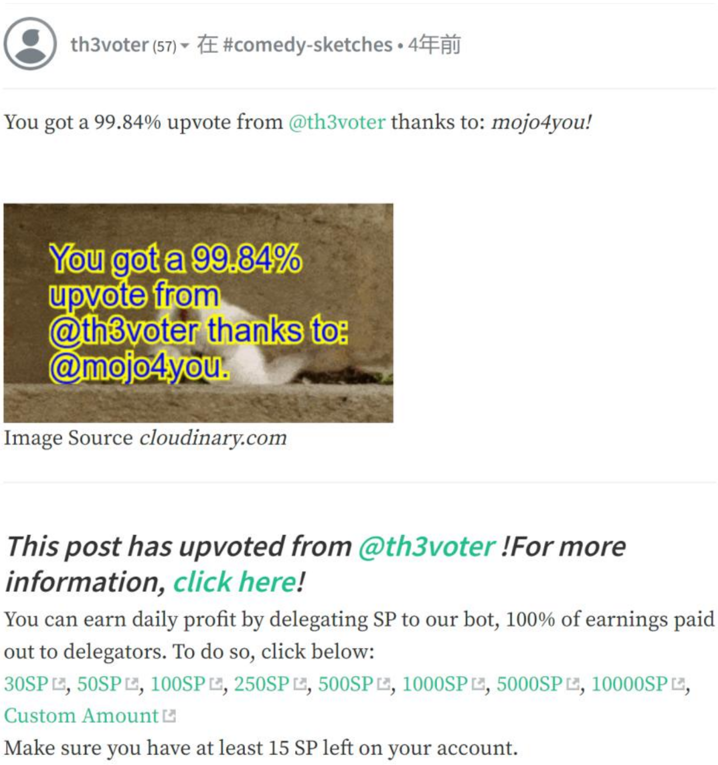

Figure 2: A Bot Comment

After completing the above steps, we obtained a list of bots and used the following two methods to verify all bot accounts on the list:

1. Check these accounts for activity evidence on the Steemit website, such as posts describing their operational rules, claiming to be curator bots on their profiles, and engaging in automated voting and commenting.

2. Examine the time correlation between these accounts' transfers and voting operations with other users. Specifically, users transfer a certain amount of tokens to a bot's wallet to purchase votes and include the post link to be voted on in the memo. We screened all transfer operations and selected those containing post links in the memo area. Curator bot will upvote the corresponding post link, so we verify that the account is a bot.

Ultimately, we identified 245 curator bot accounts and confirmed that their behavior significantly differed from that of human users in the network. Among these, 170 bots were active during our study window.

Variable Data

We collected all posts, votes, transfers, delegation operations, and token value changes on Steemit from July 22, 2019, to October 3, 2019. Due to API maintenance, the data volume for September 2, 2019, is minimal, so we excluded this day from the dataset. On August 27, 2019, Steemit introduced the downvote policy through a hard fork, creating a separate downvote pool for each user. Additionally, the hard fork changed the distribution ratio between curation rewards and author rewards in the reward pool. We regard this policy change on Steemit as a natural experiment.

Using the compiled bot list, we calculated the necessary variable data, including the total number of posts and comments by humans, the total number of posts and comments by vote-buying users, the total number of upvotes by humans, the total number of upvotes by bots, the total number of reciprocal downvotes, the total amount of transfers from humans to bots, and the total amount of delegations. Since our study focuses on the impact of the downvote policy, to control for potential disturbances caused by the change in reward distribution ratio, we selected the average of the three types of tokens (Token Average, TA) held by users as a control variable. This is because content creation and curation rewards are the primary sources of income for users, and this change directly affects the token holdings of each user on the platform. The closing price of Bitcoin (BTC) is another control variable.

To statistically analyze the variable data, all variables were log-transformed. The table below presents the log-transformed variables' mean, standard deviation (SD), minimum, maximum values, and t-test p-values for mean differences. Significant differences ($p < 0.05$) were found in the means of all variables.

Table 1: Summary Statistics For Data Set

Table. Summary statistics for data set.

