Characteristics of User Interaction Behavior in Virtual Job-Seeking Communities: A Case Study of the Fresh Graduate Job-Seeking Forum (Postprint)

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Abstract

[Purpose/Significance] Virtual job-seeking communities have become important channels for job seekers to obtain and share information and resources. By mining user interaction patterns and structures in these communities, this study proposes recommendations for their improvement. [Method/Process] Utilizing user interaction data from a fresh graduate job-seeking forum and combining applied content analysis with social network analysis methods, this research examines both user interaction content and interaction relationships. [Results/Conclusions] The study finds that users most frequently exchange factual data related to job seeking, but they also seek social support such as social networking, recommendations, and instrumental support; interaction demands vary significantly across different job-seeking topics, with users being most concerned about comprehensive information and resources related to written tests and interviews. Meanwhile, the overall user base remains largely disconnected with minimal interaction; the primary relational network is sustained by a few key members, and there is a shortage of core users to facilitate the dissemination of information and resources.

Full Text

Preamble

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Characteristics of User Interaction Behaviors in Virtual Job-Hunting Communities: A Case Study of the Yingjiesheng Job Forum

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Abstract

[**Purpose/Significance**] Virtual job-hunting communities have become important channels for job seekers to obtain and share information and resources. By mining the user interaction patterns and structures of these communities, this study proposes recommendations for community improvement.

[**Method/Process**] Using user interaction data from the Yingjiesheng job forum, this research combines content analysis with social network analysis to examine two dimensions: user interaction content and interaction relationships.

[**Result/Conclusion**] The study finds that users most frequently exchange factual data related to job hunting, but they also seek social support including social networking, referrals, and instrumental support. Different job-hunting topics exhibit significantly different interaction needs, with users showing the greatest concern for all aspects of information and resources related to written tests and interviews. Meanwhile, the overall user community remains discrete with limited communication. The primary relationship network is supported by a few key members, lacking sufficient core users to promote the dissemination of information and resources.

Classification Number: G209
Keywords: Virtual job-hunting community, Interaction patterns, Social network analysis, Content analysis, Group communication

With the rise of social network-based recruitment, an increasing number of job seekers are using online social networks to search for job information and resources. Recruitment companies are no longer limited to traditional job websites but are gradually adopting social media platforms such as microblogs and social networking sites as recruitment channels [**?**]. A Jobvite survey found that 93% of companies use or plan to use social media as a recruitment tool, with 51% planning to increase investment in mobile recruitment [**?**]. The application of various forms of virtual communities–including social websites, forums, friend circles, and Q&A platforms–in the job recruitment field has facilitated interactions between job seekers and other members (including current employees, HR personnel, and other job seekers). These interactions not only help job seekers access more opportunities but also assist them in coping with job search setbacks and understanding the knowledge and skills required for target positions [**?**].

Virtual job-hunting communities are online social media platforms where people search for and share job-related information and resources [**?**]. Currently, research on virtual job-hunting communities remains limited, primarily focusing on individual job seekers' community usage and its impact, with a lack of studies at the group interaction level [?]. However, existing research on group interaction behaviors in other virtual community domains provides strong methodological support and theoretical foundations for this study.

Compared to activities such as tourism, scientific research, online shopping, and e-learning, job hunting is a complex, time-sensitive activity that heavily relies on personal social networks [?]. Job seekers' urgent psychological state significantly influences how they participate in community interactions and causes them to rarely continue following job-related topics after securing employment. Consequently, user interaction behaviors in virtual job-hunting communities differ markedly from those in other virtual communities.

2. Related Research on Group Interaction Behaviors in Virtual Communities

Given this context, this study uses interaction data from the Yingjiesheng job forum as its foundation, combining content analysis with social network analysis from a group interaction perspective to deeply explore users' social interaction patterns in virtual job-hunting communities. The goal is to understand current job seekers' utilization of these communities, uncover their potential information value, and provide recommendations for improving user engagement.

