A Dynamic and Multilayered Examination of Comment Networks in a Crowdsourcing Challenge Community

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Abstract

This study examines how participants of crowdsourcing challenges (ideators) provide comments to one another under the dual community forces of collaboration and competition. Content analysis reveals comment types with various degrees of cooperativeness and self-interestedness. Based on comment-sending patterns, clustering analysis unveils ideators' different roles in the communities: endorsers, self-promoters, and contributors. Results of longitudinal network analysis on four layers of comment networks present nuanced interaction patterns such as reciprocity, inertia, and homophily. Results suggest that active contribution tends to receive fair returns from the community. Pairs of ideators tend to share reciprocated comments, regardless of the comment types. Therefore, to gain substantial information, ideators should take the initiative and contribute substantially to peer competitors. Moreover, ideators tend to maintain existing habits of comment-giving. Ideators with similar ideas share coopetitive relationships through both cooperative and self-interested comments.

Keywords: crowdsourcing challenge, social network dynamics, comments, network multiplexity, ideation

1. Introduction

Crowdsourcing challenges are gaining popularity and relevance because of the cost-effectiveness of leveraging crowd wisdom to solve challenging issues (Chen et al., 2021). Organizations often sponsor these challenges on third-party platforms like Kaggle, OpenIDEO, and Wazoku Crowd to crowdsource solutions on thorny issues.

Sun and Majchrzak (2020) categorized crowdsourcing challenges into three types: competitive, collaborative, and coopetitive. Collaborative challenges (e.g., Apache Firefox, Wikipedia) feature crowds of participants co-design and communicatively generate innovative outcomes (Javadi Khasraghi & Hirschheim, 2022). Competitive crowdsourcing challenges (e.g., TopCoder and Kaggle) are organized contests where only a few quality submissions win prizes (Lakhani et al., 2010). Coopetitive crowdsourcing challenges find a subtle balance between the boundary of collaborative and competitive innovation (Dissanayake et al., 2021). Challenge participants (hereafter referred to as *ideators*) compete for prizes but also exchange feedback and offer help to one another.

The dual competition and cooperation process further complicates the challenge participants' social dynamics. This research is motivated to understand *how ideators form social interactions through comments under the dual forces of collaboration and competition*. Ideators' comment patterns offer critical insights into the norms and logic of community organizing. A comprehensive inquiry of the question calls for simultaneous consideration of both social interdependencies and communication content, with a longitudinal perspective to accurately capture the community evolution. In summary, the overarching research question is: *what types of comments do ideators exchange, and how are comment networks structured and evolve over time?* Our findings provide insights into the subtle norms and organizing logic of coopetitive communities and strategies to navigate the ambiguous line between competition and cooperation. Suggestions for better knowledge innovation practices will be discussed in detail in the discussion section.

2. The Dual Forces of Collaboration and Competition

Collaboration and competition significantly impact knowledge generation (Terwiesch & Xu, 2008) and drive complex social dynamics in fostering creativity (Hutter et al., 2011). Coopetitive communities, where competition and cooperation coexist, harness these mixed logics to foster creative outcomes (Renard & Davis, 2019). Cooperative forces drive ideators to share meaningful information, knowledge, and skills from

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diverse domains (Wang, 2022). Competition encourages quality work through comparative learning (Füller et al., 2011).

However, despite the ideal expectations, sabotage behaviors can occur when facing the dual forces of competition and cooperation (Riedl et al., 2024). The existence of competition prompts territorial behaviors, self-interested actions, intentions to maximize personal gain (Xiao et al., 2022), and reduced willingness to share meaningful feedback (Xiao et al., 2022). These self-interested actions can worsen under intensified competition (Lu et al., 2014). Ideators' cooperative and competitive actions can be examined by studying their comment communication. To understand how ideators provide comments to peer competitors, a comprehensive analysis of communication content and network structures is conducted.

3. A Longitudinal and Relational View of Comments

Comments can be key carriers of information and knowledge exchange in coopetitive communities (Wang & Chen, 2023). Comments carry social, intellectual, and cultural values to the challenge communities (Chung et al., 2021). Functionally, suggestions, inquiries, and endorsements are exchanged through comments to improve innovation and ideation (Chan et al., 2018). Comments are relational, reflecting the nuanced social dynamics of the ideators, but they are also messages, varying in intentions and values provided. Despite recognizing the critical importance of studying comment relationships (e.g., Riedl et al., 2024) and the contents (e.g., Chung et al., 2021), there is a lack of longitudinal and multilayered examinations that simultaneously address structural dependencies and message types. This study seeks to delve into the complex layers of comment networks, noting that different types of comments can form distinct networks, each influencing ideators' behaviors in unique ways over time.