	Before change				After change				
Variable	Mean	SD	Min	Max	Mean	SD	Min	Max	P-value
log (Total number of human positive votes)	13.79	0.04	13.71	13.90	13.69	0.11	13.43	13.83	<0.001
log (Total number of bot positive votes)	8.85	0.08	8.70	9.01	8.65	0.14	8.27	8.92	<0.001
log (Total number of human posts and comments)	11.06	0.08	10.87	11.26	10.88	0.11	10.61	11.21	<0.001
log (Total number of transfers)	8.31	0.15	7.95	8.57	7.31	0.17	6.86	7.55	<0.001
log (Total number of delegates)	5.09	0.17	4.80	5.56	5.21	0.24	4.65	5.68	0.021
log (Total number of purchased posts and comments)	9.59	0.06	9.45	9.69	9.47	0.08	9.26	9.56	<0.001
log (Total number of reciprocal downvotes)	6.38	0.25	5.65	6.84	6.73	0.18	6.26	7.10	<0.001
log (BTC)	9.26	0.07	9.16	9.41	9.17	0.10	8.99	9.27	<0.001

Note: All variables are calculated per day at the platform level.
P-values test the comparison of whether the means before and after the change are statistically different.

RDiT Model Construction

We employ the Regression Discontinuity in Time (RDiT) method to investigate the impact of the newly introduced downvote pool on the community. The reason for using this method is that the mechanism change through a blockchain hard fork affects all users on the entire platform. Due to the unique nature of the Steemit platform, there are no other comparable platforms to serve as a control group. Consequently, we are unable to use difference-in-differences matching methods.

Given these limitations, we used the RDiT framework (Hausman & Rapson, 2018) to study the impact of the downvote policy on the activities of humans and bots. The RDiT method applies the concept of regression discontinuity design (RDD), using time as the running variable and the policy change date as the discontinuity threshold in the RDiT. This method is particularly suitable for analyzing the causal effects of policy changes or interventions occurring at a specific time point, which perfectly matches our research context. It isolates the local causal effect of the intervention using the time cutoff, allowing for strong causal inference for quasi-experiments over time.

To avoid the potential misguidance caused by overfitting, we adopted a local linear specification with a triangular kernel function as our primary method, following Gelman and Imbens (2019). Referencing the approach of Delkhosh *et al.* (2023), we refined their local linear RDiT specification by incorporating the token average (TA) of platform users as a control variable, as shown in the following equation:

$$Y_t = \beta_0 + \beta_1 policychange_t + \beta_2 t + \beta_3 TA_t + \beta_4 BTC_t + \beta_5 x_t + \varepsilon_t \quad (1)$$

where:

• Y_t is the outcome variable.

• $policychange_t$ is a binary variable for the downvote policy. If the period is after August 27, 2019, the variable equals 1; otherwise, it equals 0.

• t represents a linear time trend, which account for systematic changes over time.

• TA_t, the token average, is the average of the three types of tokens held by active users, serving as a control variable for economic reward policy changes. Introducing this variable helps control for other concurrent economic changes, such as the reward distribution ratio change, ensuring the model focuses on evaluating the downvote policy effect itself.

• BTC_t is the daily closing price of Bitcoin, serving as a control variable for isolating the effects of the main variables by accounting for broader market fluctuations.

• x_t is a set of dummy variables representing the day of the week. This variable is included in the model to control for potential day-specific effects, thus accounting for variations that may occur due to weekly patterns.

• ε_t is the error term.

RESULTS

Results Discussion

The RDiT analysis results revealed multiple impacts following the policy implementation, including positive changes and potential side effects.

Table 2: RDiT Results

Table. RDIT (regression discontinuity in time) estimates

Variable	Coefficient	Standard error
Total number of human positive votes	-174829.008***	47852.082
Total number of bot positive votes	-1695.231***	131.531
Total number of human posts and comments	-9015.981**	3756.422
Total number of transfers	-1204.018***	300.034
Total number of delegates	21.183	24.674
Total number of purchased posts and comments	-2062.692***	188.239
Total number of reciprocal downvotes	367.125 ***	64.934

Note: *p<0.1.**p<0.05.***p<0.01.