2.1 Current Status of Research on Virtual Community Group Interaction Behaviors

Through literature collection and analysis, scholars have explored group online interaction behaviors across various domains, analyzing interaction patterns and information search/sharing characteristics of specific groups, as well as examining behavioral motivations and their impact on individual decisions and collective actions. Extensive interaction research has concentrated on healthcare (e.g., A. McCormack [?], K.C. Eichhorn [?]) and education (e.g., Gan Yongcheng [?], M. Lucas et al. [?]), with several classic and mature analytical frameworks already established, such as the social support interaction analysis framework by C.E. Cutrona and J.A. Suhr [?], the epistemological interaction analysis framework by J. Pena-Shaff et al. [?], and the knowledge construction interaction analysis framework by C.N. Gunawardena et al. [?].

With the widespread application of virtual communities, some scholars have begun investigating interaction behaviors of specific target groups including IT professionals [?], investors [?], tourists [?], and consumers [?], though research in these areas remains relatively scarce and fragmented. Nevertheless, existing domain studies have fully confirmed the substantial information value of virtual communities, demonstrating that they provide rich, useful information for problem-solving and decision-making. Other scholars have focused more on group interaction characteristics or differences across various virtual community forms such as Q&A platforms [?] and blogs [?], analyzing interaction patterns or information dissemination models to guide effective community utilization. Research indicates that different virtual community forms—even within the same community—may exhibit distinct interaction patterns, which significantly affect information sharing effectiveness, quality, and credibility.

2.2 Main Research Methods for Virtual Community Group Interaction Behaviors

Overall, the most commonly used methods for virtual community group interaction analysis are content analysis and social network analysis.

Content analysis primarily involves classifying and analyzing user-generated content in virtual communities, counting category frequencies to identify interaction patterns [?]. Numerous interaction analysis frameworks describing group interaction processes exist in the literature, varying substantially in classification quantity, complexity, criteria, and applicability [?]. Examples include the universally applicable Interaction Process Analysis (IPA) framework by R.F. Bales [?] and the social support coding framework by C.E. Cutrona and J.A. Suhr [?] for healthcare domains. Some researchers apply these classic frameworks to analyze group interactions in virtual communities (e.g., C.K. Courserais and M. Liu [?]), while others develop new classification frameworks (e.g., U. Pfeil and P. Zaphiris [?]). To ensure framework validity, L. Rourke and T. Anderson [?] recommend using established frameworks developed and validated by other researchers.

Social network analysis examines interaction relationships in virtual communities to observe network structures and members' positions, exploring group interaction characteristics from a structural perspective. As a powerful relationship analysis technique, it provides opportunities to quantify complex online interaction patterns [?]. Social network analysis offers various structural metrics such as network density, centrality, and average path length, enabling researchers to analyze network characteristics at both whole-network and individual levels to identify active members and influential or resource-holding key members. These metrics have been widely applied in virtual community group interaction network studies.

Related research [?, ?, ?] demonstrates that combining content analysis with social network analysis from both content and relationship dimensions facilitates deeper, more detailed understanding of interaction nature and types among network members.

3. Research Design

3.1 Research Object Selection

Founded in 2005, Yingjiesheng.com is currently China' s largest job-hunting website for fresh graduates. This study selected interaction data from the six most active job-hunting boards on the Yingjiesheng forum. Data were collected from January 1, 2016 to December 31, 2016. Forum topics are generally called "posts" ; this study defines posts that initiate new topics as "root posts" and replies that continue these topics as "response posts" [?]. Among the 5,369 posts extracted (including 1,894 root posts and 3,475 response posts), data cleaning yielded a final dataset of 1,868 root posts and 3,078 response posts.

3.2 Research Methods and Process

Based on this data, the study first conducted content analysis of the posts themselves, then performed social network analysis of reply relationships among forum members from a social relationship dimension.

3.2.1 Content Analysis Phase In the collected data, each root post received an average of 1.77 replies and had an average of 1,297 views. Although the average reply rate was not high, the discussion content clearly concerned university student job seekers. Therefore, this study employed content analysis from an interaction process perspective to examine online interaction patterns and their variations across different job-hunting topics. Two analytical frameworks were established: an interaction process analysis framework and an interaction topic analysis framework, with data coded according to both frameworks.

