Decentralized Voting in Product Development and Consumer Engagement: Evidence from a Blockchain-Based K-pop Community

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ABSTRACT

Traditional centralized models allow consumers to provide input, but are often limited by selection biases. Instead, blockchain-based decentralized models extend all consumer voice but face sustainability challenges including unsustained contributions and voting power concentration. Utilizing data from a blockchain-based K-pop platform, this study investigates whether fans continue contributing to the platform after initially participating in voting rounds. Findings indicate that voting power becomes less concentrated over time, likely because voters who have smaller voting power value the equity of decentralized voting and increase both tangible and intangible contributions. Conversely, voters who have larger voting power experience expectation disconfirmation; they begin with high expectations about influencing outcomes but if their preferences are disappointed, they decrease tangible contributions while maintaining intangible contributions. We use value cocreation and expectation disconfirmation theory to explain the phenomenon. This study contributes to blockchain and user innovation research and offers practical insights for platform designers aiming to create equitable, sustainable consumer-driven ecosystems.

Keywords: blockchain, continuance contribution, expectation disconfirmation model, K-pop, user innovation, voting, value cocreation.

INTRODUCTION

The K-pop industry has achieved global success largely because of support from loyal fans. For example, BTS, a Korean boy band, is one of the most influential ensembles since the Beatles. Valued at $4 billion, BTS leverages its dedicated fans, called ARMY, to act as "secret weapons"[i] to promote social media content and enhance concert attendance.[ii] To cultivate loyalty, brands often integrate consumer preferences into product designs (Cossío-Silva et al., 2016; Healy & McDonagh, 2013). However, centralized consumer voice models frequently risk selection bias, favoring certain voices while marginalizing others. For instance, highly vocal social media consumers dominate attention, leaving quieter fans disproportionately unheard. Consequently, many consumers eventually withhold their opinions, so that brands find it difficult to develop products that genuinely satisfy diverse audiences. Therefore, new systems that can more effectively capture input from a broader range of consumers are needed.

Decentralized autonomous organizations (DAOs) could address the challenges facing centralized consumer voice models. Innovative IT-enabled DAO platforms are somewhat like crowdsourcing platforms in empowering consumers to participate in decision-making processes. In crowdsourcing platforms, experts or selected groups of individuals make final decisions, but DAOs promote decentralization by enabling every consumer to vote directly on creative directions, reducing selection bias and ensuring that brands will consider a wide range of perspectives. For instance, a DAO specifically designed for K-pop grants governance rights to all fans who made tangible monetary contributions through fan engagement, content creation, or community support. The DAO ultimately increases consumer-driven outcomes; it ensures that decisions reflect the collective community input, fosters a sense of ownership and belonging, gives all a stake in decision-making processes, and enhances engagement and loyalty.

By ensuring procedural fairness, centralized voice models motivate consumer participation (Kim et al., 2019). In contrast, decentralized models seek similar outcomes, but through transparent blockchain-enabled traceable voting and smart-contract-enabled process automation (Zhang et al., 2020). Although decentralized governance models elucidate outcome information, especially for undesired results, individual consumers may perceive that their voting power is insignificant compared with the collective voice, discouraging them from speaking and causing them to disengage (Peña-Calvin et al., 2024). To create equitable platforms that reflect diverse voices and encourage consistent participation, we need further understanding of the dynamics of consumer engagement in decentralized settings.

Continuance contributions leading to long-term sustainability of decentralized voice systems crucially reflect consumer loyalty. Without sustained participation, systems risk power concentration and business failures. Thus, our objective here is to analyze continuance contributions in blockchain-based user innovation systems. Focusing on decentralized governance models, we ask, 1) How does consumer voice affect continuance contributions? 2) How do effects differ for small versus large voters, and for desired versus undesired outcomes? 3) What are the underlying mechanisms?

We address the questions within the context of TripleS, a decentralized K-pop organization that allows fans to purchase NFT cards that function as digital voting tickets. When purchasing NFT cards, fans will receive governance tokens simultaneously which they can use to vote on group members, song styles, and other creative aspects. The NFT cards are collectible, transferable, exchangeable, and valueless; designers randomly assign traits such as rarity or design. In contrast, only original card purchasers can own and use the governance tokens for voting power. The backend team develops the choice sets (e.g., song members), and creates products based on voting outcomes. By January 2025, TripleS had sold more than 4 million NFT cards.[iii]

Model-free evidence shows that over time, within-platform voting power becomes more diffused and equitable. To better understand the power distribution dynamics, we analyzed the impacts of initial consumer voice on 1) tangible contributions such as purchases of NFT cards, and 2) intangible contributions such as within-community social interactions.

We used stacked differences-in-differences (DID) which constructed multiple two-period DID models for each voting round. We select treatment groups from those expressing their initial voice in local voting round and control groups from those who never voted before and during local voting round. Estimation results revealed that after consumers expressed their voice through voting, they increased tangible contributions by 1% and intangible contributions by 1.4% per day. Notably, large voters (more voting power) were less likely than small voters to augment tangible contributions although their intangible contributions remained steady. This effect was particularly pronounced when large voters received undesired outcomes.

To elucidate the underlying mechanisms, we focused on value co-creation theory and the expectation-confirmation model. First, decentralized organizations can motivate consumers to continue contributing by granting equity according to value co-creation theory. Second, large voters expect their votes to be most influential. They will be highly dissatisfied if outcomes fail to align with their preferences, and will primarily reduce tangible contributions, which are more sensitive to unmet expectations according to expectation-confirmation model. For desired outcomes, there is no significant contribution difference between large voters and small voters. Thus, consumer behavior is altered more by unmet expectations rather than expectation confirmation. Conversely, regardless of initial expectations, intangible behaviors will continue, despite met expectations, highlighting the boundary conditions of expectation-confirmation model.

Our research contributes to the blockchain and user innovation literatures by exploring how blockchain technology supports user innovation in product development. Blockchain studies have predominantly explored financial applications (Bakos & Halaburda, 2022; Malinova & Park, 2023) or NFTs (Tunc et al., 2024). Instead, we demonstrate the potential to reduce selection bias and thereby democratize consumer participation in decision-making. Using data from a decentralized K-pop organization, we show that blockchain equalizes value cocreation (Ranjan & Read, 2016), motivating small and large voters to remain engaged after sharing their input. Contrary to concerns that voting power centralization may negatively impact platform performance (Han et al., 2023; Peña-Calvin et al., 2024), our findings suggest that concentration diminishes over time. Second, contributing to user innovation research, we examine consumer motivations to share their inputs and how being heard influences their continuance contributions (Grosz & Raval, 2024; Khern-am-nuai et al., 2018; Kim et al., 2019; Raval, 2020; Safadi et al., 2024).

Our findings enhance understandings about consumer continuance contribution and sustainability of blockchain-based innovation communities. We provide practical, actionable implications that blockchain-based models can integrate consumer preferences and foster equity, so that consumers continue tangible (e.g., monetary investments) and intangible (e.g., ideas) contributions. Firms should tailor incentive structures for diverse token holders, but manage expectations by recognizing contributions, even for consumers who receive undesirable outcomes (Jeppesen & Frederiksen, 2006). Traditional innovation models often prevent consumers from giving abundant feedback. Instead, in blockchain-based organizations, consumers acquire voice equity. They must maintain realistic expectations, however, because group decisions sometimes belie personal preferences. Our findings about K-pop industries are generalizable to other industries that rely on fan bases, such as extreme sports (Franke & Shah, 2003) and outdoor sports (Lüthje et al., 2005).

RELATED LITERATURE

Our research mainly relates to blockchain and user innovation literature. Table 2 provides a summary of the literature (at the end of this section).

Blockchain and Decentralized Organizations

Blockchain technology, or decentralized databases (Ziolkowski et al., 2020), give stakeholders better traceability and coordination (Lumineau et al., 2021). In decentralized voting models, blockchain ensures that voting process details are accurately recorded, from beginning to end. Machine-mediated decentralized governance models, such as DAOs, leverage blockchain so that they function as "conjoined arresting technologies." That is, users influence decisions without altering the underlying technical protocols (Murray et al., 2021). Figure 1 shows how models develop products: In exchange for contributions, consumers acquire governance tokens used to vote on decisions. A centralized team carries out the decisions but delegates decision rights to consumers.

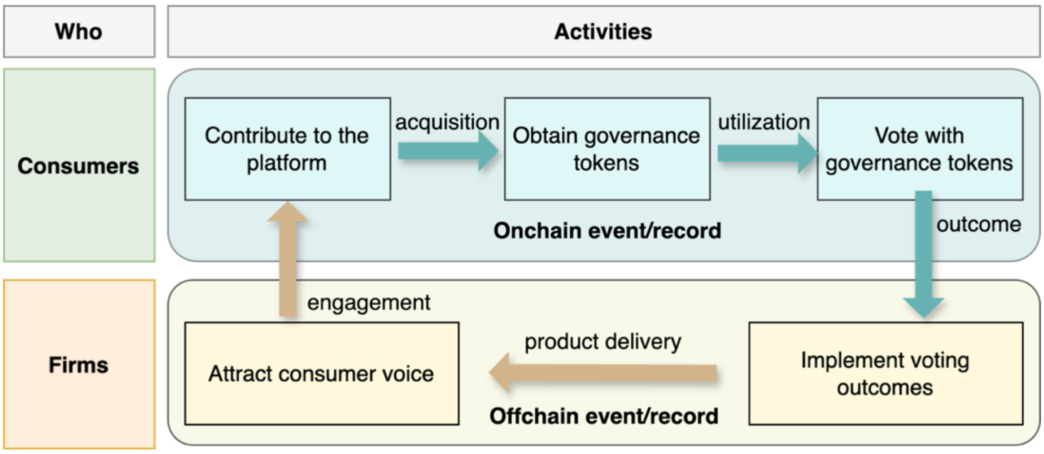


Figure 1. Decentralized governance models for product development

The governance model has several challenges. First is how to motivate more consumers to continue contributing. Financial incentives such as the resale value of governance tokens (Chen et al., 2023) may encourage short-term participation but not long-term sustainability. They may even act as Ponzi schemes (Bartoletti et al., 2020). However, little is known about how to design mechanisms that foster sustained continuance contributions. Our study shows that non-financial incentives, such as equity and ownership of product, can sustain continuance contributions.

Second, concentrated voting power is a significant obstacle to equitable governance and sustained participation because it reduces long-term participation among individual stakeholders (Ellinger et al., 2024), negatively impacts platform performance (Han et al., 2025), and is exacerbated in larger networks (Peña-Calvin et al., 2024). Concentration is further entrenched when large voters acquire greater voting rights (Fang et al., 2024). Despite these issues, few have explored strategies to mitigate power concentration and encourage broader, sustained user participation. We find consumers in user innovation model experience a value cocreation effect where small voters remain engaged over time. Our findings provide important insights for fostering equitable governance and sustained participation.

User Innovation

The user innovation literature has focused on consumer-based product development, particularly on integrating consumer insights into product design (Gambardella et al., 2017; Morrison et al., 2000; von Hippel, 1986). User innovation has significantly beneficial effects for the economy. For example, 6% of UK consumers have been involved in user innovations leading to substantial product breakthroughs (von Hippel et al., 2012).

