# Network-Structural Analysis of User Knowledge Collaboration Performance in Online Q&A Communities

**Huixuan Yang***
*Department of Information Management, Nanjing Agricultural University, Nanjing, Jiangsu, China*
**Corresponding Author*

**Abstract: Enhancing both the efficiency of collaboration and the quality of knowledge production continues to attract sustained attention in the management of information resources on online knowledge collaboration platforms. Drawing on a network-structural lens, this study investigates how user attributes, positions within the network, and interaction patterns manifested through comments collectively shape collaboration outcomes. A hypernetwork model underpins a multilayer framework linking users, content, and tags, with corresponding measures constructed at the individual, event, and network levels. Regression analysis combined with quadrant analysis is then employed to examine the proposed relationships. Results show that user activity exerts a significant influence on an individual's location within the network. At the event level, brokerage positions coincide with higher collaborative efficiency, while embeddedness in the network core bears a closer relation to collaboration quality. Interaction patterns distinguished by comment quality and participation intensity also diverge notably in their outcomes and structural properties, producing distinct forms of collaboration.**

**By explaining how user attributes, network positions, and interaction patterns are interrelated and jointly shape collaboration performance, this study offers a structural basis for understanding and improving online knowledge collaboration.**

**Keywords: Knowledge Collaboration Performance; Hypernetwork; Social Network Structure; Interaction Patterns**

## 1. Introduction

Amid the rapid advancement of digitalization and networking, online knowledge collaboration platforms have emerged as central venues for knowledge generation, sharing, and innovation [1]. By bringing together individuals from diverse disciplines and backgrounds, these platforms enable users to collaborate in answering questions, exchanging perspectives, and sharing resources. Through the integration of heterogeneous resources, they foster knowledge innovation and give rise to dynamic and complex networks characterized by multi-agent collaboration.

With the rapid expansion of user populations and knowledge content in online knowledge collaboration communities, effectively managing and guiding collaborative behaviors to enhance the efficiency and quality of knowledge generation has become a critical concern for both platform administration and academic research. Prior studies have shown that users' professional backgrounds, levels of experience, and patterns of interactive behavior shape their structural positions within collaboration networks as well as their collaborative performance [2]. Meanwhile, factors such as network structural characteristics and content relevance also exert significant influence on the efficiency and quality of knowledge collaboration [3]. However, few studies have linked individual user characteristics with network structure to investigate their combined effects on online knowledge collaboration outcomes, and interactive behaviors within the collaboration process—such as answering and commenting—have rarely been quantitatively analyzed as an integral component shaping collaboration.

Against this backdrop, the present study introduces a hypernetwork modeling approach to construct a multi-level analytical framework that integrates a three-layer associative network of users, content, and tags. This study quantitatively examines user characteristics, network positions, and event-level interaction patterns to determine the factors that shape the efficiency and quality of knowledge collaboration. It also investigates how participant composition and collaborative settings vary across interaction patterns. These results yield theoretical and empirical insights for managing online knowledge collaboration platforms and supporting knowledge innovation.

## 2. Literature Review

### 2.1 Hypernetwork and Multilayer Network Modeling

Single-relation network models have become less capable of representing real-world collaboration among diverse actors linked through heterogeneous interactions,as complex systems research has developed. Hypernetworks and multilayer networks offer complementary perspectives on complex knowledge collaboration. In a hypernetwork, hyperedges link multiple nodes—including those of different types—enabling the representation of multi-participant collaboration. Multilayer networks, by contrast, allocate distinct relations to separate but interconnected layers. By analyzing the mappings and coupling across these layers, researchers can uncover variations in system structures and interactions across multiple dimensions [4].

Studies of multilayer networks have investigated structural coupling and functional interactions across relational dimensions. According to Kivelä et al. [5] and De Domenico et al. [6], multilayer networks more effectively capture the structural heterogeneity of complex systems, whereas single-layer representations often struggle with multidimensional information. In online knowledge collaboration settings, user interactions, semantic connections between knowledge content, and tag co-occurrence patterns typically constitute separate network layers—structurally distinct yet interdependent through user behavior. Researchers frequently employ unified frameworks that integrate actors, content, and knowledge units. Zhang et al. [7] combined user networks, knowledge text networks, and knowledge gene networks to construct a hypernetwork model of user-driven knowledge co-innovation. Tang et al. [8] demonstrated that hypernetworks effectively expose multi-actor association structures within large-scale collaborative innovation communities by emphasizing complex relationship representation. Feng et al. [9] later applied this approach to online health communities and constructed a hypernetwork comprising knowledge co-creation actors, knowledge texts, and knowledge genes.

### 2.2 Online Knowledge Collaboration Networks

2.2.1 User characteristics in online knowledge communities

On online knowledge collaboration platforms, user characteristics help explain differences in knowledge contribution [10]. Existing studies have largely examined users' cognitive capabilities and knowledge attributes, their behavioral motivations and incentives, and the identification of core contributors. These individual characteristics influence the roles users assume and their patterns of participation, ultimately shaping networks of collaborative relationships.