First, after the downvote policy, the total upvotes by curator bots significantly decreased, consistent with the prediction of Hypothesis 1. This initial change confirms the policy's effectiveness, demonstrating that the policy successfully curbed vote manipulation between humans and bots in the community, thereby improving the fairness and transparency of the content evaluation system. Our explanation for bot voting is that users' transfers and delegation behaviors to bots, and our results show that the total number of transfers from users to bots significantly decreased, while the change in delegation times was not significant. Thus, our results support Hypothesis 2 but not Hypothesis 3, because the number of delegation actions does not decrease significantly as expected in Hypothesis 3.

While the downvote policy directly targeted vote-buying behavior between users and bots, it did not significantly impact users' delegation behavior to bots. This could be because delegation behavior is more covert compared to vote-buying and can provide more long-term and stable returns for both parties. Moreover, the reason for the insignificant change in delegation behaviors may be due to the inherent delay in delegation: robots are unlikely to immediately reduce the returns on delegated services following a policy change, and the SP already delegated by users also requires time to be revoked. In contrast, the practice of users purchasing upvotes from bots is subject to immediate and swift repercussions. Therefore, while the policy has a certain effect on reducing bot vote manipulation, it is also necessary to pay attention to the changes in the interaction modes between bots and human. In the future, users using bots may adjust their strategies under the new policy by delegating voting power. If the platform aims to thoroughly govern bots, it must pay attention to the long-term changes in delegation behavior.

Meanwhile, we observed a notable reduction in the total number of upvotes from human users, contrary to the prediction of Hypothesis 4. This may indicate that the policy raised content screening standards, causing users to demand higher content quality and be more cautious about giving upvotes, reflecting hesitation in providing positive evaluations in an environment with increased negative feedback. Additionally, the decrease in human upvotes might reflect users' initial discomfort with policy changes or dissatisfaction with the overall quality and atmosphere of community content. Although the increase in downvotes should theoretically improve content quality, the decrease in upvotes suggests that users may be skeptical about content improvement or believe that high-quality content has not increased due to policy implementation. It may also reflect distrust or dissatisfaction within the community due to the widespread use and potential negative application of downvotes.

Furthermore, due to the increase in downvotes, we found a significant reduction in the number of posts and comments of human users, supporting Hypothesis 5. This indicates that the policy inadvertently suppressed content creators' community participation, leading to a decrease in user discussion and interaction. This may occur because users face increased negative feedback and psychological pressure, inhibiting their creative enthusiasm and reducing overall content supply on the platform. As the total number of content decreases, users' voting options also decrease. Thus, the reduced supply of high-quality content directly results in a decline in the overall number of upvotes from human users, as observed in Hypothesis 4. For a community platform relying on user-generated content, these phenomena suggest that community interaction quality and user engagement might have decreased due to policy changes, a noteworthy issue.

For users who had long been purchasing votes from bots, their posts and comments significantly decreased after the policy, supporting Hypothesis 6. the behavioral change of vote-buying users can be analyzed through the lens of algorithmic agency and algorithm appreciation (Logg et al., 2019). Prior to the downvote policy, vote-buying users leveraged bots to amplify the visibility and economic returns of their posts, viewing these algorithmic agents as integral tools for navigating the platform's reward system. The significant voting power held by bots, combined with their automated efficiency in upvoting posts, created an environment where users heavily depended on these algorithmic agents to achieve their desired outcomes. This dependency is indicative of a broader trend of algorithm appreciation, where users exhibit trust in and reliance on algorithmic solutions to optimize their online activities.

The introduction of the downvote policy disrupted this established dynamic by increasing the availability and use of downvotes, thereby directly targeting the vote-buying practices facilitated by bots. As a result, the effectiveness of bot-assisted upvotes was substantially diminished, leading to a decline in the economic viability of engaging in vote-buying. This shift forced users to reassess their reliance on bots, as the negative feedback from increased downvotes reduced the overall profitability and attractiveness of algorithmic intervention. The reduction in posting and commenting activities post-policy can be attributed to this disruption, as users struggled to adapt to the new environment without the support of their trusted algorithmic agents.

Additionally, this observation aligns with the theoretical expectations rooted in motivation theory. According to motivation theory, users participate in online communities driven by both intrinsic and extrinsic motivations (Deci & Ryan *et al.*, 2013). For vote-buying users, extrinsic motivations primarily involve the economic rewards gained through bot-assisted upvotes, which enhance the visibility and reward potential of their posts. The introduction of the downvote policy directly undermines this extrinsic motivation by increasing the risk of negative feedback, thereby reducing the effectiveness of purchased upvotes.