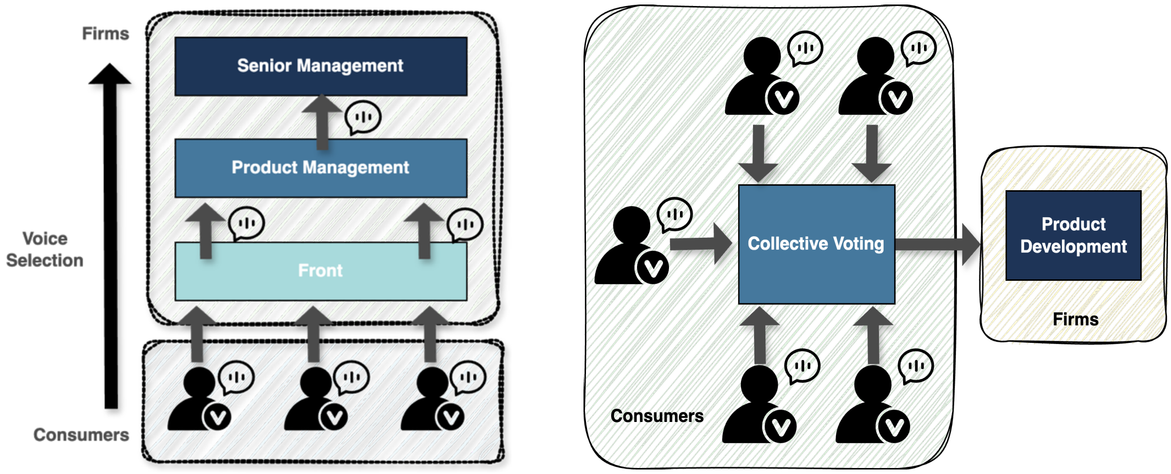
In both crowdsourcing and decentralized models, consumers express distinct preferences for product characteristics, giving firms insights for assessing market needs and enhancing loyalty (Hauser, 1978). In value co-creation processes, firms collect user preferences through various methods; consumers collaborate at different production stages so that firms can better align products with consumer preferences (Hoyer et al., 2010; Payne et al., 2008; Ranjan & Read, 2016), foster closer customer relationships, and encourage knowledge sharing (Gu et al., 2022; von Hippel & Katz, 2002; Ye & Kankanhalli, 2018).

Table 1 summarizes key types of user innovation. In consumer-based user innovation, firms benefit by adopting and integrating innovative suggestions into product designs (Jeppesen & Frederiksen, 2006). Most centralized models position firms as the ultimate decision-makers, beyond collected user input. However, few have considered the possibility that firms could transfer decision-making rights to consumers through collective voting. Decentralized models allow consumers to retain ultimate authority over product decisions. Firms are responsible only for organizing voting events and implementing outcomes. Therefore, they cede significant control to consumers, while consumers contribute tangibly to obtain governance rights, ensuring that backend teams have sufficient incentives to operate.

Table 1. Ways that Firms Use the Crowd

Example	Contribution	Product Governance	Final Decision Maker
Crowdfunding (Kim & Viswanathan, 2019)	Money	No	Firm
Crowdsourcing (Huang et al., 2014)	Knowledge	Yes	Firm
Decentralized Governance (This study)	Money + Knowledge	Yes	User

The typical centralized value-cocreation model selects consumer voice passively, such as through user reviews (Chevalier et al., 2018), social media interactions (Ma et al., 2015), and complaint channels (Raval, 2020). Passive models, however, introduce selection biases in choosing which voices are amplified. To alleviate concerns about voice selection bias, we explore blockchain-based decentralized models that contribute to product governance via voting mechanisms (Figure 2) that offer feedback and cocreative input that directly influences product development. Different from centralized voice model that includes a voice selection process with hierarchical structures, decentralized models give equity to each consumer without firm's intervention. Firms delegate decision rights to consumers, while they are only responsible for producing products.



(a) Centralized Consumer Voice (b) Decentralized Consumer Voice

Figure 2. Consumer Voice Mechanism

Platform usability, voting fairness, minority voice representation, and momentary rewards are known antecedents of consumer voice (Grosz & Raval, 2024; Khern-am-nuai et al., 2018; Kim et al., 2019; Raval, 2020; Safadi et al., 2024). However, how consumer voice affects user behaviors and platforms, such as sustained contributions and economic value, is rarely examined. Addressing this gap is crucial provide practical implications for firms in designing incentive structures that accommodate diverse consumer expectations and experiences. We also present an interesting and novel setting—the production and management of a K-pop group—in contrast with numerous studies focused on entertainment and leisure activities such as extreme sports (Franke & Shah, 2003), outdoor sports, juvenile products (Shah & Tripsas, 2007), and retail banking (Oliveira & von Hippel, 2011).

Value Cocreation and Expectation Disconfirmation Theory

Our study is based on expectation disconfirmation theory and value co-creation, two well-established concepts in behavioral economics. Value co-creation is a collaborative process in which one unilateral entity is replaced by multiple stakeholders (e.g., platforms, consumers, or sellers) who actively collaborate with firms to create value directly or indirectly at various stages of production and consumption (Hoyer et al., 2010; Kohler et al., 2011; Payne et al., 2008), such as during the initial product design phase or through feedback on prototypes before they are publicly released.

Many studies have focused on IT-enabled value co-creation (Grover & Kohli, 2012). Based on co-creation theory, Kohler et al. (2011) proposed that design principles guide virtual cocreation systems. Value cocreation requires (1) knowledge allowing firms to evaluate consumer preferences (Grover & Kohli, 2012; Ramírez, 1999), (2) equity (Hoyer et al., 2010), and (3) forms of interaction, such as dialog or forums (Payne et al., 2008). We provide evidence of value co-creation in the context of blockchain and K-pop production where consumers provide suggestions that determine product designs.

Expectation disconfirmation theory (EDT) has been widely applied to understand user satisfaction and continuance in various contexts (Brown et al., 2014), including information systems (Bhattacherjee, 2001), online services (McKinney et al., 2002), and AI agents (Han et al., 2023). The theory posits that customer satisfaction depends on whether expectations align with experience regarding products or services.

Venkatesh et al. (2012) expanded EDT by adding predictors such as effort expectancy and social influence. Han et al. (2023) used EDT to explain that AI agents can positively influence service evaluations by expressing emotions. Those studies demonstrated that EDT has ongoing relevance for user behavior across diverse technological environments. We investigate whether EDT applies to decentralized organizations, specifically whether disconfirmation will cause highly expectant consumers to stop contributing to the DAOs.

Table 2. Related Literature		
Literature	Focus	Our Study
Blockchain	Application of blockchain: - Data infrastructure (Chen et al., 2021) - Trust machine (Bakos & Halaburda, 2022) - Airdrop (Li et al., 2024) - Fundraising (Malinova & Park, 2023)	User innovation of product development.
	Focal outcome variables: - Token price (Chen et al., 2023) - ICO success (Li et al., 2024) - Platform growth (Chen et al., 2021)	User-level continuance contributions.
	Voting power concentration in DAO: - Reduces sustained participation (Ellinger et al., 2024) - Positively related to network size (Peña-Calvin et al., 2024) - Negatively related to platform performance (Han et al., 2025) - Positively related to delegation (Fang et al., 2024)	Voting power becomes more concentrated over time.
	NFT studies: - Resale royalties (Tunc et al., 2024) - Contract completeness (van Haaften-Schick & Whitaker, 2022)	NFTs are used for collection lacking financial value.
User Innovation	Ways to collect consumer inputs: - User comment (Chevalier et al., 2018) - Social media (Ma et al., 2015) - Complaint channel (Raval, 2020)	Use of blockchain to collect consumer voice.
	Antecedents of consumer inputs: - Governance alignment (Safadi et al., 2024) - Ease of use (Grosz & Raval, 2024) - Promise for justice (Kim et al., 2019) - Minority groups (Raval, 2020) - Peer feedback (Kokkodis et al., 2020) - Firm recognition (Jeppesen & Frederiksen, 2006)	Antecedents and consequences of consumer voice.
	Consequences of consumer input - Loyalty (Cossío-Silva et al., 2016) - Knowledge contribution (Kokkodis et al., 2020)	
	Context: - Extreme sports (Franke & Shah, 2003) - Outdoor sports (Lüthje et al., 2005) - Retail banking (Oliveira & von Hippel, 2011).	K-pop products.

THEORETICAL DEVELOPMENT

Consumer activities are valuable community assets (Grant, 1996). To ensure that decentralized governance models are sustainable, firms must incentivize consumers to make continuance contributions. In decentralized governance platforms, contributions can be financially tangible, often in the form of purchases, indicating financial commitment to the platform and sensitivity to reward or loss. Intangible contributions, on the other hand, reflect loyalty, social engagement, and active community involvement, often through interactions with other consumers, and are more sensitive to community status and connections.

We use expectation disconfirmation theory and value co-creation to discuss how consumer voice may influence consumers' continuance contribution in the following part.

Value Cocreation Participation and Continuance Contribution

Product cocreation involves knowledge sharing (Grover & Kohli, 2012; Ramírez, 1999), equity (Hoyer et al., 2010), and interaction (Payne et al., 2008). First, in DAOs, consumers vote their preferences, which is a form of knowledge sharing with firms (Grover & Kohli, 2012; Ramírez, 1999). Second, aligned with DAO designs for distributing decision rights through voting, firms share decision-making authority with consumers, a form of equity through empowerment (Hoyer et al., 2010). Indeed, equity is a key feature of decentralized organization. Last, interaction involves interfaces between individuals, but DAOs diverge from traditional dialog or forums (Payne et al., 2008). Instead, in blockchain transactions, consumers engage with *autonomous systems*. Machine-mediated interactions can enhance perceptions of procedural fairness (Kim et al., 2019). Thus, compared to traditional crowd-based models, DAOs provide unique equity.

Theoretically, knowledge sharing, equity, and interaction dimensions should be positively related to participation in decentralized value co-creation (Dong et al., 2008, p. 200; Grönroos & Ravald, 2011). First, consumers have an enhanced sense of ownership when they can voice their preferences by voting (Franke et al., 2009). Second, they experience equity by having decision-making authority weighted by their tangible contributions. Third, they feel more attached to the community through transparent machine-mediated mechanisms. Those factors drive consumers to continue contributing to the community.

Hypothesis 1: *Consumer voice increases continuance contribution.*

Expectation and Continuance Contribution

Prior experience is the basis for forming expectations. For instance, consumers who have invested more to acquire governance rights may be certain that their token holdings will directly influence product outcomes. Thus, token holdings may determine effects of initial expectations on continuance contributions: substantial voting power will be linked with higher expectations. EDT explains that highly expectant consumers are more prone to disconfirmation because they are harder to satisfy. In contrast, consumers with lower initial expectations are more easily satisfied, hypothesized as:

Hypothesis 2a: *High-expectation consumers, compared to low-expectation consumers, are less likely to increase continuance contributions.*

Sunk cost effects are also potentially influential (Arkes & Blumer, 1985). In decentralized governance platforms, large stakeholders may feel more committed to the platform because they want to recover or justify their investments. Even if their expectations are disappointed, they are likely to stay involved, leading us to hypothesize:

Hypothesis 2b: *High-expectation consumers, compared to low-expectation consumers, are more likely to increase continuance contributions.*

Confirmation and Continuance Contribution

Machine-mediated voting provides feedback about outcomes. Voters are more likely to continue contributing if voting outcomes align with their preferences. If they perceive that their experience with a decentralized governance model aligns with and confirms their initial expectations, they will experience *positive confirmation;* if not, they will experience *negative disconfirmation* (Bhattacherjee, 2001).