4. Research Context

Founded in 2010, OpenIDEO is a global online crowdsourcing challenge platform that hosts challenges that deal with critical social issues, such as food waste, women's education, and Ebola. Challenges are developed and designed in partnership with sponsor organizations (e.g., government and nonprofit organizations). Ideators participate by submitting idea solutions and competing for a limited number of prizes, such as monetary prizes, chances to attend social events, or support for idea implementation (Lakhani et al., 2013). In this context, comments on OpenIDEO are not merely simple interactions but are integral knowledge-creation and exchange channels.

5. What Comments?

To understand how ideators provide comments to fellow competitors, it is crucial to examine the content of the comments:

RQ1: What types of comments exist within the OpenIDEO crowdsourcing challenge community?

To answer RQ1, three researchers (with backgrounds in communication, information science, and computational social science) and one trained external coder (a master student majoring in Applied Data Science) independently reviewed all comment texts and assigned the comments into one or more categories following the instructions of the comment codebook (See Table 1). All researchers are objective observers of the OpenIDEO platform with minimal bias and no conflict of interest: no one has participated in any challenges. They achieved an excellent intercoder reliability (Krippendorff's Alpha = 0.89). The coders also resolved inconsistencies in coding through discussion. Notably, no negative or criticizing comments were found. Therefore, the ideators tend not to provide comments with obvious sabotaging intentions to each other in our research context.

Table 1. Comment Codebook

Category Types	Comment Examples	Description
A: Promotional or self-serving	Nice nutritious use of waste and more efficient use of water in growing cashews by increasing the useable crop - congrats Natasha! Please do have a look at our contribution too on a fair living wage for all in the coffee chain, from picker to barista: [URL of their challenge idea]	Promote oneself, one's own idea, or own organization, without adding value to another's idea.
B: Substantial Information sharing	hi, [identifiable names taken out] I would like to inform all of you about this School gardens Pilot that is starting in [identifiable location]! ...This way we can grow for all 12 months around the year! ... The children cannot go wrong with this and we are so excited to nourish the bodies and minds in one! ...	Provide information or resources.
C: Relationship building	We share a common interest in the importance of action learning and sharing experience and knowledge. It looks like we also have some common views about livelihood diversification and sustainability...	Building relationship or leave contact information.
D: Inquiry for more information	I would like to learn more about your product. Not sure how it works, and what kind of shelf life increase you are expecting. Thanks.	Ask questions and give chances to elaborate
E: Endorsement only without adding value	Great project idea. I'm very impressed by the work you're doing!	Mere gratitude or endorsing expressions without providing additional information.

6. Comparing Social Dynamics of Multilayered Comments

Answering RQ1, five types of comments are identified: A–Promotional and self-serving comments, B–Substantial information-sharing, C–Relationship-building, D–Inquiry for more information, and E–Endorsement without adding additional values. Cooperative comments include B-substantial information-sharing, D-inquiries, C-relationship-building, and E-endorsement-only comments. Substantial information-sharing provides informational value (Chung et al., 2021) to the receivers as well as the entire community because the comments are public. Inquires are also valuable as they clarify informational needs and promote information sharing (Bighash et al., 2018). Not only do they give receivers a stage to clarify their ideas, but they also provide the community with additional information access. Relationship-building comments drive social capital gain for the senders and receivers. They are also beneficial for building a more cohesive community. Although endorsement-only comments appear supportive, the lack of substantial information restricts its value in emotional and cultural dimensions (Chung et al., 2021). Self-promotion could increase one's own exposure, and it could be a strategic move to increase one's own likelihood of success and, therefore, is a self-interested action (Riedl et al., 2024).

6.1. Reciprocity

Reciprocity is a fundamental concept rooted in social exchange theory, which posits that social interactions create a sense of obligation to return favors or support (Blau, 1964; Gouldner, 1960). It proposes that social interactions create obligations to return favors or support, driving social behavior as individuals seek to maximize benefits and minimize costs (Homans, 1958). Reciprocity is associated closely with the underlying logic of knowledge contribution and exchange for online communities (Cheshire, 2007; Wasko et al., 2009). Studying reciprocity patterns informs us about community social norms and forms of exchange, reflecting the trust-building, solidarity, and cohesiveness of the communities (Molm, 2010).