Users differ in both their knowledge structures and cognitive abilities, and these differences shape the social construction of knowledge [11]. In online knowledge communities, knowledge attributes—especially the degree of knowledge heterogeneity—play an important role in collaboration and knowledge construction [12, 13]. Their influence is reflected in cognitive conflict, knowledge collaboration, and communication coordination [14]. Such differences may also encourage users to engage in self-presentation. Participation in online knowledge collaboration, however, arises from a broader range of motivations. Knowledge sharing may be driven by material and knowledge-related rewards [15], community identification and collectivist values [16], peer effects [14], and platform-based incentive mechanisms [17-19]. Users consequently display different behavioral patterns under different motivational and incentive conditions. Identifying those who make substantial knowledge contributions can provide a basis for improving these mechanisms. Given the characteristics of online knowledge communities, core users may be identified by assessing their activity, expertise, social ties, and overall sentiment orientation [20]. Some researchers have used hypernetwork models to identify and examine leading users or core innovators in online communities [7, 8]. Others have relied on measures such as network centrality, structural holes, and influence to locate key users, whose activities are crucial to knowledge diffusion and efficient collaboration [21, 22]. Behavioral characteristics also differ across user roles.

 

Existing studies suggest that each role performs a distinct function in the knowledge production chain, while the structure of interactions among roles directly shapes the efficiency and quality of knowledge creation [23, 24].

2.2.2 Structural studies of online knowledge collaboration networks

Given the heterogeneity of users and collaborative contexts, online knowledge collaboration networks display diverse structural characteristics. In addition to the hypernetwork approach discussed above, researchers have frequently used social network analysis (SNA) and related methods to identify structural patterns, key nodes, and the mechanisms driving network evolution [25-28].

Structural analyses have identified several topological features of online knowledge collaboration networks. Social tagging co-occurrence networks, for example, display both small-world and scale-free properties [29, 30]. Research on platforms such as Wikipedia and Stack Overflow has likewise found that online knowledge networks tend to have high clustering coefficients and power-law degree distributions. These characteristics support information diffusion and contribute to network stability [31, 32]. Social network analysis also helps identify communities of practice closely tied to the community structures of knowledge collaboration [33]. It can further reveal how knowledge topics distribute and where the boundaries of user collaboration lie [34].

Network structure exerts a considerable influence on knowledge exchange, operational efficiency, and collaboration within online communities. Within technological domains, a contracting collaboration network tends to restrict knowledge exchange, whereas an expanding knowledge network facilitates wider circulation of information [35]. A denser network, in general, affords participants more opportunities to share knowledge and exchange information. A shorter average path length further accelerates the spread of knowledge [36, 37]. Nodes marked by high betweenness centrality usually sit at critical junctures along knowledge-flow pathways and may shape the transfer of information. By contrast, nodes with high degree centrality sustain a broader range of connections and draw upon more diverse knowledge resources [38]. Scholars have resorted to social network analysis to probe online collaboration networks through structural holes, centrality, and network embeddedness, and these perspectives have demonstrated value in accounting for patterns of knowledge flow and variations in collaborative efficiency [39, 40].

## 3. Research Design and Framework

### 3.1 Data Collection

The data underpinning this study originate from Stack Overflow, with a focus on "Python," one of the platform's most active tags. To minimize potential interference from AI-generated questions and answers during the knowledge collaboration process, the sample was confined to questions posted in 2020. Each selected question carried an accepted answer and attracted at least three responses, which ensured that the relevant collaborative features and structures could be observed in adequate detail. The final dataset comprises 3,726 questions, 12,217 answers, and 21,443 comments contributed by 9,589 users.

### 3.2 Hypernetwork Model of Knowledge Collaboration

This study treats each question posted on Stack Overflow as the basic unit of collaboration. The interaction process, from the initial posting of a question to the emergence of a stable answer structure, constitutes a collaborative event and serves as the basis for constructing the hypernetwork model. Hyperedges capture the relationships among the three node types—users, content, and knowledge—while preserving the key correspondences between them. Specifically, the collaborative event associated with each question post corresponds to one hyperedge, which simultaneously connects all participant nodes, answer nodes, and the full set of tag nodes involved in that question, as illustrated in Figure 1 and Figure 2. In addition, data on comment-based interactions are stored as attributes attached to the question and answer nodes.

### 3.3 Research Content and Indicator System

In a multi-actor collaboration network, users constitute the primary agents of the collaborative process, and their structural positions within the network reflect the advantages they hold as principal participants in collaborative behavior. This study first examines how heterogeneous user characteristics shape their structural positions within the network—that is, the mapping relationship between individual attributes and their structural roles within the collective organization. Second, at the event level, the collaborative process unfolds through the joint engagement of multiple users around specific problem contexts, wherein both the role composition of participants and the patterns of network connectivity within an event jointly determine collaborative performance. This study further investigates the mechanisms through which event-level characteristics influence collaboration efficiency and quality, with particular emphasis on how varying distributions of centrality and degrees of user concentration facilitate or constrain collaborative outcomes. At the level of user interaction, comments provide an important means of regulating knowledge collaboration on Stack Overflow. The interaction patterns embedded in comments directly shape how knowledge is integrated within an event. Using comment quality and participation intensity as the two principal dimensions, this study groups events into four interaction quadrants. It then compares these quadrants with respect to knowledge organization, user composition, and collaborative performance. Network structure measures are also used to identify and describe the collaborative configurations that characterize each interaction pattern.