If voting outcomes are disappointing, highly expectant consumers will feel that their contributions have yielded low returns and are likely to cease contributing. In contrast, consumers who have more modest expectations may be more resilient toward undesired outcomes.

Hypothesis 3a: *High-expectation consumers, compared to low-expectation consumers, are* *less (more) likely to increase continuance contributions when they receive undesired (desired) outcomes.*

Procedural fairness may mitigate negative effects of undesired outcomes. Outcomes might be contrary to their preferences, but participants may maintain contributions if the procedure appears fair (Kim et al., 2019). Moreover, the sunk cost perspective argues that large voters increase continuance contributions to justify previous input. Thus, undesired outcomes may strengthen continuance contributions more, hypothesized as.

Hypothesis 3b: *High-expectation consumers, compared to low-expectation consumers, are more (less) likely to increase continuance contributions when they receive undesired (desired) outcomes.*

Figure 3 shows our theoretical framework. First, we examined the relationship between consumer voice and continuance contribution. Then, we tested whether expectation and experience moderate the relationship.

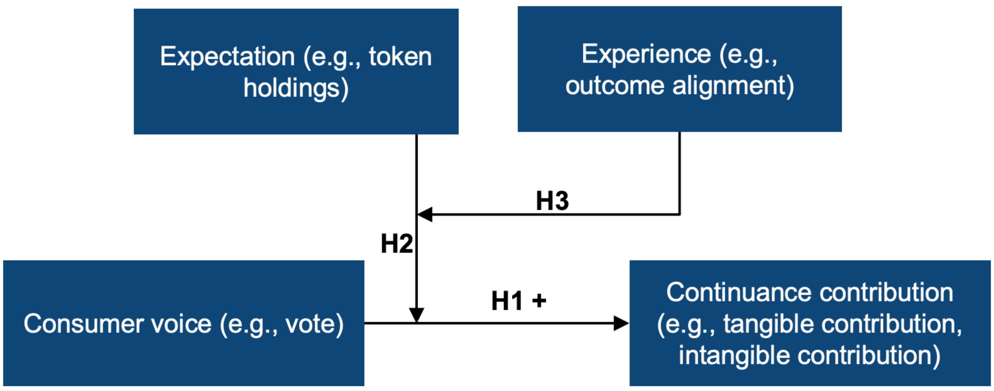
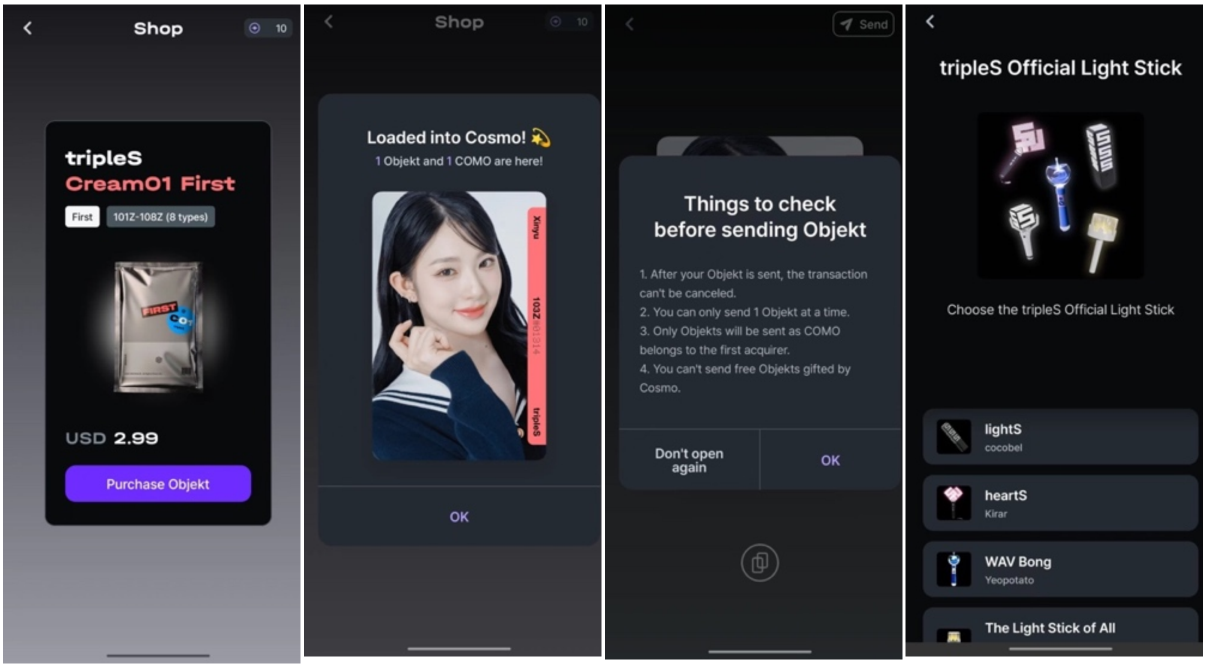


Figure 3. Research Model with Hypotheses

EMPIRICAL DATA AND DESCRIPTION ANALYSIS

TripleS, a South Korean K-pop girl group, lets fans actively participate in making important decisions about performance guidelines (Figure 4). For example, fans can vote to form a subunit that includes their favorite members or decide whether the next song should be bright and energetic or dark and intense. The group earns money by selling NFT photocards and albums. NFTs are unique digital items stored on a blockchain (Tunc et al., 2024). Fans can buy the cards for $3 online ($3.50 in stores) or earn them by showing their loyalty through daily check-ins. By January 2025, TripleS had sold over 4,200,000 NFT cards.[iv] Blockchain technology, specifically the Polygon network, ensures that all transactions and voting actions are securely recorded and tamper-proof.[v] TripleS uses a commit-reveal scheme:[vi] voting results are disclosed only after the voting period ends, ensuring that consumers express their true preferences before anyone knows the results (Guo et al., 2024).



(a) Card Purchase (b) Card Feature (c) Card Transfer (d) Vote

Figure 4. Empirical Setting

Each NFT card comes with governance tokens, which are like digital voting tickets fans can use to vote their preferences for subunit performances or K-pop songs (Figure 5). NFT cards and governance tokens are separate. NFT cards are collectible, transferrable, and exchangeable, but only first owners of NFT cards can use governance tokens. The more NFT cards a fan collects, the more governance tokens and associated voting power they acquire. Each token is used only once, and NFT card traits, such as design or rarity, are randomly assigned. (Appendix A shows a randomization check.) Voting rights carry no financial value because governance tokens cannot be traded.

TripleS is decentralized but partially autonomous. That is, fans have a major role in decisions but cannot fully control the group. Instead, the company creates voting options, such as song concepts or group formations. However, the firm is motivated to maintain the fan base by implementing the voting results.

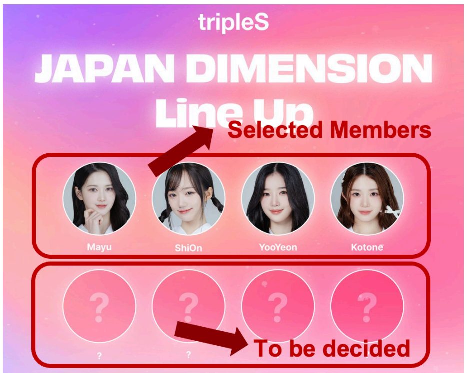


Figure 5 Product Voting Example

We collected on-chain data from PolygonScan[vii] and off-chain data from NFTScan[viii] from August 1, 2022, to February 1, 2024. The on-chain data are from three governance token contracts and one NFT contract. They include records about minting, about transferring NFTs and governance tokens, and about revealing and finalizing voting results. Off-chain data include randomly generated NFT attributes such as images, classes, members, and colors. The final dataset included 100,248 consumers and 32 voting rounds, covering both voting and nonvoting periods. We selected 15 days before and after voting periods as our sample period because the average nonvoting period lasted for 15 days in our sample period (18 months x 30 days / 32 - 1 = 15 days). We also used 10 days as robustness checks.

Arguably, the cards held in each voting round might influence voting decisions. To mitigate such concerns, we used the inventory balance data for propensity score matching (PSM). (Appendix A shows a balance check.) We generated inventory balance data using complete historical records, starting from the creation of the user profile up to the final date included in our data sample. Participants typically base their votes on their past experiences in the communities, allowing us to build comparable groups based on their past experience.

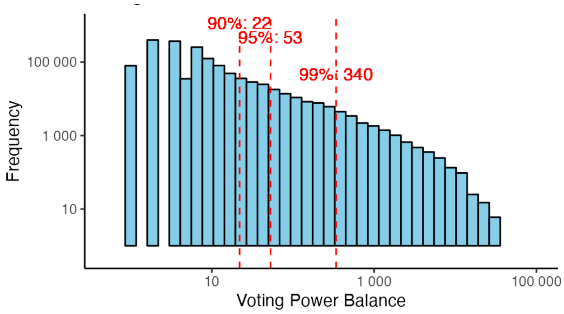
We used matching to identify pairs sharing similar card holdings. The final sample included 41,158 subjects. Table 3 presents summary statistics of matched data with 1,079,563 observations. Those *First* variables are null for control groups, leaving 592,587 observations.

Table 3. Statistics Summary

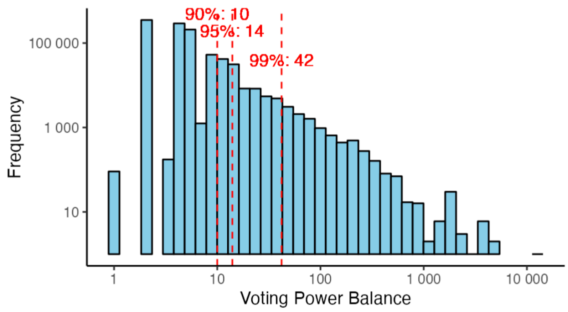
Variable	Description	N	Mean	Std	Min	Max
#Purchase	daily number of purchases	1,079,563	0.054	1.1	0	224
#Transfer	daily number of transfers	1,079,563	0.056	1.1	0	233
First vote	binary variable set to 1 after the first vote	1,079,563	0.27	0.44	0	1
First outcome alignment	binary variable set to 1 if the vote aligns with choice	592,587	0.3	0.46	0	1
First poll inequality	% of votes contributed by top 10 voters in the first voting round.	592,587	0.2	0.074	0.09	0.52
First vote time	% of time elapsed during the first vote	592,587	24	29	0.0027	100
Pre-voting balance	voting power balance one day before the voting	1,079,547	13	104	0	17215

We measured fans' tangible and intangible contributions. By purchasing cards, fans provide tangible financial support for the band and acquire voting power. Transferring cards requires finding partners, which indicates time-consuming involvement. PolygonScan's on-chain transaction data allowed us to track the exact time (in seconds) each consumer first voted. The independent variable*, FirstVote*, was operationalized as a binary indicator representing whether a consumer voted for the first time. We focused on the first vote because it represents the time that the platforms adopted decentralized governance.