(1) Determination of Interaction Content Analysis Framework. Preliminary analysis of raw data revealed that job seekers' online interactions aim to obtain social support in a broader sense through online social networks, including seeking job information and resources, solving specific job-hunting problems, requesting advice or experience, emotional exchange, and finding peers. To ensure content analysis validity, this study referenced the classic Interaction Process Analysis (IPA) framework by R.F. Bales [?] and the social support coding framework by C.E. Cutrona and J.A. Suhr [?], adapting them to job seeker interaction characteristics. Interaction behaviors were divided into two major categories—task information and social emotion—further subdivided into 20 subcategories, as shown in Table 1 .

(2) Coding Rules and Methods. Since post lengths varied dramatically (from a dozen to over a thousand characters) with inconsistent richness and random arrangement, simply coding entire posts or comments as single categories, or coding sentence-by-sentence or paragraph-by-paragraph, would not correspond to actual content nature. Therefore, this study adopted the "meaning unit" segmentation standard, which is closer to content semantics [?], before coding meaning units using the two frameworks. A meaning unit refers to a single thought or idea unit that can be extracted from content, exist independently, and still express a complete single thought [?].

Three collaborators who reached consensus on classification standards after coding training performed the coding work. First, post content was divided into meaning units. To ensure reliability, consistency was tested using the formula

2M/(N1+N2) [?], achieving 90% consistency after multiple rounds of testing. Second, meaning units were coded using the two frameworks. To ensure reliability, Cohen' s Kappa coefficient was used to test coding consistency [?]. Both frameworks achieved coefficients exceeding 0.75 (0.791 and 0.871 respectively), indicating good reliability. Inconsistent coding results were discussed among the three collaborators until consensus was reached.

(3) Determination of Interaction Topic Analysis Framework. When establishing the job seeker interaction topic analysis framework, this study categorized interaction topics into 11 types based on different job-hunting process stages and initial data analysis, as shown in Table 2 .

3.2.2 Social Network Analysis Phase The reply relationship network formed by users' posts and replies represents the concrete manifestation of online interaction. Social network analysis of this network helps understand user groups' social interaction patterns and structures. This study constructed a directed, weighted social network with all posting and replying users as actors, reply relationships as interactions, and reply frequency as relationship strength. In this network, a directed edge from user A to B indicates A replied to B, with edge weight representing reply count. After removing self-links (users replying to themselves) and isolated nodes (posting users who received no replies), the final network comprised 1,990 member nodes and 1,833 directed edges. Using social network analysis software Ucinet, this study analyzed the reply network from network structure and centrality perspectives to explore information dissemination forms and user interaction levels.

4. Research Results and Analysis

4.1 Content Analysis Results

When statistically analyzing coding results, if a post contained multiple meaning units of the same type (e.g., advice), it was counted only once—multiple identical meaning units within the same post were recorded as one unit.

4.1.1 Analysis of Job Seeker Interaction Processes The interaction process analysis framework yielded 7,831 meaning units, including 3,703 from root posts and 4,128 from response posts. Statistical results for each meaning unit type in root and response posts are shown in Figure 1 [Figure 1: see original paper].

As Figure 1 shows, users primarily create root posts to share job-hunting facts (15.18%) and personal experiences (14.2%), providing social support to others based on their own experiences—mainly offering advice (6.83%) or opinions (5.97%). To solve job-hunting problems, users also actively seek social support by creating root posts, most frequently consulting about facts (10.80%) such as job-hunting process details and company recruitment information, followed by seeking advice (9.94%) and opinions (5.24%) for various job-hunting decisions.

Conversely, users rarely post specifically to express emotions or seek emotional support. Instead, they express emotional appeals while sharing experiences or seeking help. The most frequent emotional expression is friendliness (11.18%)—encouraging questions, wishing others success, or expressing gratitude—followed by displaying tension (6.54%) and relieving tension (3.86%). The former includes frustration from job-hunting failures and anxiety over decision-making, while the latter involves adjusting mindset and relaxing during stressful job searches.