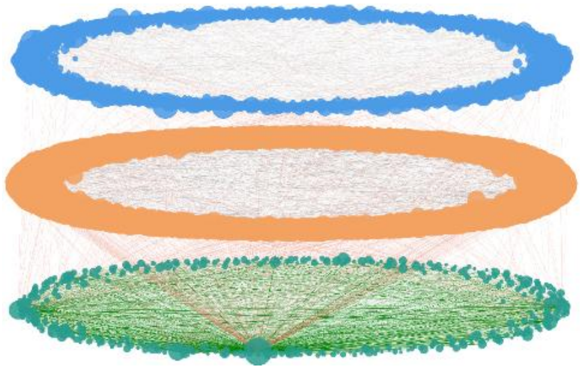

**Figure 1. Schematic Diagram of the Hypernetwork (Top 30% of Events by Efficiency)**

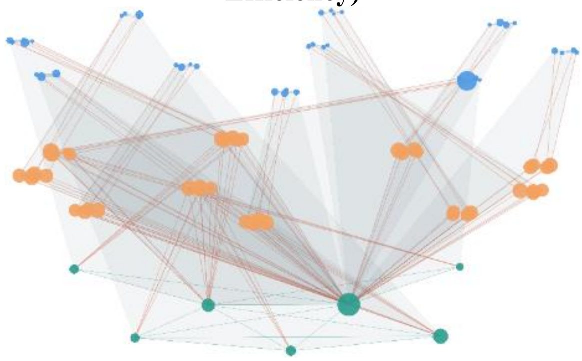

**Figure 2. Schematic Diagram of Hyperedge Collaborative Events (Top 10 Events by Efficiency)**

Drawing on the preceding analysis, this study constructs an indicator system across three dimensions: individual, event, and network (Table 1)

**Table 1. Research Indicator System**

| Dimension | Category | Indicator | Measurement |
|---|---|---|---|
| Individual | User individual characteristics | Reputation score | Existing indicator provided by Stack Overflow |
| | | Activity level | Number of posts published |
| | | Knowledge breadth | Number of distinct tags engaged with |
| | | Knowledge depth | Intensity of repeated participation under the same tag |
| | User structural position | Collaborative breadth | Number of times co-participating in questions with others |
| | | Path control capability | Betweenness centrality within the user collaboration network |
| | | Core embeddedness | Eigenvector centrality within the user collaboration network |
| | | Local clustering coefficient | Clustering coefficient within the user collaboration network |
| Event | Participant role characteristics | Critical path control capability | Maximum betweenness centrality among participants |
| | | Overall influence level | Mean eigenvector centrality among participants |
| | | Local collaborative cohesion | Mean clustering coefficient among participants |
| | | User centrality concentration | Gini coefficient (based on the centrality distribution) |
| | Internal | Collaboration scale | Number of collaborative ties within the event |

 

| | | | |
|---|---|---|---|
| | structural characteristics | User contribution concentration | Degree of inequality in node participation |
| | | Average collaboration intensity | Mean weight of a single collaborative tie |
| | Interaction patterns | Comment quality | Mean score of the comment set within the event |
| | | Comment participation intensity | Number of comments / number of answers |
| | Event collaborative performance | Collaboration efficiency | Time interval between question creation and resolution |
| | | Collaboration quality | Mean answer score |
| Network | Knowledge organization | Knowledge diversity | Proportion of tag clusters relative to the total number of tag clusters |
| | | Knowledge structural complexity | Modularity of the tag network |
| | Overall structural indicators | Community structure modularity | Louvain modularity |
| | | Quadrant density | Actual number of edges / maximum possible number of edges |
| | | Centralization | Betweenness centralization; strength centralization |
| | | Core–periphery structure fit | Core–Periphery Fit Index |

## 4. Empirical Analysis

### 4.1 The Influence of User Characteristics on Structural Positions in the Network

4.1.1 The relationship between user characteristics and degree value

Table 2 reports the regression results for the effects of user characteristics on weighted degree. Activity level shows a strong positive association with weighted degree ($\beta = 60.733$, $p < 0.001$). Once activity level enters the model, the coefficient for reputation declines substantially, suggesting the two variables share explanatory power. Users' actual participation frequency, in other words, largely determines both the number of collaborative ties they establish and the intensity of those collaborations. Models 3 and 4 further show that participation across a wider range of knowledge domains helps users extend their collaborative ties and engage more intensively with others. Once participation frequency and knowledge coverage are controlled for, however, repeated engagement concentrated within a limited set of tags appears to restrict the development of collaborative ties and reduce overall collaboration intensity.

Activity level functions as the principal determinant of the number and strength of collaborative ties within the network. A broader knowledge base widens the scope of collaboration, while excessive specialization markedly constrains the formation of such ties. Relative to a "deep but narrow" pattern of participation, a "broad but not deep" structure of knowledge engagement appears more conducive to fostering abundant and sustained collaborative relationships across the network.