Finally, we found that the increase in downvotes brought by the policy change lead to the predicted negative social dynamics of Hypothesis 7, namely, reciprocal downvoting among users. After the policy implementation, the number of reciprocal downvotes among users significantly increased, indicating an uptick in the retaliatory use of downvotes. This demonstrates the double-edged sword effect of the policy. While more downvotes were utilized to combat bot vote manipulation and low-quality content, these additional downvotes also became weapons for community members to attack each other. Such malicious behavior could deteriorate the positive atmosphere of the community, partially explaining the decrease in upvotes by human users observed in Hypothesis 4. The abuse of downvotes poses a long-term threat to the community's development, and future research could focus on this issue and propose countermeasures.

Moreover, Mustafa *et al.* (2023) found that the quality of future posts by authors who received negative evaluations might be lower, and these authors were more likely to negatively evaluate others. Therefore, future research should focus on changes in the quality of community posts.

Robustness Checks

Our primary model is based on the RDiT analysis method. However, one concern with RDiT is that the observed effects might occur by chance. To verify the robustness of the primary analysis results, we conducted placebo tests to estimate the likelihood of the observed results occurring by chance. Placebo tests involve re-estimating the policy effect under multiple hypothetical thresholds outside the actual policy implementation date to test whether similar effects can be observed without policy changes. Specifically, we used dates other than the actual policy implementation date (August 27, 2019) for RDiT estimation. We selected dates between August 7, 2019, and September 17, 2019, as hypothetical thresholds for each outcome variable and performed RDiT analysis for each hypothetical threshold.

Then, we conducted two diagnostic statistical tests commonly used in placebo tests in the literature (Cheng *et al.*, 2020). The first test is a two-tailed t-test (t-test (1) in the table below) to check whether the mean of the RDiT estimates for each placebo test is statistically different from zero. If the p-value is less than the significance level (e.g., 0.05), it indicates that the mean of the placebo estimates is significantly different from zero, suggesting the presence of potential estimation bias. The second test is a one-tailed t-test (t-test (2) in the table below) to check whether the magnitude of the actual RDiT estimate is significantly different from the mean of the placebo RDiT estimates. The table below reports the mean and standard error of the placebo RDiT estimates, as well as the t-scores and p-values for the two diagnostic tests.

We found that for all outcome variables, we could not reject the null hypothesis that the mean of the placebo RDiT estimates is zero. Furthermore, for most outcome variables(except for the total number of delegates), the mean of the placebo RDiT estimates was statistically different form the actual RDiT estimate ($p < 0.05$). Together, these results suggest that our findings are unlikely to have occurred by chance.

Table 3: Placebo Test Results

Table. Placebo Test Results

Variable	Actual RDiT Estimate	Mean of Placebo RDiT Estimates	SD of Placebo RDiT Estimates	t-score of t-test (1)	p-value of t-test (1)	t-score of t-test (2)	p-value of t-test (2)
Total number of human positive votes	-174829.00	19407.41	685473.22	1.20	0.24	0.56	p<0.01
Total number of bot positive votes	-1695.23	1603.23	3835.88	0.77	0.45	3.27	p<0.01
Total number of human posts and comments	-9015.981	10045.83	49207.93	0.78	0.44	0.71	p<0.01
Total number of transfers	-1204.02	512.09	6092.01	-0.83	0.41	-0.71	p<0.01
Total number of delegates	21.18	-12.85	72.96	-1.22	0.23	-0.49	0.69
Total number of purchased posts and comments	-2062.69	45103.38	308368.91	1.03	0.31	-0.98	0.03
Total number of reciprocal downvotes	367.13	273.17	1221.83	-0.09	0.93	0.87	0.02

Note: The null hypothesis for t-test (1) is that the mean of the placebo RDiT estimates is equal to zero.
The null hypothesis for t-test (2) is that the magnitude of the actual RDiT estimate is significantly different from that of the mean of the placebo RDiT estimates.

Additionally, we conducted two different robustness checks using different methods. These methods are manually setting different bandwidths and robustness checks with a virtual control group.