Different from existing research that explores reciprocity patterns in online communities (e.g., Chan & Li, 2019; Wasko & Faraj, 2005; Hsu et al., 2007; Ye et al., 2015), this current research aims to take a step further and identify different types of contribution patterns through different layers of comment networks (See Table 1 for the comment typology).

From a network structural perspective, two types of reciprocity—ego-level reciprocity and dyadic reciprocity—are directly related to the multilayered inquiry of knowledge-sharing dynamics.

Ego-Level Reciprocity focuses on how an individual's (the ego's) actions are reciprocated by others within their immediate local network. From a network structural perspective, ego-level reciprocity is defined as balanced indegree and outdegree connections for individuals. This concept emphasizes the interactions between the ego and their direct social connections, analyzing how often favors, support, or even representational or performative communication (Shumate & Contractor, 2013) are exchanged between egos and alters. Ego-level reciprocity is crucial for understanding the dynamics of social support and the balance of interactions within personal networks (Wasserman & Faust, 1994). Communities with balanced ego-level reciprocity are more likely to be sustainable, as members feel that their contributions are adequately reciprocated (Pan et al., 2017).

Dyadic Reciprocity, on the other hand, involves the mutual exchange of resources, support, or communication between two individuals (i.e., on the dyadic level), focusing on the balance or imbalance in direct interactions. This concept is essential for studying the quality, stability, and strength of relationships within social networks (Easley & Kleinberg, 2010). Dyadic reciprocity can be observed in direct exchanges between users, such as in conversations or collaborative efforts, where the expectation of mutual benefit drives continued interaction. Dyadic reciprocity fosters trust enhances social bonds and fosters sustainable contributions among involved actors (Molm, 2010; Resnick, 2001; Dissanayake et al., 2021). This type of reciprocity leads to sustainable contributions, broadened perspectives, and even enhanced performance within the community, as observed in challenge participants (Dissanayake et al., 2021). Dyadic reciprocity also reflects the self-interestedness in a knowledge community, because community members carefully calculate gains and directly return to the senders (Poquet & Dawson, 2018; Wasko et al., 2009).

Driven by social exchange mechanisms, ideators may expect reciprocal interactions that mirror the quantity and quality of their own contributions. On the ego-level, we hypothesize that egos' (individual ideators') previously received comments tend to feel indebted to the community (Chan & Li, 2010) and would be more likely to contribute. Similarly, egos may put more effort into contributing comments with the expectation that they would be rewarded with reciprocation from the community (Tsai & Kang, 2019).

Hypothesis 1a: All types of comment networks manifest reciprocity at the ego level.

On the dyadic level, social exchange theory also predicts that favor is directly returned between two actors. However, the value of contributions can vary significantly across different types of comments regarding commitment, usefulness, and contribution. We hypothesize that ideators may expect reciprocal interactions that mirror the quantity and quality of their own contributions. This leads to the formulation of the following hypotheses:

Hypothesis 1b: All types of comment networks manifest reciprocity at the dyadic levels.

6.2. Inertia

Network inertia is described as the repeating tendency of existing network ties (Kim et al., 2006) and is a frequently observed network structure reflecting stable relationships and resistance to change (Mao et al., 2023). In organizational research, while network inertia can sustain and mature relationship-building, it may also impede diverse information and innovative outcomes

(Shi & Zhang, 2020). However, current research on network inertia does not consider whether this dynamic remains consistent across different communication types.

Previous research has found consistent patterns of network inertia and often describes them as endogenous evolution mechanisms (Pilny et al., 2016). Therefore, the following hypotheses propose that network inertia is also a consistent pattern for all types of comment networks:

Hypothesis 2a: Outdegree comment ties predict future comment sending for all types of comment networks.

Hypothesis 2b: Indegree comment ties predict future comment receiving for all types of comment networks.

6.3. Multiplexity

The concept of network multiplexity, which describes actors engaging across multiple types of relationships within a network (Uzzi, 1997), has not been extensively explored within the context of crowdsourcing communities, except in the study by Yu et al. (2024). Yu and colleagues (2024) found multiplexity leads to community-embeddedness and sustainable volunteer activities. Research has supported that network actors sharing multiplex ties tend to have stable and supportive relationships (Li & Piezunka, 2020; Yu et al., 2024).