**Table 2. Regression Results of User Characteristics on Weighted Degree Value**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| Independent Variable | Coef(B) | t | Coef(B) | t | Coef(B) | t | Coef(B) | t |
| Reputation score | 127.530*** | 27.482 | 33.500*** | 11.784 | 27.050 *** | 9.921 | 29.623 *** | 11.604 |
| Activity level | | | 60.733*** | 132.839 | 44.554 *** | 64.221 | 46.871 *** | 71.852 |
| Knowledge breadth | | | | | 0.964 *** | 30.030 | 1.593 *** | 46.095 |
| Knowledge depth | | | | | | | -5.728 *** | -36.862 |
| Adjusted $R^2$ | 0.073 | | 0.674 | | 0.702 | | 0.739 | |

4.1.2 The relationship between user characteristics and bridging position

Tables 3 and 4 set out the regression results concerning the effects of user characteristics on betweenness centrality and eigenvector centrality. The two measures exhibit broadly consistent relations with user characteristics, though the estimated effect sizes differ. A comparison of Models 1 and 2 indicates that reputation shapes a user's structural position chiefly through actual participation. Engagement across multiple domains strengthens users' capacity to bridge otherwise disconnected groups and to become embedded in the network core. Once participation frequency and knowledge coverage are held constant, however, concentrating activity on a narrow set of tags diminishes the likelihood that users occupy bridging positions or attain a central position within the collaboration network.

Activity level stands out as the primary factor shaping bridging roles and core embeddedness. Reputation exerts an indirect influence on these structural positions via its association with user activity. A broader knowledge base also extends users' reach within the network to a certain extent, while excessive specialization may erode their structural advantages.

4.1.3 The relationship between user characteristics and local clustering structure

Table 5 reports the regression results for user characteristics on the clustering coefficient. Reputation score registers significance in Model 1 but loses it in Model 2, suggesting that local collaborative cohesion is shaped mainly by users' participation behaviors. When knowledge breadth enters the model, its overall effect remains fairly weak. Once knowledge depth is incorporated as well, knowledge breadth shifts to a significant positive effect ($B = 0.002$, $p < 0.001$), whereas knowledge depth exerts a significant negative effect on the clustering coefficient ($B = -0.017$, $p < 0.001$). Highly active users, the findings suggest, tend to form open rather than closed collaborative structures, yielding markedly lower levels of local clustering. Knowledge breadth, against this backdrop, helps foster more tightly knit collaborative relationships within local neighborhoods, whereas repeated engagement concentrated on a small number of tags weakens the closure of local collaboration.

**Table 3. Regression Results of User Characteristics on Betweenness Centrality**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| Independent Variable | Coef(B) | t | Coef(B) | t | Coef(B) | t | Coef(B) | t |
| Reputation score | 0.017 *** | 23.524 | 0.005 *** | 8.851 | 0.003 *** | 6.170 | 0.004 *** | 7.389 |
| Activity level | | | 0.008 *** | 86.620 | 0.003 *** | 25.181 | 0.004 *** | 29.549 |
| Knowledge breadth | | | | | 0.000 *** | 44.882 | 0.000 *** | 57.199 |
| Knowledge depth | | | | | | | -0.001 *** | -32.552 |
| Adjusted $R^2$ | 0.054 | | 0.470 | | 0.562 | | 0.605 | |

**Table 4. Regression Results of User Characteristics on Eigenvector Centrality**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| Independent Variable | Coef(B) | t | Coef(B) | t | Coef(B) | t | Coef(B) | t |
| Reputation score | 0.062 *** | 15.972 | 0.025 *** | 6.710 | 0.022 *** | 6.066 | 0.023 *** | 6.303 |
| Activity level | | | 0.024 *** | 40.214 | 0.018 *** | 19.057 | 0.019 *** | 19.803 |
| Knowledge breadth | | | | | 0.000 *** | 8.200 | 0.001 *** | 11.110 |
| Knowledge depth | | | | | | | -0.002 *** | -8.015 |
| Adjusted $R^2$ | 0.026 | | 0.166 | | 0.172 | | 0.178 | |

This indicates that different user characteristics exert a significant influence on the trade-off between "collaboration scale" and "structural cohesion of collaboration."

**Table 5. Regression results of user characteristics on clustering coefficient**

| | Model 1 | | Model 2 | | Model 3 | | Model 4 | |
|---|---|---|---|---|---|---|---|---|
| Independent Variable | Coef(B) | t | Coef(B) | t | Coef(B) | t | Coef(B) | t |
| Reputation score | -0.228 *** | -16.895 | -0.002 | -0.219 | -0.001 | -0.089 | 0.007 | 0.673 |
| Activity level | | | -0.146 *** | -87.059 | -0.142 *** | -53.578 | -0.135 *** | -52.765 |
| Knowledge breadth | | | | | 0.000 | -1.647 | 0.002 *** | 12.315 |
| Knowledge depth | | | | | | | -0.017 *** | -27.986 |
| Adjusted $R^2$ | 0.029 | | 0.458 | | 0.458 | | 0.499 | |

## 4.2 The Influence of Event Characteristics on Knowledge Collaboration Outcomes

Based on the indicator system developed in this study, event characteristics are introduced along two dimensions, resulting in the construction of seven models. The model fit statistics indicate that the AIC values decrease consistently across both sets of models as additional independent variables are incorporated, reflecting continual improvements in explanatory power.