Similarly, response posts most frequently involve providing (21.03%) and requesting (16.67%) factual information, indicating users' primary focus on exchanging real-time job-hunting information and data. This is followed by expressing opinions (11.92%) or giving advice (4.97%), with some directly requesting instrumental support (4.70%) such as materials or practical assistance.

Regarding emotional exchange, friendliness also dominates response posts (21%), mainly expressing gratitude and praise to information providers, followed by expressing job-hunting anxiety and nervousness (4.26%).

Table 3 summarizes the community' s user interaction patterns. The job-hunting community primarily focuses on job task information exchange, with a greater tendency toward information sharing. Factual content exchange dominates, with frequent advice and opinion exchanges—consistent with other virtual community research findings. However, virtual job-hunting communities have unique characteristics: root post authors more frequently share personal job-hunting experiences, while responders more often directly request instrumental and social network support from root post authors or provide instrumental support to others. In emotional categories, both root post authors and responders tend to show positive, friendly emotions to other job seekers, attempting to adjust tense emotions and maintain a positive mindset to cope with the intense job-hunting environment.

Root and response posts have different emphases. Beyond factual content exchange, root posts more frequently request advice and opinions, while response posts directly request instrumental and social network support—likely because responders have more specific request targets (root post authors or other responders), making it more feasible to obtain connections and direct help. In information provision, root posts emphasize sharing personal experiences, while response posts focus more on providing advice, opinions, or direct help. In emotional categories, both root post authors and responders prefer showing positive, friendly emotions.

4.1.2 Analysis of Job Seeker Interaction Processes by Topic The interaction topic analysis framework yielded 5,274 meaning units, including 2,422 from root posts and 3,249 from response posts. As shown in Figure 2 [Figure 2: see original paper], written tests/interviews dominate both root and response posts (43% and 50% respectively), indicating users' greatest concern for this critical job-hunting stage that directly affects outcomes. Interaction content covers all aspects including process, test content, experiences, results, progress, materials, interview partners, and discussion groups. Offer/signing ranks second (18% in both), mainly involving sharing offers and seeking advice on signing decisions. Other topics receive less attention but remain relevant to some users.

To further explore interaction processes across topics, cross-tabulation analysis was performed between topics and task information meaning units (emotional exchange being topic-independent). Results reveal:

(1) Significant topic-specific interaction pattern differences. Personal job status differs most from other topics, involving only factual data exchange—primarily providing basic personal information.

In root posts, written tests/interviews, job-hunting experiences, and internship/work experiences all emphasize sharing personal experiences, showing similar patterns: personal experience > facts > advice/opinion/instrumental support (with minor ordering differences) > social network/referral. Resume, career planning, and offer/signing topics focus on requesting advice, with the latter two showing nearly identical patterns: advice > facts > opinion > social network > instrumental support/personal experience/referral. Resume topics additionally request instrumental support and opinions, but rarely social network support. Recruitment information, online applications, and company topics primarily involve factual exchange.

In response posts, all topics except written tests/interviews show the top three patterns: facts, opinions, and advice. Written tests/interviews additionally involve requesting instrumental support such as test materials.

(2) Overall, factual, advice, and opinion exchanges are frequent across topics. Personal experience and referral support are more often provided than requested, indicating users' willingness to share experiences and resources. The former mainly appears in online application, written test/interview, internship/work experience, and overall job-hunting experience posts, while the latter appears in resume and company topics, recommending resume template websites and suitable companies.

Social network and instrumental support are more frequently requested than provided, revealing unmet community demand. Social network support appears mainly in written test/interview, offer/signing, and company topics, seeking connections for subsequent job-hunting activities. Instrumental support appears primarily in online application, resume, and written test/interview topics, requesting materials or direct help for preparation.

4.2 Social Network Analysis Results

4.2.1 Overall Network Structure Analysis Network density reflects the closeness of user connections—high density indicates frequent knowledge sharing interactions [**?**]. The community network' s average density is only 0.0006, far below the 0.14 for public communities, 0.05 for hierarchical communities, and 0.004 for square-type communities reported in existing research [?]. The network is extremely sparse, lacking widespread close connections, with many users having loose interaction relationships. Figure 3 [Figure 3: see original paper] visually shows the user reply network: most nodes have only one or two connections at the network periphery, while only a few nodes have many connections, presenting a loose structure consistent with the density finding.