Multiplexity has been studied as endogenous to social networks reflecting structural embeddedness and has been particularly noted in inter-organizational contexts (Lee & Monge, 2011; Uzzi, 1997). For example, knowledge-sharing networks could increase the likelihood of implementation networks among organizations, which reflects an increased embeddedness or strengthened relationship between organizations (Lee & Monge, 2011). However, for individuals' social interactions, it may not always hold true. When resource exchanges exist, relationships tend to persist in a multiplex way until better options surface (Methot & Cole, 2023). The formation of multiplex relationships also indicates stable and often mutually beneficial relationship-building (Methot & Cole, 2023).

Studying whether multiplexity exists with different types of communication networks allows a deeper understanding of the patterns and evolution of different types of relationships. Here, for a coopetitive research context, an exploratory research question is raised:

RQ2: Does the existence of one type of comment lead to another type of comment between pairs of ideators over time?

In addition, individuals' engagement in multiple layers of networks tends to reflect their social identities (Li & Piezunka, 2020). To better understand the social roles of ideators in a community of challenge competitors, a further research question is raised:

RQ3: Based on ideators' comment-sending behaviors across different comment types, could we identify different types of community members?

7. Methods

7.1. Data

Challenge data was scraped using *Selenium* from OpenIDEO in April 2022 on a randomly selected community entitled "The Food Systems Game Lab Challenge." This challenge crowdsourced solutions to the problem of "How might we build a better food for everyone, everywhere?" The food challenge began on March 24, 2021, and went through an open ideation phase that called for submission until May 25, 2021. Ideas submitted during this phase were eligible for competition. Detailed data processing procedures can be found in the appendices.

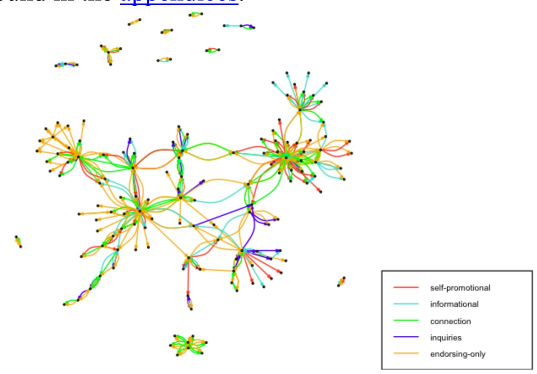

Figure 1. Ideator Comment Network By Types

7.2. Latent Class Analysis

To identify types of community members based on their comment-sending behaviors (RQ3), Latent Class Analysis (LCA) was adopted. LCA is a person-centered approach widely adopted to identify memberships to latent classes (Weller et al., 2020). One of the primary advantages of using LCA over other clustering algorithms is its clear evaluation criteria on the number of categories and fit statistics (e.g., AIC, BIC, and entropy) to assess class assignment performance. Additionally, innovative practices have adopted LCA to inform more nuanced relational patterns using social network analysis (Adams et al., 2024). Therefore, LCA was applied to the data of 157 ideators who participated in comment networks and the types of comments they sent.

7.3. Relational Event Modeling

To understand the social network dynamics among ideators, Relational event modeling (REM) was adopted, employing the *relevant* package for modeling (Butts, 2008). REM assumes that "actions arise independently conditional on the realized history of previous actions" (Butts, 2008, p. 160). REM does not require data aggregation over time windows and allows modeling the exact timing of the relational event (comments in this case). By treating relational events as sequential and observing them in a granular manner, REM provides a nuanced understanding of temporal dependencies, reducing the need to account for traditional fixed effects (Butts, 2008). REM calculates the rate of tie-sending and receiving, with each relational event as both the dependent variable of previous events and the independent variable of subsequent events (Welles et al., 2014). Similar to other temporal network models (e.g., TERGM, SAOMs), REM has the flexibility of incorporating both endogenous (i.e., the inherent network structures such as reciprocity and clustering) and exogenous variables (e.g., external attributes of the nodes or ties) into modeling the sequences of the relational ties. Therefore, by ordering relational events rather than aggregating them into concurrent networks over time windows, REMs provide a richer understanding of social interdependencies than traditional aggregated models (Butts, 2008). Moreover, potential time-varying confounding variables such as platform-level environment changes (e.g., updates in platform design or disruptive system bugs) could be accounted for in exogenous variables.

REM is particularly useful for this study for two reasons. First, REM is particularly suitable for short-lived relational events, such as comments, compared to other longitudinal models based on exponential statistics, such as Temporal Exponential Random Graph Models (TERGM) and Stochastic Actor-Oriented Models (SAOM), because the latter is usually more applicable for long-lasting relationships such as friendships or collaboration (Leifeld & Cranmer, 2019). Secondly, REM models the exact timing of the events when they occur without aggregating them into network snapshots over a time window, thus giving us more nuanced observation.