Table 6 reports the regression results for event-level knowledge collaboration efficiency. Within the dimension of participant role characteristics, structural bridging exhibits a stable and significantly positive effect on collaboration efficiency. The coefficient for maximum betweenness centrality consistently falls within the range of β ≈ 8.3–9.1 (all $p < 0.001$), suggesting that the presence of a key bridging actor within an event significantly enhances collaboration efficiency. In contrast, the coefficient for mean eigenvector centrality indicates that the effect of core embeddedness on efficiency depends on the overall structural configuration. Conversely, the mean clustering coefficient and the concentration of user structural advantages are consistently and significantly negative across all relevant models, indicating that neither excessive embedding of participants within tight local cliques nor domination of collaboration by a small number of structurally advantaged users is conducive to efficiency improvement.

**Table 6. Regression Results of Event Characteristics on Problem-Resolution Efficiency**

| Independent Variable | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | | Model 7 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z |
| Maximum betweenness centrality | 9.287*** | 8.584 | 8.297*** | 7.004 | 4.946*** | 3.963 | 9.139*** | 6.276 | 8.582*** | 5.651 | 8.709*** | 5.734 | 9.084*** | 6.000 |
| Mean eigenvector centrality | | | 1.094* | 2.044 | 0.500 | 0.933 | 0.307 | 0.574 | 0.393 | 0.729 | 0.894 | 1.525 | 2.790*** | 4.125 |
| Mean clustering coefficient | | | | | -5.438*** | 7.951 | -5.109*** | 7.472 | -4.921*** | 7.041 | -4.520*** | 6.254 | -4.263*** | 5.911 |
| User structural advantage concentration | | | | | | | -0.590*** | 5.530 | -0.531*** | 4.577 | -0.551*** | 4.736 | -0.640*** | 5.475 |
| Number of collaborative ties within event | | | | | | | | | 0.008 | 1.288 | 0.009 | 1.505 | 0.047*** | 5.177 |
| Inequality of participation contribution | | | | | | | | | | | -1.982* | 2.164 | 3.029* | 2.362 |
| Mean node strength | | | | | | | | | | | | | -0.200*** | 5.559 |
| AIC | 10505.968 | | 10503.792 | | 10443.101 | | 10414.644 | | 10414.986 | | 10412.308 | | 10383.531 | |
| 2×log-likelihood | 10499.968 | | 10495.792 | | 10433.100 | | 10402.644 | | 10400.986 | | 10396.308 | | 10365.532 | |

Regarding the results for the dimension of internal event structural characteristics, more extensive interactive ties help accelerate the problem-resolution process. The inequality of participation contribution reaches marginal significance in Model 6, but its direction and stability remain limited. Mean node strength is significantly negative in Model 7, suggesting that excessively strong collaboration intensity among a small number of users may undermine overall efficiency.

Table 7 presents the regression results for event-level collaboration quality. In contrast to the primary determinants of collaboration efficiency, the mean eigenvector centrality of participants exhibits the most stable and significantly positive effect on collaboration quality, indicating that the overall degree of participants' core embeddedness constitutes a key structural condition for enhancing answer quality. The effect of bridging actors on quality is less stable than their effect on efficiency, remaining only marginally or weakly significant in a subset of models. The mean clustering coefficient and the concentration of user structural advantages continue to exert negative effects, suggesting that excessive localization or structural monopolization is detrimental to the production of high-quality knowledge.

With respect to the internal collaboration network characteristics of events, a moderate increase in collaborative interaction contributes to improving content quality. In contrast, the explanatory power of the inequality of participation contribution and mean node strength remains relatively limited.

**Table 7. Regression Results of Event Structure on Mean Answer Quality**

| Independent Variable | Model 1 | | Model 2 | | Model 3 | | Model 4 | | Model 5 | | Model 6 | | Model 7 | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z | Coef | z |
| Maximum betweenness centrality | 6.695*** | 5.934 | 2.849* | 2.308 | 0.186 | 0.141 | 4.029** | 2.622 | 3.107 . | 1.947 | 3.104 . | 1.945 | 3.327* | 2.079 |
| Mean eigenvector centrality | | | 3.740*** | 7.584 | 3.313*** | 6.660 | 3.110*** | 6.245 | 3.260*** | 6.485 | 3.239*** | 5.714 | 3.869*** | 5.790 |
| Mean clustering coefficient | | | | | -4.377*** | 5.732 | -4.016*** | 5.240 | -3.704*** | 4.747 | -3.717*** | 4.662 | -3.616*** | 4.523 |
| User structural advantage concentration | | | | | | | -0.554*** | 4.806 | -0.451*** | 3.616 | -0.450*** | 3.593 | -0.491*** | 3.852 |
| Number of collaborative ties within event | | | | | | | | | 0.013* | 2.150 | 0.013* | 2.137 | 0.026** | 2.756 |
| Inequality of participation contribution | | | | | | | | | | | 0.072 | 0.079 | 1.715 | 1.319 |
| Mean node strength | | | | | | | | | | | | | -0.063. | 1.781 |
| AIC | 9618.592 | | 9563.056 | | 9532.264 | | 9511.207 | | 9508.576 | | 9510.570 | | 9509.404 | |
| 2×log-likelihood | 9612.592 | | 9555.046 | | 9522.264 | | 9499.206 | | 9494.576 | | 9494.570 | | 9491.404 | |