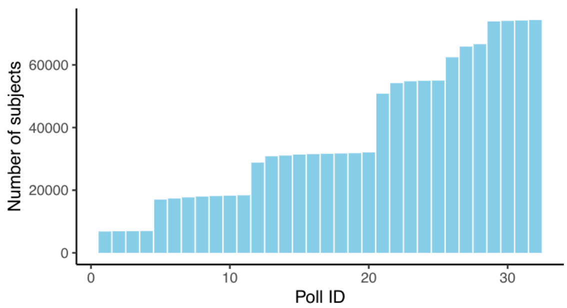
Although fans have accumulated significant voting power, over 60% never vote (Figure 6c), indicating a critical need for incentive mechanisms designed to engage "never voters," leveraged as the control group in our alter analysis. Figure 6a shows voting power balances, calculated for each round to differentiate between large and small voters. Voters are categorized as large if their voting rights exceed the 90th percentile, making them a minority block. Figure 6d further reveals that nonvoters tend to concentrate their activity in the first and last minutes of the voting period, often generating substantial voting power.



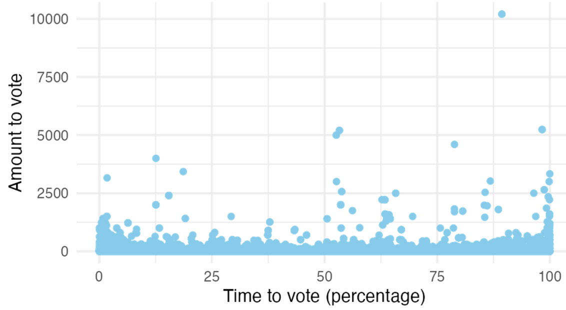
(a) Voting power for all consumers



(b) Voting power for never voters



(c) Number of never-voters over polls



(d) Time to vote and amount of votes

Figure 6. Descriptive Analysis

IDENTIFICATION STRATEGIES AND RESULTS

Model-Free Evidence

To understand how voting power is distributed on the platform over time, we first examined the Herfindahl–Hirschman Index (HHI), a standard measure of concentration. A higher HHI indicates that voting power is concentrated among fewer consumers, while a lower HHI suggests a more even distribution. Figure 7 shows how HHI decreases, indicating that voting power is becoming more evenly distributed.

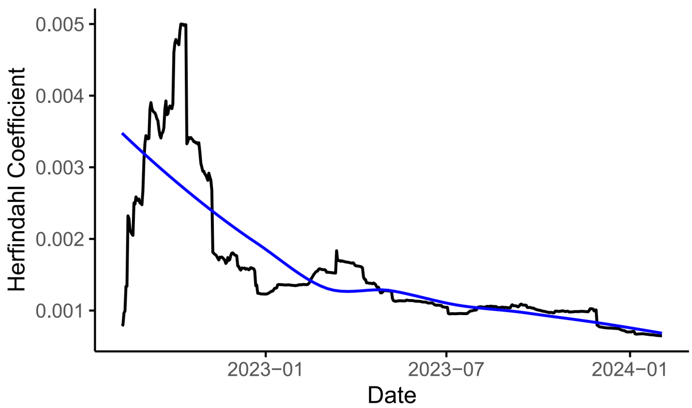
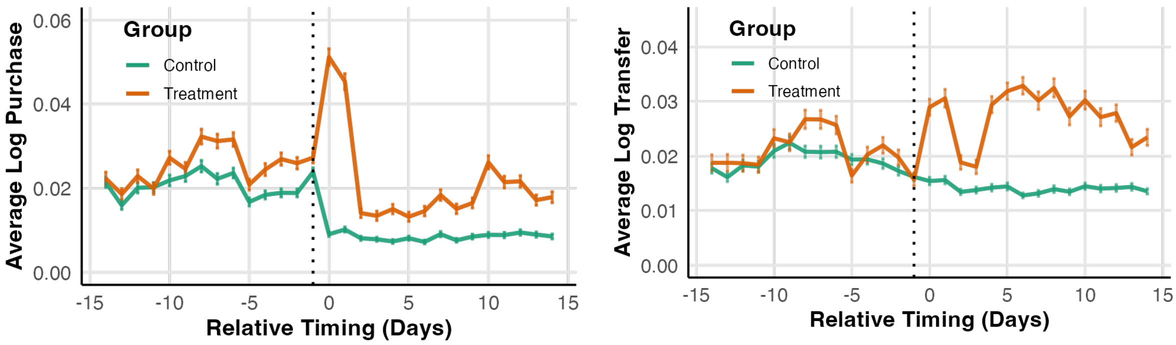


Figure 7. Concentration of Voting Rights Over Time

This finding is intriguing because small and minority voters often struggle to exert influence in decentralized systems, leading to disengagement over time and allowing a few influential consumers to dominate voting power (Ellinger et al., 2024). However, we show that the platform is becoming more inclusive as voting power is more evenly shared.

To better understand the factors driving this shift, we performed an individual-level analysis. Figure 8 presents the model-free evidence about how first votes affected continuance contribution, specifically focusing on tangible contributions (number of purchases) and intangible contributions (number of transfers). We considered a relative timeline of -15 to +15 days, with day 0 representing the first day after the first vote.



Number of Purchase **Number of Transfer**

Figure 8. Model-Free Evidence of the First Vote on Continuance Contribution

In both panels, the treatment group noticeably increased contributions immediately following the first vote. Increased contributions were more pronounced for transfers, which lack financial costs. Conversely, the control group remained relatively flat across the timeline. These visual trends suggest that first votes positively impacted both tangible and intangible contributions.

If small voters become more engaged after voting, they may collectively dilute the dominance of large voters and shrink concentration. For instance, if participation is empowering, small voters may increase contributions and broaden the base of active participants. Additionally, if large voters become disengaged, they might disdain decentralized governance models and reduce concentration. These potential mechanisms underscore the need to test how varying voting power and voting participation influences continuance contribution and how these effects contribute to the sustainability of decentralized governance systems.

Stacked Difference-in-Differences (DID)

To establish causal relationships, we used stacked DID with voting-round two-way fixed effects as our identification strategy. The traditional two-way fixed effects model assumes treatment effect homogeneity (Sun & Abraham, 2021) and can introduce biases when this assumption is violated. The stacked DID approach avoids these pitfalls by structuring the analysis into multiple two-period DID models. Each model isolates treatment effects for different groups, ensuring that later adopters are not used as controls for earlier adopters, thereby reducing contamination and conflation of treatment effects (Geiping et al., 2022).

We explain stacked DID in Figure 9. Treatment group 1 consisted of consumers who first voted during round 1. Control group 1 abstained in the first round and then transitioned into treatment group 2 in subsequent rounds (e.g., voting round 2, 3, 4). Control group 2, comprising consumers who never voted, served as a consistent baseline across all rounds. We used data within a relative timeline of -15 to +15 days, where day 0 represented the first day after the first vote. To mitigate potential bias, we excluded post-voting period observations that overlapped with the next voting period.

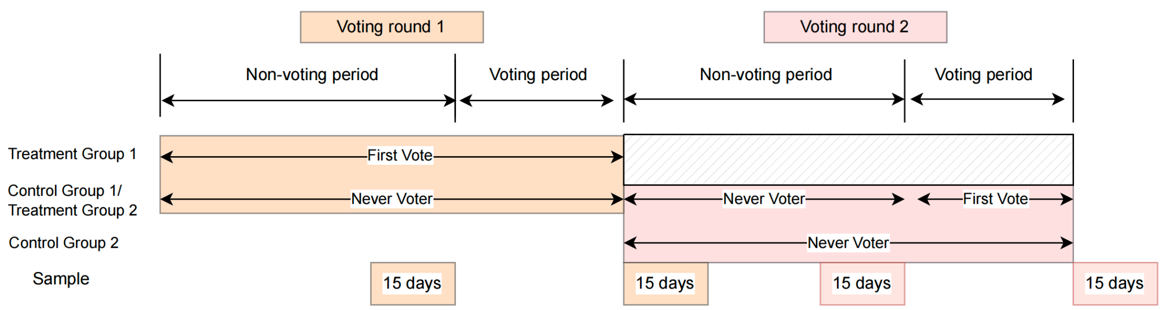


Figure 9. Stacked Difference in Differences (DID)

To enhance the precision of our estimates, we captured systematic differences tied to individual and temporal characteristics within each voting round by including voting-round consumer and voting-round time fixed effect. Our method disentangled the causal effects of first-time voting from other confounding influences for a reliable interpretation of user behavior dynamics after first vote. Our stacked DID model for the analysis is:

$$Y_{ikt} = \beta_0 + \beta_1 First\ Vote_{ik} + \gamma_{ik} + \delta_{tk} + \varepsilon_{itk}$$

where Y_{ikt} indicates the continuance contributions of user *i* in day *t* within the subsample of voting round k, including both tangible and intangible contributions. Voting-round consumer fixed effect γ_{ik} and voting-round time fixed effect δ_{tk} are included. Our two-way fixed effects allowed us to control the time-invariant or user-invariant confounders. $FirstVote_{ik}$ indicates whether individual i first voted in round k.

Table 4 presents the estimation results. The first vote led to a 1% increase in the number of purchases (column 1) and a 1.4% increase in the number of transfers (column 2), supporting hypothesis 1. The effect indicates that consumers contributed continually after they experienced the decentralized consumer voice model.

Table 4. Effect of Consumer Voice on Purchases and Transfer

	(1)	(2)
Outcome variables	Log(#Purchase)	Log(#Transfer)
First vote	0.010***	0.014***
	(0.001)	(0.001)
Observations	1,087,094	1,087,094
subject	41,158	41,158
R^2	0.158	0.299
Poll × subject fixed effects	Yes	Yes
Poll × date fixed effects	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$.

Primary Tests for Endogeneity Concerns

In our setting, voting was an endogenous decision. Thus, we were particularly concerned that the issue may have biased our causal estimation and conducted further analyses.

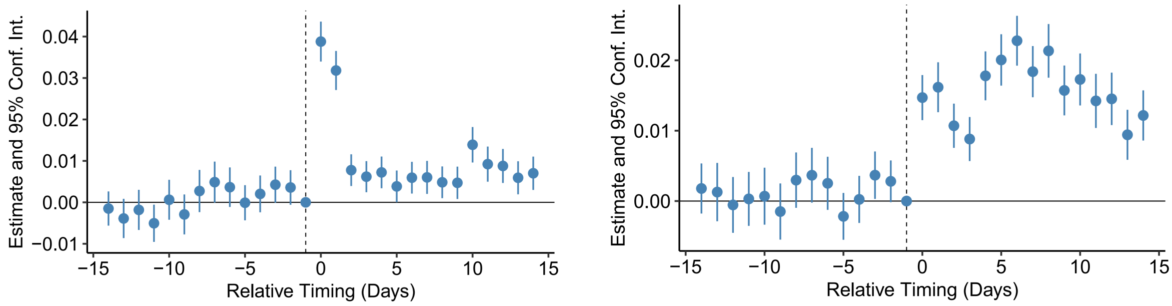
Event Study Figure

DID designs adhere to the parallel trend assumption that treatment and control groups should show similar trends before voice opportunities. To test the assumption, we estimated an event-study version of the stacked DID model with indicators for distance to/from the adoption of the decentralized governance model (first vote). Our regression model is:

$$Y_{ikt} = \beta_0 + \beta_k \sum_{k=-15}^{14} D_{k(it)} + \gamma_{ik} + \delta_{tk} + \varepsilon_{itk}$$

where Y_{ikt} indicates the continuance contributions of user i in day t within subsample data of voting round t, including both tangible and intangible contributions. Voting-round consumer fixed effect γ_{ik} and voting-round time fixed effect δ_{tk} are included. $D_{k(it)}$ is a set of indicator variables that take value one if, for individual user i in day t, the voting adoption was k days away. We used -1 period as the benchmark period and normalized the coefficient to 0.