Each relational event (e.g., directed comment network ties in this context directed from comment sender to receiver) is ordered by sequence of occurrence for modeling. Measures of the REMs are described below.

7.3.1. Reciprocity. To test Hypothesis 1a concerning ego-level reciprocity, the analysis focuses on two primary measures: a. *indegree send* (H1a): to assess whether the number of comments an ideator has received (indegree) predicts the number of comments they send out (outdegree). It examines whether ideators who receive many comments are more likely to engage by sending comments to others. b. *outdegree receive* (H1a): to measure whether ideators who have sent many comments (outdegree) are more likely to receive comments in return (indegree) in the future. A positive and significant result would indicate that active participation in sending comments leads to reciprocal engagement from others.

Dyadic reciprocity (H1b) is tested by examining whether comment exchanges between pairs of ideators are reciprocated. This measures whether an ideator who comments on another's submission is likely to receive a comment in return from that ideator, reflecting mutual engagement and interaction within the community.

7.3.2. Inertia. To test Hypothesis 2 concerning inertia, ideator behavior over time is assessed using two specific measures: c. *outdegree send* (H2a): This measure tests whether ideators who have been active in sending comments in the past (high outdegree) continue to send comments in the future. A positive and significant result would support the hypothesis that ideators tend to maintain their activity level over time, indicating behavioral inertia. d. *indegree receive* (H2b): This measure assesses whether ideators who have received many comments (high indegree) are likely to continue receiving comments. The hypothesis posits that ideators who are central in the network (with high indegree) will continue to attract engagement, reflecting inertia in their role as recipients of interaction.

7.3.3. Multiplexity. To answer RQ2, all the other types of comments were included as edge covariates.

7.3.4. Control variables: Three variables were added as control variables: ideators' co-location, industry homophily, and idea homophily. Rationale and detailed measures can be found in the appendices.

8. Results

8.1. Comment-Sending Behavior Clustering

LCA assigned ideators into three categories (See Figure 2; note that all categories were included as binary variables. "A. Pr. 1" reflects the possibility of Category A being absent, while "A. Pr. 2" indicates the possibility of A being present). The model with the lowest BIC was chosen. The entropy for the category assignment was acceptable (i.e., 0.81; Weller et al., 2020). Class 1 features a low probability of A, B, and D while showcasing a moderate probability of C and a high probability of E. Ideators in Class 1 are highly active in endorsement activities with moderate involvement in connection-building, thus named *"endorsers."* Class 2 has a high probability in A, a moderate probability in C and E, a low to moderate probability in B, and a very low probability in D. Class 2 was labeled as *"self-promoters"* because of their high activity of self-promotional comments and moderate participation in endorsement-only and relationship-building activities. Ideators in Class 3 tend to be highly active in sharing substantial information (B) and making inquiries (D), so they were named *"contributors."*

We found that B (substantial information sharing) and D (making inquiries) follow relatively consistent patterns: Both B and D appear significant for Class 3, and moderate to low probability for Class 2. This finding is consistent with previous literature that suggests that questions and inquiries contribute to informational public goods by revealing informational needs and seeking attention to key points, and therefore, should be treated as public goods contributions too (Bighash et al. 2018). Inquiries also provide an additional stage for the ideator being commented to explicate points and express opinions. Therefore, both B and D signal quality contribution to the ideas, and based on observed data patterns and theoretical conceptualization, we merged B and D into a single category as substantial public good contributions for further network analysis. REMs were adopted on the four comment network layers, revealing different interaction patterns within each type of comment network (See Table 2).