## 4.3 Quadrant Analysis of Comment Interaction Patterns

### 4.3.1 Classification of interaction patterns

As a critical interactive mechanism connecting questions and answers, comments play a substantial role in shaping the collaborative process of events, and different comment interaction patterns may give rise to structural differences in the knowledge collaboration context. Drawing on two dimensions—the quality and participation intensity of comment interactions—and using the median of the sample distribution as the demarcation, this study constructs four quadrants corresponding respectively to: (1) high participation × high quality, denoted as "high-quality in-depth collaboration" (HP_HQ); (2) high participation × low quality, denoted as "high-participation but low-efficiency collaboration" (HP_LQ); (3) low participation × high quality, denoted as "concise value-adding collaboration" (LP_HQ); and (4) low participation × low quality, denoted as "weak comment-dependent collaboration" (LP_LQ). The results of the quadrant classification are presented in Table 8. The overall distribution exhibits a certain degree of structural skewness, as shown in Figure 3.

**Table 8. Results of the Comment Intensity–Comment Quality Quadrant Classification**

| Comment Intensity | Comment Quality | Type | Category Name | Number of Events |
|---|---|---|---|---|
| >=4.0 | >=0.1111 | High participation × High quality | High-quality in-depth collaboration (HP_HQ) | 1370 |
| >=4.0 | <0.1111 | High participation × Low quality | High-participation but low-efficiency collaboration (HP_LQ) | 980 |
| <4.0 | >=0.1111 | Low participation × High quality | Concise value-adding collaboration (LP_HQ) | 869 |
| <4.0 | <0.1111 | Low participation × Low quality | Weak comment-dependent collaboration (LP_LQ) | 507 |

The Kruskal–Wallis test results for between-group comparisons indicate that most indicators exhibit statistically significant differences across the quadrants, with the direction of these differences displaying strong consistency across different indicator groups. These findings indicate that the proposed framework adequately differentiates among various collaborative contexts and offers strong explanatory power. The patterns are examined further using box plots overlaid with violin plots.

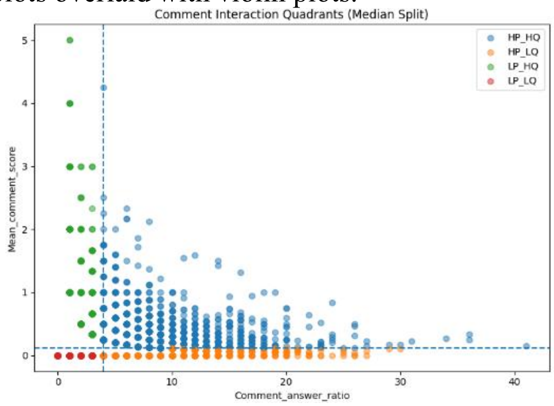


**Figure 3. Results of the Comment Interaction Pattern Quadrant Classification**

4.3.2 The association between interaction patterns and collaboration outcomes

For problem-resolution efficiency (Kruskal–Wallis test, $p < 10^{-38}$), the availability of answers is the dominant factor. When sufficient answers are provided, collaboration can converge rapidly even if comment interactions are limited or of low quality. Frequent commenting, by contrast, does little to accelerate the process when too few answers are available. Collaboration quality also differs significantly across the four types ($p < 10^{-28}$). High-quality comments improve the final answer by clarifying the scope of the problem, assessing possible solutions, and steering the discussion. Their benefits cannot be fully converted into high-quality outcomes without an adequate supply of responsive answers. The HP_HQ type represents a comparatively balanced collaborative state in terms of efficiency and quality. LP_HQ performs particularly well in efficiency but offers limited scope for further quality improvement. HP_LQ, by contrast, reflects a collaborative dilemma of "intensive interaction but insufficient output." Figures 4 and 5 present violin plots of the quadrant-level differences in collaboration efficiency and quality, respectively.