Figure 10 shows the graphic results. Before voting, both groups had stable and parallel trends, supporting the parallel trend assumption. In addition, we used instrumental variable estimation approach to further solve endogeneity concerns.



(a) Number of purchases (b) Number of transfers

Figure 10. Relative Timing Model

Instrumental Variable (IV) Approach

To account for the endogeneity of first voting, we used IV estimation approach (Bharadwaj et al., 2007). A valid IV must be correlated with the endogenous variable but should not directly influence the dependent variable (Wooldridge, 2012). Drawing from Todri (2022), we constructed an IV based on peer effects: the percentage of connections who voted. Previous transfer interactions indicate connections between consumers. A higher percentage of voting connections influenced individual voting decisions but did not directly affect individual continuance contributions. Figure 11 shows model-free evidence about the IV validity. As voting connections increased, nonvoters decreased, while more local connections voted. Our two-stage model is:

$$FirstVote_{ik} = \beta_0 + \beta_1 FriendAdoptionPercentage_{ik} + \delta_{tk} + \varepsilon_{it}$$

$$Y_{ikt} = \beta_0 + \beta_1 First\ Vote_{ik} + \delta_{tk} + \varepsilon_{itk}$$

where Y_{ikt} indicates the continuance contributions of user *i* in day *t* within subsample data of voting round *t*, including both tangible and intangible contributions. Voting-round time fixed effect δ_{tk} are included. $FriendAdoptionPercentage_{ik}$ represents the percentage of connections who voted in the same voting round.

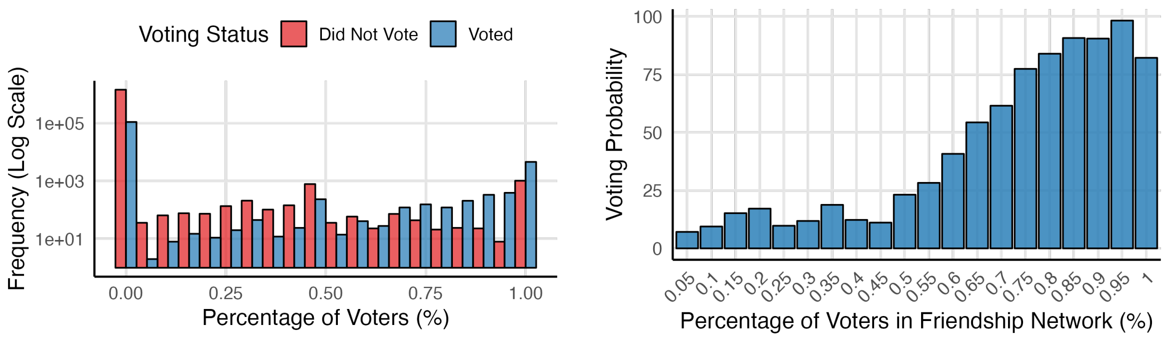


Figure 11. Percentage of Connections Who Voted and Voting Frequencies

Table 5 shows the estimation results. F-statistic for the first-stage regression was 420.187, far exceeding the conventional threshold of 10 (Staiger & Stock, 1994), indicating that our instrument is strongly correlated with the likelihood of treatment, thereby passing the weak identification test. The estimation results were consistent with our baseline results. First vote significantly increased the number of purchases (column 2) and transfers (column 4). The IV results further ensured that results were robust.

Table 5. IV Estimation Results				
Model	(1)		(2)	
Stage	1	2	1	2
Outcome variables	Treatment	Log(#Purchase)	Treatment	Log(#Transfer)
Friend Adoption Percentage	0.243***		0.243***	
	(0.017)		(0.017)	
First vote		0.243***		0.551***
		(0.024)		(0.043)
Observations	1,087,007	1,087,007	1,087,007	1,087,007
Dependent variable mean	0.270	0.016	0.270	0.015
F-test	420.187	16.061	420.187	36.017
Poll × date fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Heterogenous Effects

We assessed the heterogenous effects of consumer voice depending on the voting balance (large or small voters) and outcome alignment (desired or undesired outcome). To control potential confounders related to voting-round characteristics, or specific days, we used the two-way fixed effects. Our stacked DID model is:

$$Y_{ikt} = \beta_0 + \beta_1 First\ Vote_{ik} \times \mathrm{I}(PreVotingBalance > 90\%\ Quantile)_{i,k} + \gamma_{ik} + \delta_{tk} + \varepsilon_{itk}$$

where Y_{ikt} is the continuance contributions of user i in day t of voting round k, including both tangible and intangible contributions. $I(PreVotingBalance > 90\%\ Quantile)_{i,k}$ equals one if the voting right balance is larger than 90% of quantile of voting right distributions. Voting-round individual fixed effect γ_{ik} and voting-round time fixed effect δ_{tk} are included.

Table 6 presents the estimation results. The interaction term showed that consumers with high voting power exhibit a 1% lower effect size per day in purchases after their first vote (column 1), which aligns with EDT suggestions that higher expectations are harder to meet, potentially reducing tangible activities. However, effects on transfers are not significantly different between high- and low-voting-power consumers (column 2), indicating that EDT may have boundary conditions. Thus, hypothesis 2a is partially supported for tangible but not intangible contributions, indicating the effectiveness of EDT for tangible contributions.

Table 6. Effect with Different Balance		
	(1)	(2)
Outcome variables	Log(#Purchase)	Log(#Transfer)
First vote × I(pre-voting balance > 90% quantile)	-0.010*	0.001
	(0.004)	(0.005)
First vote	0.012***	0.014***
	(0.001)	(0.001)
Observations	1,087,094	1,087,094
Subject	41,158	41,158
R^2	0.158	0.299
Poll × subject fixed effects	Yes	Yes
Poll × date fixed effects	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

According to EDT, met expectation result in positive confirmation, while unmet expectations result in negative disconfirmation. Following undesired (desired) voting outcomes, high-expectation consumers are likely to reduce (increase) contributions. In contrast, consumers who have low expectations are more resilient to the negative effects of undesired outcomes and less excited to the positive effects of desired outcomes. To understand the heterogenous effects based on outcome alignment, we conducted a subsample analysis.

Table 7 reports the estimation results. Columns 1 and 2 show that small and large voters responded similarly when they desired the outcomes of their first votes. Such results show that desired outcomes do not provide additional incentives for large voters to maintain their influences. Thus, both hypothesis 3a and 3b are not supported when the voting outcomes are desired. Interestingly, when large voters receive undesired outcomes, column 3 shows that their made fewer purchases. However, column 4 shows that they maintained indifferent transfer activity, potentially because intangible contributions, are primarily driven by intrinsic motivations and less tied to material returns. Thus, tangible contributions are more sensitive to expectation disconfirmation, while intangible contributions remain relatively stable, suggesting that platforms should carefully manage user expectations to sustain contributions, especially among high-stake contributors. Thus, hypothesis 3a is partially supported for tangible but not intangible contributions and for desired outcomes but not undesired outcomes.

Table 7. Effect with Different Balance and Realized Outcomes

First vote outcome	Desired		Undesired	
	(1)	(2)	(3)	(4)
Outcome variables	Log(#Purchase)	Log(#Transfer)	Log(#Purchase)	Log(#Transfer)
First vote × I(pre-voting balance > 90% quantile)	0.006	0.007	-0.017***	-0.002
	(0.007)	(0.009)	(0.005)	(0.006)
First vote	0.012***	0.012***	0.012***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	325,771	325,771	761,323	761,323
Subject	12,384	12,384	28,774	28,774
R^2	0.166	0.312	0.155	0.294
Poll × subject fixed effects	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

ANALYSES OF UNDERLYING MECHANISMS

To understand the underlying mechanisms, we conducted additional analyses, summarized in Table 8. To further verify using EDT, we used moderators indicating first voters' different expectations or experiences and provided indirect evidence that expectation disconfirmation affects tangible but not intangible contributions, with wide implications in various scenarios.

Table 8. Summary of Analyses of Underlying Mechanisms

Question	Analysis	Result	Location
Does inequality affect sustained voter contribution?	DID with varying inequality levels	Large (small) voters decrease (increase) monetary contributions when voting rounds are highly unequal and yield undesired outcomes.	Table 9
Do choice sets matter?	DID with different choice sets	Large (small) voters decrease (increase) monetary contribution when they receive undesired outcomes in choice sets with members.	Table 10
Does early or late voting affect voter types differently?	DID with different voting times	Large (small) voters decrease (increase) monetary contributions when they vote early and receive undesired outcomes.	Table 11
What factors drive voting decisions?	Logistic regression of voting with consumer activities	Acquiring voting rights through any channel increases the likelihood of voting, though the effect varies based on the balance of voting frequency.	Table 12

Within decentralized voting systems, voting power inequality is a structural factor reflecting the distribution of influence. In high-inequality rounds, large voters who have a greater share of voting power may perceive that the concentration of voting power has reduced their ability to secure favorable outcomes. We examined whether the misalignment between their voting power and preferred outcomes will cause them to perceive a loss of marginal utility and reduce contributions.

Table 9 shows that large voters are less likely than small voters to increase tangible contributions when they receive undesired outcomes in relatively high-inequality poll rounds (column 2) but not in low-inequality poll rounds (column 4). When they receive desired outcomes, large and small voters react similar (column 1 and column 3). The result suggests that when voting power is distributed unevenly, large voters may perceive that the system fails to translate their voting power into favorable outcomes because of perceived unfairness, thereby dampening incentives to make further tangible contributions.

Table 9. Effect with Different First Poll Inequality

First poll inequality	High		Low		High		Low	
First outcome alignment	Desired	Undesired	Desired	Undesired	Desired	Undesired	Desired	Undesired
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome variables	Log(#Purchase)				Log(#Transfer)			
First vote × I(pre-voting balance > 90% quantile)	-0.004	-0.017**	0.013	0.003	0.013	0.003	0.002	-0.008
	(0.013)	(0.006)	(0.017)	(0.007)	(0.017)	(0.007)	(0.010)	(0.008)
First vote	0.006***	0.009***	0.016***	0.013***	0.016***	0.013***	0.010***	0.017***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
Observations	99,202	434,007	99,202	434,007	99,202	434,007	226,425	327,074
Subject	3,742	16,438	3,742	16,438	3,742	16,438	8,636	12,326
R^2	0.167	0.130	0.266	0.259	0.266	0.259	0.319	0.325
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

For intangible contributions, shown in columns (5) to (8), large and small voters react similarly to undesired outcomes and high inequality (column 6). Both tend to increase intangible contributions despite unequal results or undesired outcomes. The findings contrast with columns (1) to (4), where inequality and undesired outcomes cause large voters to be less willing to contribute financially. Thus, intangible contributions are less sensitive than tangible contributions to inequality and unfavorable outcomes.

Second, we assessed whether choice sets influences the disconfirmation effect. Specifically, we distinguish between highly personal polls in which voters select TripleS members versus impersonal polls in which voters select styles or other options. Member-related polls can foster strong emotional connections, loyalty, and deep personal investment in outcomes. The polls tend to be associated with heightened expectations, so undesired outcomes will evoke greater dissatisfaction and disparate reactions. Figure 12 shows that member-related polls tend to have greater inequality of voting power: large voters have elevated expectations and are motivated to increase their use of governance rights.