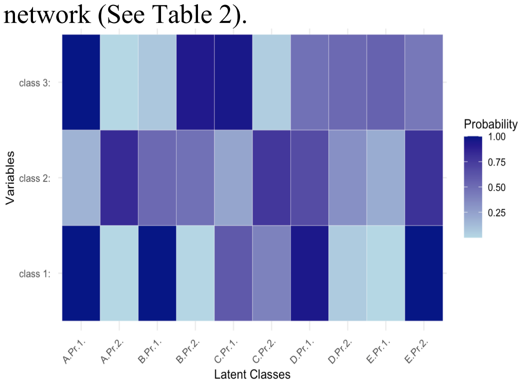

Figure 2. Probabilities Comparison Heatmap

8.2. Multilayered Dynamic Network Models

8.2.1. Reciprocity. To test ego-level reciprocity (H1a), the analysis found that *indegree send* was negatively significant in Network A (Model 1), which is based on promotional comments and the whole comment network (Model 5). This suggests that ideators who receive many promotional comments and all comments, in general, are less likely to send comments in return. *Outdegree receive*, on the other hand, was positively significant in Networks B+D, C, E, and the whole network (Models 2, 3, 4, and 5), indicating that ideators who actively send all types of comments except for promotional comments are more likely to receive comments in return, supporting the concept of ego-level reciprocity in these networks. Thus, H1a is partially supported. *Dyadic reciprocity* (H1b) was consistently positive and significant across all networks (Models 1-5), confirming that mutual exchanges between ideators are a stable and pervasive feature of community interaction. This fully supports H1b.

8.2.2 Inertia. To test H2a regarding inertia, *outdegree send* was consistently positive and significant patterns across all networks (Models 1-5). This supports the hypothesis that ideators who have been active in sending comments continue to send over time. H2a is supported. However, *indegree receive* (H2b), was not significant in Networks A, C, or E (Models 1, 3, and 4) and was negatively significant in Network B+D and the whole network (Models 2 and 5). These findings suggest that ideators who receive many comments may not continue to attract the same level of engagement over time. H2b is not supported.

Table 2. Relational Event Model Results

	Model 1 (Network A)	Model 2 (Network B+D)	Model 3 (Network C)	Model 4 (Network E)	Model 5 (Whole Network)
Ego-Level Reciprocity					
Indegree Send	-47.75 (14.59)**	-1.62 (2.19)	-5.31 (4.32)	-3.08 (3.01)	-14.35 (3.72)***
Outdegree Receive	3.01 (1.76)	10.63 (1.67)***	7.88 (1.14)***	10.51 (1.11)***	15.70 (1.36)***
Dyadic Reciprocity	5.26 (1.09)***	4.27 (0.61)***	4.80 (0.47)***	4.05 (0.46)***	5.05 (0.35)***
Multiplex (A)		0.14 (63.25)	0.11 (63.24)	0.52 (0.47)	
Multiplex (B+D)	0.47 (1.22)		0.32 (0.80)	-0.36 (0.66)	
Multiplex (C)	-0.07 (1.17)	0.19 (1.22)		-7.88 (24.86)	
Multiplex (E)	-0.21 (1.31)	0.13 (63.25)	0.10 (63.24)		
Inertia					
Outdegree Send	8.06 (0.83)***	10.08 (1.44)***	10.98 (1.14)***	12.97 (1.09)***	16.75 (1.27)***
Indegree Receive	-0.80 (3.62)	-14.95 (4.46)***	1.48 (1.97)	0.99 (2.55)	-14.05 (3.99)***
Endorser Send					0.33 (0.34)
Self-Promoter Send					1.18 (0.31)***
Endorser Receive					0.13 (0.25)
Self-Promoter Receive					0.26 (0.24)
Control Variables					
Co-Location	-6.94 (62.53)	1.86 (0.72)***	2.31 (0.45)***	2.99 (0.28)***	2.53 (0.31)***
Industry Homophily	-0.26 (0.34)	-0.02 (0.27)	0.11 (0.22)	0.49 (0.16)***	0.17 (0.15)
Idea Homophily	0.92 (0.47)*	1.11 (0.41)**	1.48 (0.31)***	1.09 (0.26)***	1.35 (0.23)***
Model Fit Statistics					
AIC	1146.38	1583.54	2088.37	3460.73	4744.62
BIC	1171.42	1611.86	2119.74	3497.01	4787.57
Chi-Square	135.83 (11df)***	116.21 (11df)***	240.37 (11 df)***	427.11 (11df)***	628.82 (11df)***

Note: * $p < .05$, ** $p < .01$, *** $p < .001$. Standard deviation statistics are reported in parentheses. For Model 5, the contributor group was treated as dummy. The numbers in the parentheses are standard errors.

8.2.3. Multiplexity. None of the multiplex relationships were significant (See Models 1 - 4), which indicates that one type of existing comment network between pairs of ideators does not lead to other types of future connections.

8.2.4. Multilayered Comment Patterns. To further probe whether different types of ideators—self-promoters, endorsers, and contributors—exhibit distinct patterns in tie-sending, their ideator types were added to the social network model fitting. Contributors were treated as the dummy variable in the analysis. In Model 5, endorsers' and promoters' tie-sending and receiving are compared with the contributors. There is not much difference between their tie-sending and receiving patterns. One exception is that self-promoters send significantly more comments than contributors. Findings for the control variables are discussed in the appendices.