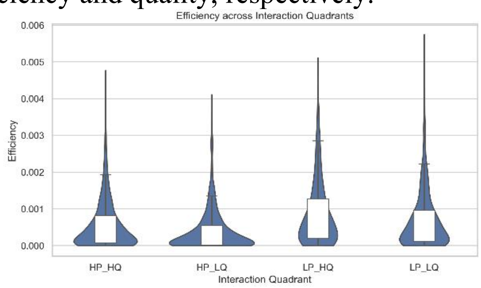


**Figure 4. Violin Plot of Problem-Resolution Efficiency**

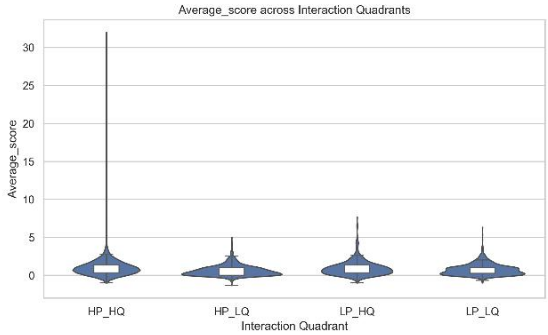


**Figure 5. Violin Plot of Mean Answer Quality**

4.3.3 Differences in user composition and knowledge configuration across interaction patterns

Distinct patterns of participant composition and knowledge organization accompany differences in collaborative outcomes. Two dimensions receive attention here: the knowledge profiles of participating users and the structural organization of tag-based knowledge. A close look at these dimensions helps explain the characteristics of the user groups and the organizational foundations associated with different collaborative outcomes.

Participants' average knowledge depth and domain breadth vary significantly across interaction-pattern quadrants. The difference in knowledge depth is highly significant ($p < 0.001$), whereas domain breadth reaches only marginal significance ($p = 0.048$). User composition, then, differs mainly in terms of who leads the core answering process, rather than whether participants represent a wider range of knowledge domains. In the LP_LQ pattern, overall participation in an event is relatively limited, and answers are generally contributed by a small group of users with extensive experience in the relevant domain. Such users tend to provide answers with high information density that do not depend on the unfolding of discussion. Their collaborative strategy does not rely on sustained interaction, resulting in fewer comments and lower interaction intensity. The HP_LQ pattern, by contrast, exhibits markedly higher interaction frequency, but its participant composition leans toward the joint engagement of low- to mid-experience users. The collaborative process revolves primarily around fragmented exchanges such as problem clarification, incremental supplementation, and error correction, and lacks sustained leadership from high-knowledge-depth users on the core answer, which in turn constrains the overall level of knowledge depth.

With respect to the organizational characteristics of tag-based knowledge, high-quality comment contexts (HP) exhibit only a slight increase over low-quality contexts (LP) in the multi-category range, and no clear dominant advantage emerges across the types. Furthermore, the HP_LQ group displays more pronounced modular differentiation, reflecting a knowledge structure in which multiple topics unfold in parallel but remain insufficiently integrated; the LP_HQ group, by contrast, exhibits lower modularity, with knowledge elements more concentrated on core themes and rapidly converging around key issues. The violin plots depicting the quadrant-level differences in the number of tag categories and in tag-network modularity are presented in Figures 6 and 7, respectively.

4.3.4 The response mechanism of network organization to interaction patterns

Having conducted between-group analyses of participants, concentration levels, and knowledge structures across different interaction patterns, this study further examines, at the level of the overall network, whether these differences crystallize at the quadrant level into stable and distinguishable configurations of collaboration networks. The relevant network structural indicators are presented in Table 9.

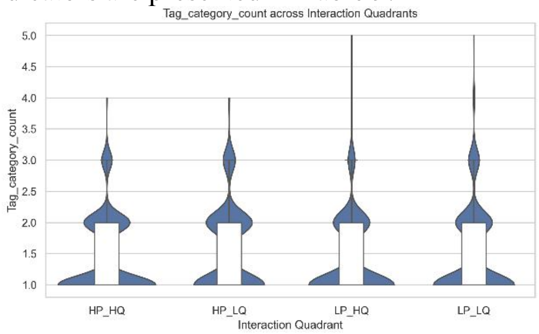


**Figure 6. Violin Plot of the Number of Tag Categories**

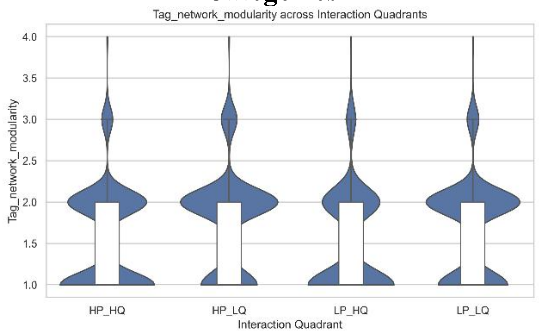


**Figure 7. Modularity of the Tag Co-Occurrence Network**

**Table 9. Comparison of Overall Network Structural Indicators across Interaction Patterns**

| Quadrant | Number of Nodes | Number of Edges | Global Density | Betweenness Centralization | Strength Centralization | Core–Periphery Structure | Modularity |
|---|---|---|---|---|---|---|---|
| HP_HQ | 4150 | 11273 | 0.001 | 1.84E-05 | 0.957 | 3.575 | 0.711 |
| HP_LQ | 2763 | 6983 | 0.001 | 2.20E-05 | 0.953 | 3.380 | 0.725 |
| LP_HQ | 1759 | 4832 | 0.003 | 5.10E-05 | 0.935 | 3.629 | 0.694 |
| LP_LQ | 3068 | 8108 | 0.002 | 2.96E-05 | 0.954 | 3.477 | 0.718 |