To verify information flow efficiency, complex network parameters "average path length" and "clustering coefficient" were used to test for small-world effects through comparison with random networks having identical node and edge counts. If the actual network' s average path length approximates the random network' s while its clustering coefficient far exceeds it, the network exhibits small-world effects [?]. Table 4 compares actual and three random networks, confirming small-world effects. This means that although most users are not closely connected, tightly-knit groups exist in local subnets. Meanwhile, any two users can connect through an average of nearly 7.5 intermediaries, enabling relatively fast information dissemination and convenient communication.

4.2.2 Network Centrality Analysis Analysis focuses on network centralization (group-level) and centrality (node-level). Network centralization measures the degree of network concentration toward the center, indicating reliance on a few actors [?]. The community network' s out-degree centralization is 0.075% and in-degree centralization is 0.201%—both extremely low, indicating poor network cohesion and no obvious centralization, instead showing clear "decentralization" with low and dispersed user participation. Average out-degree and in-degree are both 1.141, with 92% and 89% of nodes having degree <3, respectively, confirming low user activity and lack of highly influential users.

However, the network' s betweenness centralization is 14.07%, suggesting minimal possibility of individual nodes controlling resources and connections, with relatively dispersed node relationships. Only 1.86% of users have relatively high betweenness centrality (>1), serving as bridges connecting other users, while 73% of nodes have zero betweenness centrality, indicating most users remain at the network periphery with poor information sharing.

Conclusions

Based on the above analysis:

(1) Job seekers'urgent psychological state significantly influences their community participation. The job-hunting community network structure is extremely loose, even far below square-type communities [?], with most users showing low stickiness and activity. Despite small-world effects, overall network cohesion is low, lacking enough highly influential and active core members to ensure network stability.

(2) Users have clear utilitarian purposes, focusing on sharing and seeking job-related information and resources, supplemented by psychological support. More users tend to share and provide various information and resources, participating with positive attitudes.

(3) Factual information exchange is the primary interaction mode, with frequent advice and opinion exchanges—consistent with other virtual community research. Virtual job-hunting communities have unique characteristics: root post authors more frequently share personal job-hunting experiences, while responders more often directly request instrumental and social network support or provide instrumental support to others. The community shows imbalance in social network and instrumental support (more seeking than providing), with many users unable to obtain desired connections, resources, and direct help.

(4) Job-hunting complexity leads to diverse interaction topics, with nearly half related to written tests/interviews—likely due to recruitment market emphasis on this critical stage directly affecting outcomes. Different topics show distinct interaction patterns: root posts on written tests/interviews, job-hunting experiences, and internship/work experiences emphasize sharing personal experiences; resume, career planning, and offer/signing topics focus on requesting advice; recruitment information, online applications, and company topics primarily involve factual exchange. Response posts (except for written tests/interviews) mainly exchange facts, opinions, and advice.

In summary, although virtual communities have become important venues for job seekers to obtain and share job-hunting information and resources, growing demand for job-related connections, physical resources, and direct services is not adequately met by current community management models and platforms. Differentiated interaction needs across topics are only roughly addressed through board divisions, making effective satisfaction difficult. Meanwhile, most users show low stickiness and activity, lacking sufficient core users to promote information and resource dissemination, resulting in unmet personalized and diverse interaction needs.

Therefore, communities should enhance social elements to facilitate relationship building and social interaction among members, while establishing comprehensive member management models and incentive systems. They should emphasize core members while encouraging them to interact with others, promoting active community participation.

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Author Contributions

Wang Xuefen: Coding framework determination, data coding, statistical analysis, and paper writing;
Zhu Qinghua: Theoretical foundation construction and paper revision;
Chang Liyan: Coding framework determination and data coding;
Guo Lili: Data coding;
Tong Hu: Data crawling and cleaning.

Note: Figure translations are in progress. See original paper for figures.