9. Discussion

Existing research on the crowdsourcing community's knowledge-sharing dynamics either focuses on network structures (e.g., Wasko et al., 2009) or contribution content (e.g., Chung et al., 2021). However, an integrated analysis of both structural dynamics and contribution content is rare. The current study separates the comment networks into four layers based on the contribution made to the tie-receivers and the community: substantial public-serving, relationship-building, endorsement-only, and self-promotional comments. This categorization speaks to Chung et al. (2021)'s conceptualization of different types of values offered to the communities: social, intellectual, and cultural, matching the values provided through relationship-building, information-sharing, and endorsement comments, respectively. Adding to these cooperative contributions, we also identified less-valuable actions that are self-serving and self-promotional comments, likely the outcomes of the dual logic of cooperation and competition.

In addition, this research has provided insights into the detailed structure of each type of comment network to compare evolving communication patterns among competitors. This research contributes to existing literature on reciprocity and coopetitive communities (e.g., Dissanayake et al., 2021; Riedl et al., 2024) and provides a longitudinal perspective to the existing social networks studies on crowdsourcing platforms (e.g., Chung et al., 2021).

9.1. Reap What You Sow

Findings suggest that egos contributing comments are likely to be reciprocated by the community. The social exchange theory could explain this: ideators expect their contribution to garner quality information and knowledge from the community (Tsai & Kang, 2019). This finding is consistent with what Dissanayake et al. (2021) found in Kaggle, which is that the help offered tends to be repaid by the community. However, challenge communities only partially follow the logic of social exchange and reciprocity. Comment receiving, in general, does not lead to future comment sending, which could be explained by rational action theory, which suggests that individuals act in a way that benefits exceed costs (Coleman, 1990). The benefits of receiving incoming benefits could include recognition and trust-building. However, the temporary nature of the community lowers the value of social capital building. The cost of returning comments to the community after receiving them may outweigh the benefits because they may increase others' competitive advantages in the challenge by improving others' knowledge and information access, endorsements, social support, and more. For the self-promotional network and the whole comment network, in particular, the reverse is true: those receiving more tend to send fewer comments in the future, which aligns with Fuge and Agogino's study results (2014).

In summary, taking a step further from previous reciprocity research (e.g., Dissanayake et al., 2021), our study analyzes the direction of contribution and return for different layers of comments and finds that social exchange dynamics on the ego level tend to work unidirectionally: contributing tends to be rewarded, but receiving does not lead to future sending. A novel finding of this research is that a challenge community features dual logics of social exchange and rational action: to gain cooperative feedback, including substantial information-sharing, one needs to be a cooperative comment-sender first. However, contributions from popular comment receivers are minimal in the community when faced with the pressure of competition, as their motivation to help others lowers as they have already secured incoming contributions from others.

Practically, for ideators who wish to gain insightful and informational comments, taking the initiative to contribute substantially to others can be rewarding. For platform managers and organizers, the findings reflect an unbalanced contribution from the popular ideators, which may not benefit the sustained and diverse knowledge contribution of the community.

Consistent results for the dyadic reciprocity also support what was predicted by the social exchange theory. Taking a step further from existing social exchange research (e.g., Wasko & Faraj, 2005; Lampe et al., 2010; Hsu et al., 2007; Ye et al., 2015), our findings indicate that ideators are attentive to not only who they received the communication from but also the type of comments: they would reciprocate with the same type of comments to return the favor. Canonical research has suggested that communities featuring significant direct reciprocity emphasize self-interested norms (Poquet & Dawson, 2018; Wasko et al., 2009) as members carefully balance their contributions against potential gains. This is further validated in Figure 1 of the rareness of triadic closure of all types of comment networks. By examining the layers of different types of communication networks, this research further contributes to the understanding of the social exchange norms within crowdsourcing challenge communities. Challenge participants maintain mutual communication in the community and reciprocate the same type of communication messages with their peers. Comparing ego-level and dyadic-level findings, in general, the reciprocated social norm applies to most users in the challenge community, which may benefit participating actors' short-term relationship-building and information exchange, except for popular users who have secured enough attention and information and become reluctant to give back their fair share.