With respect to centralization indicators, the collaboration networks associated with different interaction patterns exhibit a clear divergence regarding the question of "whether the network relies on a small number of key nodes." In contexts characterized by ample answer supply but low interaction quality, the collaboration network depends more heavily on a small number of key intermediary nodes to connect different answers and discussion branches, thereby giving rise to an efficiency-oriented "channel-type" structure. By contrast, high-quality comments reduce the structural reliance on intermediary bridging nodes, enabling information to diffuse more evenly across the network and yielding a lower overall level of betweenness centralization. Regarding the core–periphery structure, a high supply of answers is more conducive to the formation of a stable core composed of a few highly active answerers, around whom peripheral users engage in interaction; in contexts where answer supply is insufficient and interactions are fragmented, however, a clearly delineated core–periphery division of labor has yet to emerge. This finding corroborates the earlier event-level result that user participation concentration is relatively higher under LP conditions.

To further enable a comprehensive comparison of the overall differences in multidimensional structural indicators across collaboration networks under different interaction patterns, this study standardizes the key network structural indicators via z-score transformation and conducts a unified comparison at the quadrant level, thereby revealing the relative position of each interaction pattern with respect to the overall configuration of network organization. The standardized differences across quadrants are illustrated in Figure 8.

As shown in the figure, different interaction patterns exhibit consistent and distinguishable combinations of features across multiple structural indicators. The LP_HQ group scores above the mean on betweenness centralization, the core–periphery index, modularity, and network density, indicating that the collaboration network associated with this pattern displays an efficiency-oriented, core-driven, and structurally concentrated form of organization. The HP_HQ group is characterized by a relatively large network scale, a comparatively balanced structure, and a lower degree of reliance on key intermediary nodes. The collaboration network of the HP_LQ group comprises several relatively independent discussion clusters but lacks a stable collaborative core, giving the network a dispersed structure. The LP_LQ group, by contrast, occupies a middle ground between concentration and dispersion, displaying a comparatively balanced and stable network configuration.

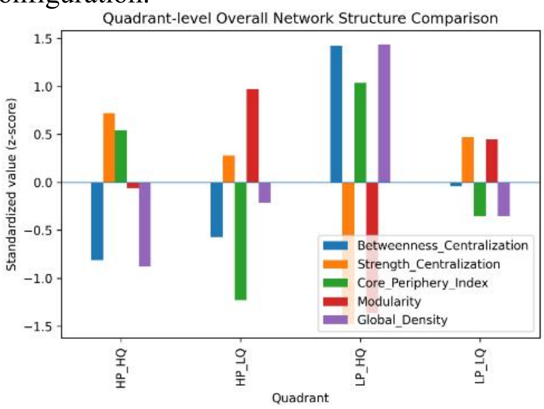


**Figure 8. Standardized Comparison of Overall Network Structures across Interaction Patterns**

## 5. Conclusion

This study examines how knowledge collaboration develops and varies structurally in online question-and-answer communities. Three aspects receive attention: user characteristics, the structure of collaboration networks, and patterns of interaction in comments. The analysis identifies the principal mechanisms shaping knowledge collaboration at the individual, event, and network levels.

Individual characteristics have systematic and enduring effects on users' positions within collaboration networks. Activity level is the strongest predictor of network position: frequent participation helps users establish open collaborative ties across communities. A broad engagement with knowledge, even without substantial depth in a specific area, therefore offers greater structural advantages than narrow specialization. Participants' ability to bridge otherwise disconnected groups also remains a reliable determinant of collaboration efficiency. Events involving a key bridging actor tend to resolve problems more quickly, whereas closed, clique-based structures impede the effective integration of knowledge.

Viewed within the broader interaction context, the four interaction patterns differ markedly in collaborative outcomes, user dominance, and knowledge organization. At the event level, low-participation contexts tend to be led by a small group of highly experienced users. Although interaction is limited, the knowledge exchanged is often highly concentrated. High-participation, low-quality contexts generally involve users with low or moderate levels of experience. Exchanges are frequent, but the resulting knowledge remains fragmented. These patterns reflect how different combinations of participants and collaborative practices operate at the event level and, in turn, give rise to distinct collaboration networks.

The HP_HQ cluster functions as a well-developed collaboration network. Its considerable scale and structural balance stand out, with minimal reliance on bridging nodes. HP_LQ, in contrast, exhibits a fragmented discussion pattern—modules are clearly present, yet cross-module ties remain weak. LP_HQ is tighter and smaller, centered around a handful of key users who drive most of the activity, suggesting a more streamlined, efficiency-focused mode of collaboration. LP_LQ occupies middle ground: sparse interactions coexist with a surprisingly steady overall architecture. Together, these four types reveal how participation patterns, interaction dynamics, and the organization of shared knowledge vary systematically across different community settings.

This paper takes a multilevel approach to unpack knowledge collaboration in online Q&A platforms. Individual attributes influence where people sit in the network, and those positional differences, in turn, shape the overall structure and how efficiently the group functions. When user characteristics and collaboration approaches combine in different ways, they generate recognizable interaction styles and network shapes. The findings offer new insight into how collaboration unfolds in these spaces, and they provide a practical framework for thinking about incentive design, platform features, and ways to strengthen collaborative practices going forward.

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