Firstly, to assess the sensitivity of the results to bandwidth selection, we manually set multiple bandwidths and ran local polynomial regression models for each bandwidth. By calculating both robust and conventional standard errors, we examined the impact of bandwidth selection on the estimated results, ensuring the consistency of our estimates across different bandwidth settings.

Next, to further validate the robustness of the treatment effects, we constructed a virtual control group. Specifically, we used pre-policy implementation data to fit an autoregressive integrated moving average (ARIMA) model and then compared its predictions to the actual values post-policy implementation. By calculating the differences between actual values and predicted values, we estimated the treatment effects of the policy change on each outcome variable. This method provided an independent approach to estimating treatment effects apart from the RDD analysis, helping to verify the robustness of the results.

Through these two different robustness check methods, we confirmed the consistency and robustness of our results under various model specifications and parameter choices, thereby enhancing the credibility of our research conclusions.

CONCLUSION

This study employed the Regression Discontinuity in Time (RDiT) method to comprehensively analyze the impact of downvote policy on the engagement behavior of human and bot users on Steemit.

Firstly, the downvote policy effectively curbed vote manipulation behavior between humans and bots on the platform, as evidenced by the significant reduction in the total number of upvotes by bots. As an explanatory mechanism for this voting manipulation, users' direct transfers to bots significantly decreased, but there was no significant change in delegation behavior, suggesting the need for further policy adjustments to regulate this complex interaction pattern. However, we also observed some potential side effects. Human users' upvotes and the total number of posts and comments significantly decreased after the policy change, reflecting hesitation in content creation and interaction when negative feedback increases, which may have long-term negative impacts on community content quality and user engagement. Moreover, the policy also significantly increased reciprocal downvoting behavior among users on the platform, indicating that a portion of the newly available downvotes were used as retaliatory tools for malicious attacks between users. Finally, the content creation behavior of users who had long been purchasing votes from bots also significantly decreased, as the bot service they relied on were directly impacted by the policy. This phenomenon has a dual aspect: on the one hand, the abusive practices of these speculative users were curbed. On the other hand, it further demonstrates the negative impact of the increased downvotes on the content creation enthusiasm of community members.

Given that we found the increase in negative feedback suppressed community content generation and discovery behaviors, we recommend that users provide detailed feedback during the voting process to improve the effectiveness of negative feedback and reduce its negative impact on recipients. For example, users can choose to comment while downvoting a post, detailing the reasons for their vote and offering suggestions for improvement. The platform can also provide options for users to explain their downvotes. This additional effort can help recipients improve their future content creation and reduce irrational behavior associated with downvotes.

Furthermore, to prevent the abuse and malicious attacks of downvotes while maintaining their role as an important tool for community health, the platform could establish an arbitration committee to oversee the use of downvotes. The committee should consist of respected users within the community, possess sufficient voting power, and intervene in severe cases (e.g., continuous attacks by large accounts on small users). The committee's presence can enhance fairness within the community and reduce abuse and personal attacks.

This study is the first to focus on changes in voting system mechanisms on BOSM platform. Our investigation expands our understanding of how user engagement in BOSM is affected by platform-level design features. The findings highlight the need to balance policy incentives and side effects when designing and implementing community management policies, considering their impact on different user behaviors. Our results have practical implications for online platforms seeking to optimize their voting systems. Future research could further explore how to optimize voting system mechanisms to enhance content quality control on BOSM while promoting healthy community interaction. Additionally, our study deepens the understanding of the interaction between bots and human users on BOSM, focusing on the delegation of voting power between them for the first time. Overall, this study provides policy guidance for BOSM platforms and valuable insights into the complexity of digital social interactions.

There are some limitations in this study that we will address in future research. First, although the RDiT research design allows us to causally identify the effects of policy implementation, the results are limited by local validity. Future research can use more robust research designs to strengthen our causal inferences and focus on the policy's impact over longer time windows. Second, although bot and vote manipulation issues are not unique to the Steemit platform, it is unclear whether our findings apply to other BOSM and OSM. Our study only focused on vote manipulation between users and bots through upvotes. Future research could consider whether the increased availability of downvotes would lead to vote manipulation based on downvotes. Third, our study only focused on the frequency changes in user-generated content. Future research can investigate changes in content quality and additional textual features following the downvote policy implementation, such as examining whether the quality and sentiment of posts and comments changed significantly. We will further explore these aspects as we advance our research.

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