9.2. Comment Sending Inertia

Consistent "outdegree send" inertia patterns across all comment networks indicate that ideators tend to repeat existing behaviors, which further justifies the practice of categorizing members based on their commenting behaviors. Although the challenges communities are short-lived (as they dissolve after each challenge concludes), it seems that the habit of contribution tends to form and sustain. This is consistent with the "habit of cooperation" patterns found by Wasko and Faraj (2005) and the path dependency theory, which argues that when behavior patterns are established, they tend to be repeated and further reinforced (David, 1985). In addition, this study found that such habits not only sustain cooperative behaviors (e.g., providing substantial information or establishing relationships) but also self-interested behaviors.

However, incoming ties do not lead to future tie receiving. For substantial contributions, more incoming comments could, in fact, lead to fewer future comments being received. This may reflect the lack of meaningful conversation engagement in the knowledge community: receiving substantial comments does not generate further incoming substantial conversations nor other cooperative connections (e.g., relationship-building comments; see multiplexity findings). Through our content analysis, the authors found that back-and-forth discussion is very rare.

Moreover, the lack of indegree receive dynamic may reflect that the community does not manifest the tendency for the Matthew Effect, a common structure for most other online communities (Merton, 1968). On the contrary, "rich do not tend to get richer" regarding comment receiving. The social structures develop in a relatively non-hierarchical manner over time.

9.3. The Lack of Multiplexity

There does not appear to be any multiplexity norms in the community. Multiplexity across types of relationships indicates relational embeddedness (Lee & Monge, 2011; Uzzi, 1997), as well as stable and cooperative relationship-building (Methot & Cole, 2023). The lack of multiplexity relationship-building in the crowdsourcing challenge community may reflect the coopetitive forces ideators face. Sustaining and nurturing relationships across substantial or relational-building connections do not exist, nor do self-promotional comments. This might also be caused by the temporary nature of the challenge communities. Relationships are formed for challenges, and once the challenge ends in a few months, the community dissolves, and ideators may not see the value in creating embedded engagement with other ideators across layers.

9.4. Ideators' Community Roles

This research contributes to understanding challenge participants' different roles in communities based on their commenting behaviors: self-promoters, endorsers, and contributors. We further examined their positions in the whole comment network to understand their activity and popularity in the community. There is no significant difference in the amount of comment-sending and comment-receiving for the three types of ideators–self-promoters, endorsers, and contributors. This indicates that being contributors, although beneficial to the community because they offer substantive feedback to peer ideators, they do not tend to gain significantly more attention from the community compared to the other types of ideators. Instead, the high commenting activities by the self-promoters may not be beneficial in creating a nurturing and supportive innovative community. To maintain a healthy community culture, management should consider ways to reward contributors to sustain and encourage knowledge-sharing.

9.5. Generalizability, Limitation & Conclusion

The proposed multilayered communication framework, participant roles, and the research procedure of a combined view of relationship and message could be applied to online communities facing similar coopetitive pressure. However, one limitation of this research is that the analysis has focused on one challenge community. Researchers have collected additional challenge data and will apply the analysis to these to better understand the boundary of generalizability of the findings.

Future research should extend this analysis to compare dynamics across different types of online crowdsourcing challenge communities to validate and refine the proposed framework. For example, competitive platforms such as Topcoder and Kaggle (Sun & Majchrzak, 2020) may manifest different comment dynamics. whether findings apply to more competitive challenges Such studies could explore how different platform designs influence social interactions and the formation of community roles, thereby providing further suggestions on practical applications and strategies. Notably, this research found that negative comments are extremely rare on OpenIDEO challenges. However, such culture may not be shared in all coopetitive challenge platforms. For example, Saif et al. (2018) have noted the existence of toxic comments in Kaggle. We prompt future research to explore other types of platforms with different affordances, infrastructure, and cultures and compare findings. Additionally, further investigation may need to understand how these dynamics evolve over longer periods, especially in communities that do not dissolve after a challenge concludes. In addition, we acknowledge that social media trace data can be limited in collecting people's thoughts behind behaviors and recognize that interpretation needs to recognize researchers' own disciplinary norms and theories that inform the interpretation (boyd & Crawford, 2012). We prompt future research efforts to collect additional primary data that triangulate and inquire about motivations behind behaviors in challenge communities and consult broader disciplinary knowledge to understand the comment behaviors in challenge communities.

In summary, this research proposes important frameworks and procedures to understand relational dynamics in coopetitive crowdsourcing online communities in layers and lays a foundation to further theorize innovative dynamics toward productive online crowdsourcing environments. The insights offered here should be valuable for platform designers and community managers seeking to optimize user collaboration and competition.

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