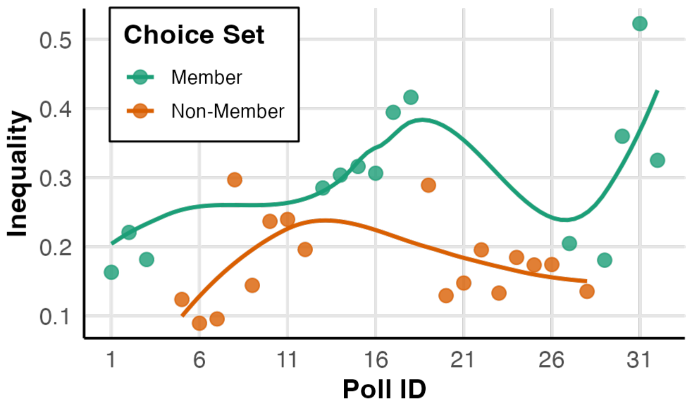


Figure 12. The Relationship Between Inequality and Choice Sets

Table 10 shows that large voters are less likely than small voters to increase monetary contributions when they receive undesired outcomes in member-related poll rounds (column 2), but not in non-member-related poll rounds (column 4), suggesting that large voters are more sensitive to unmet expectations when they have higher personal stakes in outcomes.

However, personal stakes and expectations are lower in non-member-related polls, reducing disconfirmation effect to undesired outcomes. Columns (5) to (8) show similar attitudes among large and small voters when the dependent variable relates to intangible contributions. Transfers increase even when choice sets include members or when outcomes are undesired. Thus, intrinsic motivations drive intangible contributions such as commitment to the process or habitual participation.

Table 10. Effect with Different Choice Sets

Poll Type	Member		Non-Member		Member		Non-member	
First outcome alignment	Desired	Undesired	Desired	Undesired	Desired	Undesire d	Desired	Undesired
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome variables	Log(#Purchase)					Log(#Transfer)		
First vote × I(pre-voting balance > 90% quantile)	-.001	-.028***	.009	-.010	-.014	-.017	.017	.008
	(0.012)	(0.008)	(0.008)	(0.006)	(0.013)	(0.009)	(0.011)	(0.007)
First vote	.013***	.012***	.011***	.011***	.011***	.011***	.012***	.018***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)
Obs.	103,792	310,819	221,979	450,504	103,792	310,819	221,979	450,504
Subject	3,854	11,894	8,530	16,880	3,854	11,894	8,530	16,880
R^2	0.167	0.167	0.165	0.146	0.280	0.275	0.322	0.310
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Third, we analyzed how voting time influences the impacts of undesired outcomes. Early voters tend to have high expectations and attention to the voting event. Large voters already have higher stakes in decision-making processes, but those who vote early have the stronger expectations, experience amplified disappointment if outcomes are undesired, and are less likely than small voters to increase monetary contributions. In contrast, late voters have lower expectations or less emotional investment, so undesired outcomes will have less impact. We differentiated between early and late voters by observing the middle timing of each voting round.

Table 11 shows that large voters who receive undesired outcomes and vote early are less likely than small voters to increase monetary contributions (column 2), but not large, late voters (column 4). Both large and small voters respond similarly to desired outcomes regardless of voting time (columns 1 and 3). Similarly, columns (5) to (8) show that when the dependent variable relates to intangible contributions, large and small voters both tend to increase transfers whatever the outcomes or time of voting.

Table 11. Effect with Different Vote Timing

First vote time	Early		Later		Early		Later	
First outcome alignment	Desired	Undesired	Desired	Undesired	Desired	Undesired	Desired	Undesired
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome variables	Log(#Purchase)				Log(#Transfer)			
First vote × I(pre-voting balance > 90% quantile)	.006	-.020***	.005	-.007	.004	-.001	.015	-.004
	(0.008)	(0.005)	(0.012)	(0.008)	(0.011)	(0.006)	(0.013)	(0.010)
First vote	.013***	.012***	.009***	.010***	.013***	.015***	.008*	.014***
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.002)
Observations	237,921	574,642	87,850	186,681	237,921	574,642	87,850	186,681
Subject	9,062	21,854	3,322	6,920	9,062	21,854	3,322	6,920
R^2	0.165	0.155	0.177	0.159	0.325	0.300	0.281	0.271
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$.

We analyzed the individual-specific factors that influence endogenous voting decisions. Variables representing diverse pathways through which consumers interact with the system included online and offline purchases, loyalty programs, and transfers. Within the system, (1) voting rights obtained through loyalty programs are nontransferable, and (2) voting rights obtained through offline channels have card numbers starting with "A." To further explore voter size influence, we included interaction terms with pre-voting balance, which separates large and small voters. We accounted for historical voting participation and included consumers who participated in multiple voting rounds:

$$I(Vote_{ik}) = \beta_0 + \beta_1 OnlinePurchase_{ik-1} + \beta_2 OfflinePurchase_{ik-1} + \beta_3 LoyaltyProgram_{ik-1} + \beta_4 Transfer_{ik-1} + \beta_5\, I(PreVotingBalance > 90\%\, Quantile)_{i,k} + \beta_6 OnlinePurchase_{ik-1} \times I(PreVotingBalance > 90\%\, Quantile)_{i,k} + \beta_7 OfflinePurchase_{ik-1} \times I(PreVotingBalance > 90\%\, Quantile)_{i,k} + \beta_8 LoyaltyProgram_{ik-1} \times I(PreVotingBalance > 90\%\, Quantile)_{i,k} + \beta_9 Transfer_{ik-1} \times I(PreVotingBalance > 90\%\, Quantile)_{i,k} + \beta_{10} I(Vote_{ik-1}) + \varepsilon_{ik}$$

where $I(Vote_{ik})$ equals 1 if individual i voted in round k. The interaction included online channel $OnlinePurchase_{ik-1}$, offline channel $OfflinePurchase_{ik-1}$, loyalty program $LoyaltyProgram_{ik-1}$. We also included the interaction term $I(PreVotingBalance > 90\%\, Quantile)_{i,k}$ to distinguish large voters and small voters.

Table 12 shows the estimation results. Although voting rights acquired through any channel increases voting likelihood, the extent depends on a voter's former balance. Large rather than small voters are more likely to participate, but responsiveness varies by channel. The loyalty program channel has more influence than online and offline purchase channels in influencing voting probability, but the effects are greater for large rather than small voters. Overall, the results highlight the importance of tailoring strategies to encourage voter engagement based on consumer characteristics and the mechanisms through which they acquire voting rights.

Table 12. The Factors Influencing Voting Decisions

	(1)	(2)
Outcome Variables	$I(vote_{i,k}>0)$	
$\#OnlinePurchase_{i,k-1}$	0.532***	0.966***
	(0.015)	(0.025)
$\#OfflinePurchase_{i,k-1}$	0.119***	0.020
	(0.015)	(0.038)
$\#LoyaltyProgram_{i,k-1}$	4.189***	4.254***
	(0.036)	(0.036)
$I(vote_{i,k-1} > 0)$	0.065**	0.316***
	(0.022)	(0.058)
$\#Transfer_{,k-1}$	0.920***	0.863***
	(0.015)	(0.014)
I(pre-voting balance > 90% quantile)	1.421***	1.570***
	(0.028)	(0.029)

$\#OnlinePurchase_{i,k-1} \times I$(pre-voting balance > 90% quantile)		-0.483***
		(0.027)
$\#OfflinePurchase_{i,k-1} \times I$(pre-voting balance > 90% quantile)		0.185***
		(0.036)
$\#LoyaltyProgram_{i,k-1} \times I$(pre-voting balance > 90% quantile)		-2.779***
		(0.089)
# Transfer $_{,k-1} \times I$(pre-voting balance > 90% quantile)		-0.262***
		(0.061)
Observations	605,226	605,226
#Subject	32,070	32,070
Subject fixed effects	Yes	Yes
Poll fixed effects	Yes	Yes

Notes: Standard errors are clustered at the subject level and reported in parentheses. We include fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Robustness Checks

We summarize robustness checks in Table 13. First, to address the analysis period selection, we conducted DID analyses using different analysis periods and confirmed consistent results. Second, we tested the sensitivity of the balance threshold by applying different cutoff values, which yielded consistent results. Finally, we examined the robustness of results across multiple voting rounds and confirmed that the results remained consistent after two rounds. Notably, first votes had lasting impact on long-term engagement. In this section, we discuss the long-term effects. Additional results are provided in the online appendix.

Table 13. Summary of Robustness Checks

Issues	Test	Finding	Location
The control group may be incomparable to the treatment group.	Relative time model analyses	Pretreatment trends across the two groups have no significant differences.	Figure 10.
	Propensity score matching	Results are consistent after matching estimation.	Table 4.
	Instrumental variable estimation	Results are consistent after IV estimation.	Figure 11, Table 5
Period length is self-selected.	DID with different analysis periods	Results are consistent after using different analysis periods.	Online Appendix Table B5, B6, B7.
Balance threshold is self-selected.	DID with different balance threshold	Results are consistent after using several different thresholds.	Online Appendix Table B1, B2, B3, B4.
Results may fail after multiple voting rounds.	DID with consecutive voting rounds	Results are consistent after two voting rounds.	Table 14, 15, 16, 17.

In this section, we discuss the long-term impacts of consumer voice as it not only serves a robustness check but also can provide practical implications on motivating users dynamically. To examine the long-term effects, we continue using the stacked DID strategy but modify the sampling method. Instead of defining the post-treatment period as 15 days after the first voting round, we redefine it as 15 days after the second voting round. We then compare the differences between the pre- and post-treatment periods for both the treatment and control groups. A visual representation of this approach is provided in Figure 13. Since the final voting round does not include a second voting round, this analysis is based on data from only 31 voting rounds.

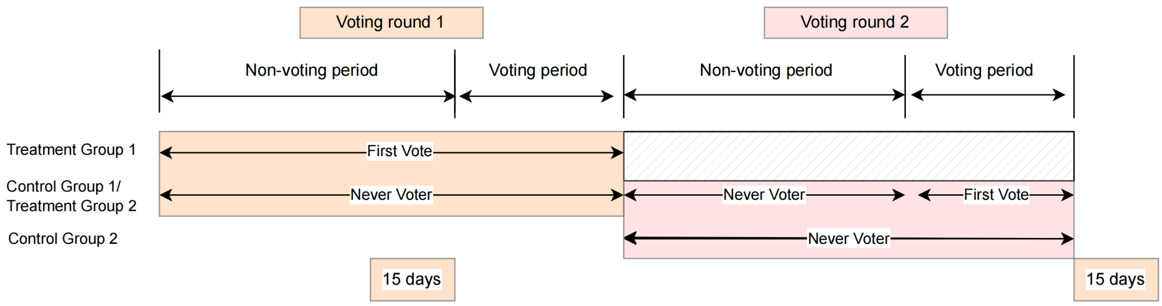


Figure 13. Data Selection for Second Vote

We begin by examining whether users who participated in the first voting round are more likely to participate in the second voting round. Table 14 shows that users who voted in the first round, regardless of being large or small voters, exhibit a higher likelihood of participating in the second round compared to those who did not vote in the first round (0.298, $p < 0.001$). Notably, those who receive desired outcomes have a relatively stronger effect size (0.348, $p < 0.001$) than those who receive undesired outcomes (0.240, $p < 0.001$).

Table 14. Effect of First Vote on Second Vote			
First Outcome Alignment	-	Desired	Undesired
	(1)	(2)	(3)
Outcome Variables	I(Second Vote)		
First Vote × I(Pre-Voting Balance > 90% Quantile)	-0.031	-0.116	-0.016
	(0.060)	(0.095)	(0.062)
First Vote	0.298***	0.302***	0.294***
	(0.003)	(0.006)	(0.004)
I(Pre-Voting Balance > 90% Quantile)	0.257***	0.348***	0.240***
	(0.060)	(0.094)	(0.062)
Observations	41,158	13,180	29,872
Matched Pair	20,579	6,590	14,936
Poll × Pair fixed effects	Yes	Yes	Yes

Notes: All are logistic regression models. Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll pair. *** p < 0.001, ** p < 0.005, * p < 0.01.

Next, we investigate how the alignment of outcomes in the first voting round affects voters' subsequent contributions after the second voting round. Our two-way fixed effect DID regression model is:

$$Y_{ikt} = \beta_1 I(First\ Vote)_{ik} \times I(PreVoting\ Balance > 90\%\ Quantile)_{ik} + \beta_2 I(First\ Vote)_{ik} + \beta_3 I(PreVoting\ Balance > 90\%\ Quantile)_{ik} + \gamma_{ik} + \delta_{tk} + \varepsilon_{ikt}$$

where Y_{ikt} is the continuance contributions of user *i* in day *t* of voting round *k*, including both tangible and intangible contributions. $I(PreVotingBalance > 90\%\ Quantile)_{i,k}$ equals one if the voting right balance is larger than 90% of quantile of voting right distributions. Voting-round individual fixed effect γ_{ik} and voting-round time fixed effect δ_{tk} are included.

Table 15 reveals that the alignment of voting outcomes in the first round significantly affects voters' continued contributions, especially for large voters. Large voters show a stronger negative response to undesired outcomes in the first round. The long-term effect (-0.032, $p < 0.001$) is nearly twice as large as the short-term effect (-0.017, $p < 0.001$), showing that dissatisfaction persists and grows over time. These results highlight the greater sensitivity of large voters to misaligned outcomes due to their higher stakes in decision-making. This provides clear evidence of the lasting impact of undesired outcomes, particularly for large voters.

Table 15. Long-Term Effect of First Vote with Different First Outcome Alignment				
Fist Vote Outcome Alignment	Desired		Undesired	
	(1)	(2)	(3)	(4)
Outcome Variables	Log(#Purchase)	Log(#Transfer)	Log(#Purchase)	Log(#Transfer)
First Vote × I(Pre-Voting Balance > 90% Quantile)	-0.023	-0.010	-0.032***	-0.009
	(0.009)	(0.012)	(0.006)	(0.008)
First Vote	0.013***	0.017***	0.012***	0.016***
	(0.001)	(0.002)	(0.001)	(0.001)
Observations	343,214	343,214	786,213	786,213
Subject	12,494	12,494	28,554	28,554
R^2	0.155	0.300	0.150	0.285
Poll × subject fixed effects	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Finally, we examine how outcome alignment in the first and second voting rounds affects voters' continued contributions. Table 16 shows that large voters who face undesired outcomes in both rounds experience a much stronger negative impact on their contributions compared to small voters (column (4), -0.061, p < 0.001). This supports EDT, as repeated misaligned outcomes increase dissatisfaction over time. However, a desired outcome in the second round reduces the negative effects of an earlier undesired outcome, showing the importance of recent experiences. On the other hand, voters who receive a desired outcome in the first round but an undesired one in the second round show significant dissatisfaction, emphasizing the greater influence of recent outcomes over past ones. For intangible contributions, such as transfers, columns (5)–(8) reveal no significant differences between large and small voters. This suggests the observed effects are mainly driven by tangible contributions, where stakes and financial implications are more pronounced.

These findings highlight the need to balance the preferences of different consumer groups to reduce dissatisfaction. Addressing the cumulative impact of undesired outcomes and considering the importance of recent experiences can help optimize voting systems and sustain participation.

Table 16. Long-Term Effect of First Vote with Different Consecutive Outcome Alignment								
Fist Vote Outcome Alignment	Desired		Undesired		Desired		Undesired	
Second Vote Outcome Alignment	Desired	Undesired	Desired	Undesired	Desired	Undesired	Desired	Undesired
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variables	Log(#Purchase)				Log(#Transfer)			
First Vote × I(Pre-Voting Balance > 90%Quantile)	-0.032	-0.039*	-0.023	-0.061***	-.047	-.024	.016	-.030
	(0.023)	(0.014)	(0.019)	(0.012)	(0.033)	(0.025)	(0.027)	(0.015)
First Vote	0.045***	0.024***	0.034***	0.024***	.039***	.038***	.037***	.033***
	(0.005)	(0.003)	(0.004)	(0.002)	(0.005)	(0.005)	(0.005)	(0.003)
Observations	52,628	64,110	72,390	189,539	52,628	64,110	72,390	189,539
Subject	1,860	2,306	2,576	6,754	1,860	2,306	2,576	6,754
R^2	0.164	0.194	0.197	0.159	0.328	0.328	0.345	0.318
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$.

CONCLUSION

Current centralized consumer voice models frequently exhibit selection bias, favoring certain voices while marginalizing others. This study examines how consumer voice in decentralized governance models influences continuance contributions, focusing on the mechanisms underlying the dynamics between small versus large voters and desired versus undesired outcomes. By analyzing data from the decentralized K-pop organization TripleS, where fans actively participate in decision-making via voting, the findings reveal that initial consumer voice positively impacts both tangible (financial) and intangible (social) contributions. However, the effects differ across voter groups—large voters reduce tangible contributions, particularly when faced with undesired outcomes, while their intangible contributions remain stable. Based on value co-creation theory and the expectation-confirmation model, the study highlights that decentralized systems motivate sustained contributions by granting equity, but unmet expectations, especially among large voters who have higher expectation, significantly dampen tangible contributions because of expectation disconfirmation. Additionally, we validated our findings by testing for robustness across different analysis periods, balance thresholds, and consecutive voting rounds, ensuring that the results remain consistent regardless of the chosen timeframes, thresholds for comparison, or longer-term effect.

Moreover, we analyzed factors that influence subsequent contributions. First, we found that when voting rounds are highly unequal and outcomes are undesired, large voters reduce tangible contributions. Second, choice sets have significant effects: large voters contribute less when choice sets related to group members yield undesired results. Third, large early voters are less likely to sustain monetary contributions if they receive undesired outcomes. We discuss the implications of our findings as follows.

Theoretical Implication

Our research has several theoretical implications. First, we contribute to the blockchain literature and extend the prior focus on financial applications by examining blockchain applications of user innovations (Chen et al., 2023; Chen et al., 2021; Han et al., 2023; Li et al., 2024). While Peña-Calvin et al. (2024) highlighted issues like voting power concentration in DAOs, we reveal that blockchain used for product development may show decreasing concentration over time by leveraging value-cocreation and expectation disconfirmation theories. Thus, we highlight the potential for blockchain to foster sustainable decision-making processes in product development.

Second, we contribute to the user innovation literature. By studying a blockchain-based model where consumers have decision-making authority over product development, we shift the literature's focus on centralized models (Grosz & Raval, 2024; Khern-am-nuai et al., 2018; Kim et al., 2019; Raval, 2020; Safadi et al., 2024). Specifically, our study looks at consumer voices, both antecedents and consequences, for effects on continuance contributions. Our findings suggest that the value-cocreation effect encourages small voters to contribute to decentralized models, while the expectation disconfirmation effect causes large voters to disengage from tangible but not from intangible contributions.

Finally, we build on value cocreation and expectation-confirmation theories and apply them to blockchain contexts (Brown et al., 2014; Ramírez, 1999). We find that unmet expectations have greater effects on tangible rather than intangible contributions: after large voters receive undesired outcomes, they reduce tangible contributions but maintain intangible contributions. Such finding shows the boundary condition of expectation disconfirmation theory, which works more effectively when continuance behaviors are tangible.

Practical Implication

Our findings provide valuable insights for designing sustainable blockchain systems that effectively balance user expectations with collective decision-making. Many industries currently rely on centralized crowdsourcing mechanisms, such as entertainment (football games: supporter of FC Barcelona (2018)[ix]), fashion (Nike's crowdsourced design campaign (2019)[x]), to engage consumers in product development. Firms grant consumers consultative roles and collect their input, but keep decision-making authority centralized within the firm. Centralized crowdsourcing is sometimes effective but it limits user participation and is biased in selecting voice. To address the limitations, firms can adopt more inclusive and participatory blockchain-enabled decentralized models. By granting decision-making authority and embedding consumer voices directly into governance processes, firms can foster deeper engagement and create sustainable ecosystems for value co-creation.

To sustain contributions, firms adopting this model should design incentive structures that balance voting rights among users. For instance, large voters could be rewarded with community recognition or exclusive benefits when final decisions do not align with their preferences. Additionally, firms could create tailored choice sets to better align outcomes with the preferences of different user groups, as subsequent desired outcomes have the potential to offset the negative effects of prior undesired outcomes.

For consumers, when they participate in traditional crowdsourcing models, they are often limited to consulting roles. Firms collect their input but they cannot directly influence outcomes, leading to frustration, disengagement, and feelings of being undervalued. Instead, blockchain-based decentralized governance systems allow direct consumer engagement and decision-making power. Realistically, however, collective decisions sometimes belie personal preferences. Consumers can sustain their motivation and ensure that their contributions remain impactful by participating in systems that offer alternative rewards such as community recognition or exclusive perks.

Policymakers, on the other hand, often focus on regulating centralized governance systems and fail to consider decentralized governance structures. We recommend that policymakers promote equitable participation by leveraging semi-decentralized governance models where governments still control proposals and executions. Such measures can help create sustainable and inclusive decentralized ecosystems while fostering innovative governance and value cocreation.

Generalizability

Although our setting is related to K-pop production, our findings have broader implications, particularly for culturally significant and creative industries like fashion and entertainment. Consumer contributions are examined in entertainment and leisure activities such as extreme sports (Franke & Shah, 2003), outdoor sports, juvenile products (Shah & Tripsas, 2007), and retail banking (Oliveira & von Hippel, 2011), but we focus on production and management of a K-pop group. Highlighting the principle of value co-creation, we show that decentralized models can foster deeper engagement in fields where user input and collaboration are essential. For example, the entertainment industry could use decentralized platforms allowing fans to directly vote on content creation, such as storylines or new projects, ensuring that creative outputs reflect diverse community preferences. Similarly, the fashion industry could use decentralized systems enabling consumers to codesign products or select collections, strengthening the sense of ownership and brand connection.

Second, by differentiating tangible from intangible contributions, we enhance understandings about user behavior in decentralized ecosystems. In creative industries, for example, consumers may prioritize intangible contributions like idea-sharing or community recognition over tangible investments like financial support, particularly when outcomes are uncertain. Thus, decentralized systems should design incentive structures tailored to the unique contributions of different user segments, ensuring that consumers value and sustain both tangible and intangible contributions.

Finally, we urge governance mechanisms to be adaptive. As consumers interact with decentralized systems over time, their expectations and behaviors may evolve, necessitating ongoing iterations to governance models to maintain user trust and engagement while addressing unique challenges of different domains. For instance, platforms could incorporate dynamic voting rights, reputation-based incentives, or hybrid governance structures that combine decentralized decision-making with expert oversight.

Limitation and Future Research

Our study has limitations that may inspire future studies. First, consumer voice is an endogenous decision rather than random treatment, although we adopt multiple methods to demonstrate robustness. Second, we need demographic data for more precise matching. Future research should leverage a comprehensive dataset that includes user demographics for a more expansive and granular analyses that identifies specific factors influencing continuance contributions post-voting.

Our findings bridge the gap between the consumer voice literature and the emerging domain of agentic governance structures and thus provide a foundation for extending the theory. Although we focus on decentralized governance for product development, future work could explore how similar models might operate in areas such as policy development or community resource management. Additionally, researchers could investigate how the model influences broader organizational dynamics such as team collaboration or innovation. By stimulating extended studies, we hope to inspire research that develops both theoretical and practical applications of blockchain as transformative governance structures.

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ONLINE APPENDIX A: DETAILS OF DATA AND ANALYSIS

Table A 1. Randomization Check for Card Issuance (Collection-Level)			
Season Edition	Collection	n	Percentage
Cream01 1	101Z	29572	12.49%
Cream01 1	102Z	29651	12.52%
Cream01 1	103Z	29489	12.46%
Cream01 1	104Z	29620	12.51%
Cream01 1	105Z	29380	12.41%
Cream01 1	106Z	29854	12.61%
Cream01 1	107Z	29624	12.51%
Cream01 1	108Z	29546	12.48%

Table A 2. Randomization Check for Card Issuance (Member-Level)				
Member ID	Season Edition	n	Percentage	Member Onboard Date
S1	Atom01 1	8968	13.87	1/5/2022
S2	Atom01 1	7929	12.26	17/5/2022
S3	Atom01 1	7394	11.44	1/6/2022
S4	Atom01 1	6264	9.69	22/6/2022
S5	Atom01 1	7921	12.25	11/7/2022
S6	Atom01 1	5586	8.64	8/8/2022
S7	Atom01 1	6636	10.26	22/8/2022
S8	Atom01 1	5786	8.95	9/9/2022
S9	Atom01 1	4988	7.71	9/11/2022
S10	Atom01 1	3187	4.93	3/12/2022

Table A 3. Balance Check After Matching						
	Control Group		Treatment Group		Diff. in Means	P value
Variable	Mean	Std. Dev.	Mean	Std. Dev.		
voting power balance	2.490	0.895	2.410	0.775	-0.079	0.243
S1	0.087	0.268	0.083	0.259	-0.004	0.860
S2	0.095	0.278	0.081	0.264	-0.014	0.512
S3	0.065	0.231	0.068	0.242	0.004	0.851
S4	0.077	0.246	0.086	0.264	0.009	0.657
S5	0.077	0.245	0.062	0.229	-0.015	0.422
S6	0.060	0.216	0.066	0.230	0.006	0.750
S7	0.092	0.268	0.078	0.256	-0.014	0.526
S8	0.065	0.237	0.069	0.246	0.004	0.834
S9	0.047	0.198	0.058	0.218	0.011	0.525
S10	0.056	0.213	0.069	0.243	0.013	0.470
S12	0.043	0.191	0.041	0.182	-0.002	0.875
S11	0.053	0.212	0.039	0.187	-0.014	0.381
S13	0.018	0.115	0.020	0.127	0.002	0.850

S14	0.022	0.121	0.028	0.151	0.007	0.553
S15	0.018	0.107	0.019	0.116	0.001	0.872
S16	0.050	0.200	0.056	0.215	0.006	0.719
S17	0.002	0.031	0.003	0.057	0.002	0.690
S18	0.000	0.000	0.000	0.000	0.000	X
S19	0.000	0.000	0.001	0.017	0.001	0.318
S20	0.005	0.063	0.003	0.057	-0.002	0.760
distance	0.013	0.026	0.013	0.025	0.000	0.975

ONLINE APPENDIX B: ROBUSTNESS CHECK AND ALTERNATIVE EXPLAINATION

Table B 1. Sensitivity Analysis (Undesired Outcome for Monetary Contribution)

Balance Cutpoint X	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variables	Log(#Purchase)							
First Vote × I(Pre-Voting Balance > X Quantile)	0.003.	0.002	0.000	-0.002	-0.004.	-0.006*	-0.007.	-0.017***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)
First Vote	0.007***	0.008***	0.009***	0.010***	0.011***	0.011***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	761,323	761,323	761,323	761,323	761,323	761,323	761,323	761,323
Subject	28,774	28,774	28,774	28,774	28,774	28,774	28,774	28,774
R2	0.155	0.155	0.155	0.155	0.155	0.155	0.155	0.155
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$.

Table B 2. Sensitivity Analysis (Desired Outcome for Monetary Contribution)

Balance Cutpoint X	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variables	Log(#Purchase)							
First Vote × I(Pre-Voting Balance > X Quantile)	0.017***	0.014***	0.012***	0.010***	0.007.	0.006	0.006	0.006
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.007)
First Vote	0.000	0.003	0.005***	0.007***	0.010***	0.011***	0.011***	0.012***
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	325,755	325,755	325,755	325,755	325,755	325,755	325,755	325,755
Subject	12,383	12,383	12,383	12,383	12,383	12,383	12,383	12,383
R2	0.166	0.166	0.166	0.166	0.166	0.166	0.166	0.166
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** $p < 0.001$, ** $p < 0.005$, * $p < 0.01$.

Table B 3. Sensitivity Analysis (Undesired Outcome for Social Engagement)								
Balance Cutpoint X	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variables	Log(#Transfer)							
First Vote × I(Pre-Voting Balance > X Quantile)	0.007***	0.005**	0.005*	0.005.	0.004	0.003	0.003	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.006)
First Vote	0.010***	0.011***	0.012***	0.012***	0.013***	0.014***	0.014***	0.015***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	761,323	761,323	761,323	761,323	761,323	761,323	761,323	761,323
Subject	28,774	28,774	28,774	28,774	28,774	28,774	28,774	28,774
R2	0.294	0.294	0.294	0.294	0.294	0.294	0.294	0.294
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Table B 4. Sensitivity Analysis (Desired Outcome for Social Engagement)								
Balance Cutpoint X	20%	30%	40%	50%	60%	70%	80%	90%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Outcome Variables	Log(#Transfer)							
First Vote × I(Pre-Voting Balance > X Quantile)	0.006*	0.006.	0.005	0.005	0.004	0.006	0.007	0.007
	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)	(0.004)	(0.006)	(0.009)
First Vote	0.008***	0.009***	0.010***	0.010***	0.011***	0.011***	0.011***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	325,755	325,755	325,755	325,755	325,755	325,755	325,755	325,755
Subject	12,383	12,383	12,383	12,383	12,383	12,383	12,383	12,383
R2	0.312	0.312	0.312	0.312	0.312	0.312	0.312	0.312
Poll × subject fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01

Table B 5. Effect of First Vote on Continuance Contribution (10-Day Period)		
	(1)	(2)
Outcome Variables	Log(#Purchase)	Log(#Transfer)
First Vote	0.010***	0.015***
	(0.001)	(0.001)
Observations	801,754	801,754
subject	41,158	41,158
R^2	0.174	0.329
Poll × subject fixed effects	Yes	Yes
Poll × date fixed effects	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Table B 6. Effect of First Vote with Different Balance (10-Day Period)		
	(1)	(2)
Outcome Variables	Log(#Purchase)	Log(#Transfer)
First Vote × I(Pre-Voting Balance > 90% Quantile)	-0.011*	-0.001
	(0.004)	(0.005)
First Vote	0.012***	0.015***
	(0.001)	(0.001)
Observations	801,754	801,754
Subject	41,158	41,158
R^2	0.174	0.329
Poll × subject fixed effects	Yes	Yes
Poll × date fixed effects	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

Table B 7. Effect of First Vote with Different Outcome Alignment (10-Day Period)				
First Outcome Alignment	Desired		Undesired	
	(1)	(2)	(3)	(4)
Outcome Variables	Log(#Purchase)	Log(#Transfer)	Log(#Purchase)	Log(#Transfer)
First Vote × I(Pre-Voting Balance > 90% Quantile)	0.007	0.008	-0.020***	-0.005
	(0.007)	(0.009)	(0.005)	(0.006)
First Vote	0.012***	0.013***	0.012***	0.016***
	(0.001)	(0.001)	(0.001)	(0.001)
Observations	239,929	239,929	561,825	561,825
Subject	12,384	12,384	28,774	28,774
R^2	0.176	0.344	0.175	0.323
Poll × subject fixed effects	Yes	Yes	Yes	Yes
Poll × date fixed effects	Yes	Yes	Yes	Yes

Notes: Standard errors are clustered at the subject level and are reported in parentheses. The analysis includes fixed effects for poll date and poll subject. *** p < 0.001, ** p < 0.005, * p < 0.01.

[i] Ben Dooley, and Su-Hyun Lee, "BTS's loyal army of fans is the secret weapon behind a $4 billion valuation," *The New York Times*. Link: https://www.nytimes.com/2020/10/14/business/bts-ipo.html

[ii] https://www.newyorker.com/culture/culture-desk/joining-the-bts-army

[iii] We can easily check the number of unique NFTs on NFTScan, which already has 4,290,420 NFTs minted and sold out. https://polygon.nftscan.com/0xA4B37bE40F7b231Ee9574c4b16b7DDb7EAcDC99B?module=NFTs

[iv] We can easily check the number of unique NFTs on NFTScan, which already has 4,290,420 NFTs minted and sold out. https://polygon.nftscan.com/0xA4B37bE40F7b231Ee9574c4b16b7DDb7EAcDC99B?module=NFTs

[v] Polygon Labs, https://polygon.technology/, is a blockchain platform designed to aggregate Web3 technologies and provide scalable solutions for decentralized applications (dApps). It creates a unified ecosystem that combines scalability, security, and interoperability to support the growth of blockchain-based systems. Polygon's mission is to enable an infinitely scalable web of sovereign blockchains, making a seamless and interconnected blockchain experience.

[vi] *Commitment scheme*. *Wikipedia*. Retrieved from https://en.wikipedia.org/wiki/Commitment_scheme. In a voting system using a commitment scheme: 1) During the commit phase, voters submit a cryptographic commitment to their vote (e.g., a hashed version of their choice combined with random data). This commitment is securely stored. 2) During the reveal phase, voters disclose their original vote along with the random data used in the commitment. The system verifies that the revealed vote matches the original commitment, ensuring both secrecy and integrity. Voters are more likely to express their true preferences, not influenced by others.

[vii] *Polygonscan*. Retrieved from https://polygonscan.com/. Polygonscan is a blockchain explorer specifically designed for the Polygon network. It enables users to view and verify blockchain transactions, smart contracts, token transfers, and other network activity in real time. By providing transparency and accountability, it fosters trust in decentralized systems like Polygon.

[viii] NFTScan, *t*he largest NFT data infrastructure, is a comprehensive multichain NFT explorer and data infrastructure platform, offering robust tools for Web3 developers, blockchain projects, and NFT users. It provides detailed insights into NFT collections, marketplaces, and financial trends, enabling data-driven decisions across ecosystems such as Ethereum, Polygon, and Solana. With features like the NFTScan API for accessing on-chain data, portfolio management tools for tracking multichain NFT assets, and analytics for market trends and rankings, NFTScan empowers users to manage and understand the NFT ecosystem. Retrieved from https://www.nftscan.com/

[ix] https://en.wikipedia.org/wiki/Supporters_of_FC_Barcelona

[x] https://www.complex.com/sneakers/a/riley-jones/nike-air-max-day-2018-on-air-sneaker-design-workshop