Motivations for User Reputation Conferral Behavior in Social Q&A Communities: A Postprint Study

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Abstract

[Purpose/Significance] Crowd voting is currently one of the most prevalent content ranking methods in social Q&A communities. Analyzing the motivations behind users' reputation-giving behavior in such communities, devising targeted reward and penalty measures, and properly guiding users to responsibly participate in UGC collaboration can ensure the healthy development of social Q&A communities, fully exploit their role in netizens' informal learning, enhance public literacy, and promote self-governance of the online information environment. [Method/Process] Employing the grounded theory methodology, through sample selection and data collection, 250 original answer materials were selected from relevant Zhihu questions and subjected to coding analysis. Integrating customer participation theory and attribution theory, a motivational model for users' UGC reputation-giving behavior in social Q&A communities was ultimately constructed. [Results/Conclusions] Users' UGC reputation-giving behavior in social Q&A communities is influenced by reputation-giving intention and facilitating factors; reputation-giving intention is affected by perceived usefulness and social influence; moreover, users' assessment of the perceived usefulness of reputation-giving behavior is impacted by the information quality, information source, and social influence of UGC.

Full Text

Preamble

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Research on User Motivation for Reputation Bestowal Behavior in Social Q&A Communities

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Abstract: [Purpose/Significance] Voting is currently one of the most common content sorting methods in social Q&A communities. Analyzing the motivations behind users' reputation-bestowing behavior in these communities, formulating targeted reward and punishment measures, and correctly guiding users to participate responsibly in UGC collaboration can ensure the healthy development of social Q&A communities, fully leverage their role in informal learning among netizens, improve national literacy, and promote autonomous governance of the internet information environment. [Method/Process] Using grounded theory methodology, this study selected 250 original responses from Zhihu-related questions through sample selection and data collection, conducted coding analysis, and combined customer participation theory and attribution theory to construct a model of user UGC reputation-bestowing behavior motivation in social Q&A communities. [Result/Conclusion] Social Q&A community users' UGC reputation-bestowing behavior is influenced by reputation-bestowing willingness and facilitating factors. Reputation-bestowing willingness is affected by perceived usefulness and social influence, while users' judgment of the perceived usefulness of reputation-bestowing behavior is influenced by UGC information quality, information source, and social influence.

Keywords: Social Q&A community; Grounded theory; Reputation system

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Introduction

The massive volume of user-generated content (UGC) has created information overload, making content popularity within communities increasingly determined by user voting mechanisms, particularly in social Q&A communities such as Quora.com in the United States and Zhihu in China. These Q&A platforms sort answers based on vote counts, achieving effective information filtration. Other social media platforms like Digg.com and Instagram.com also rely on similar mechanisms to identify popular content. Voting in content communities is important because it reflects collective quality assessment and influences readers' attention allocation. Some scholars consider user voting behavior a form of information adoption and analyze antecedents such as UGC content attributes and author characteristics. However, most of these studies focus on e-commerce websites rather than social Q&A communities. The key differences are that UGC in social Q&A communities typically features much richer topics and substantially longer content. Moreover, while online reviews have become important references for consumer shopping on e-commerce platforms, they remain essentially product-dependent and far less comprehensive, rich, and open than UGC in social Q&A communities. This makes issues such as information quality evaluation and early identification of high-reputation information more challenging in social Q&A communities.

For UGC in social Q&A communities, reputation-bestowing behavior can be viewed as a spontaneous mass filtering, sorting, and dissemination activity. This behavior reduces users' information search costs, incentivizes knowledge contribution, and significantly influences user satisfaction with the community. These factors not only drive active user behavior but also serve as important guarantees for "lurkers" to continue using the site and represent core drivers for community development. Reputation-bestowing behavior in social Q&A communities can motivate high-quality content production, help platforms quickly identify, select, organize, and extract suitable content for dissemination, and enhance the visibility of quality content providers, creating more opportunities for spiritual and material rewards that further incentivize knowledge contribution. As traditional media discourse becomes diluted and internet information governance costs increase, user reputation-bestowing behavior effectively promotes information ordering in social Q&A communities. Given the proportion of social Q&A community users among internet users and the role these platforms play, information ordering and self-organization in these communities can improve internet information governance and reduce problems such as rumor propagation, cyber violence, and information cocoons caused by information overload.

The influence of social Q&A community users' UGC reputation-bestowing behavior is shown in Figure 1 [Figure 1: see original paper].

Literature Review

2.1 Reputation Systems in Social Q&A Communities

Sociologist S.L. Nock defines reputation as "a common or collective view of a person." Reputation has become essential for ensuring trust in Web services and service-oriented architectures across artificial intelligence, e-commerce, social media, peer-to-peer networks, and multi-agent systems. Scholars have made various attempts to define reputation ontology, though the term is sometimes used interchangeably with "trust" or "influence." After synthesizing these studies, M. Jarcovi et al. propose that reputation should encompass four dimensions: trust, influence, expertise, and impact, representing expectations about an entity' s behavior derived from observing its past actions.

In online environments, reputation systems generally refer to mechanism designs that track and display users' past behaviors and achievements on platforms based on established criteria. Effective reputation systems can promote active platform usage and influence user satisfaction. Guo Kaiqiang et al. found that in e-commerce websites, consumers' perceived usefulness of online reputation systems even exceeds the impact of shopping experience satisfaction on posting positive reviews. S. Dvir-Gvirsman demonstrated through experiments that reputation characteristics of news information on social media affect users' attention allocation, though this effect varies among users. While some scholars have used small samples to survey collaborative evaluation attitudes in online communities, and Q. Tang et al. used YouTube and Twitter data to prove that content popularity and user sentiment polarity (whether positive or negative) drive reputation-bestowing behavior, no mature, repeatedly validated theory exists for UGC reputation-bestowing behavior in social Q&A communities. Therefore, this study adopts grounded theory methodology to conduct exploratory research on the behavioral mechanisms of social Q&A community users' UGC reputation-bestowing behavior.

2.2 User Reputation-Bestowing Behavior in Social Q&A Communities

Xu Yang et al. argue that reputation characteristics of answers in social Q&A communities reflect their popularity and influence. Therefore, user UGC reputation-bestowing behavior must feature public display and mass evaluation, representing essentially a form of "social endorsement" through which users declare their adoption of certain UGC to connected members. Unlike simple information adoption, social endorsement includes information sharing and public backing, thus influencing other users' perceptions of UGC. P. Borah et al., using Facebook as a sample, found that health information receiving substantial reputation bestowal gains trust. M. Chung, studying U.S. and Korean news information, found that social endorsement reduces the impact of source credibility on news quality perception, though this effect differs between the two countries. However, like other public behaviors, reputation bestowal may influence adolescent imitation. L.E. Sherman et al. experimentally proved that teenagers' photo preferences are easily influenced by virtual peers' endorsement behaviors, even for neutral or dangerous behaviors (such as drinking or smoking), with heavier photo viewers being more susceptible.

Reputation-bestowing behavior also serves as social feedback that motivates other users and provides non-monetary rewards satisfying knowledge sharers' psychological needs. Zhang Baosheng et al., using grounded theory, identified social relationships and psychological rewards from reputation-bestowing behavior as factors influencing knowledge contribution intention. M.M. Wasko et al. also noted that users' pursuit of reputation motivates knowledge contribution. Since UGC creation, editing, and modification occur before potential audiences, reputation-bestowing behavior provides examples for subsequent respondents and facilitates further answers. Therefore, reputation-bestowing behavior encompassing UGC evaluation, endorsement, dissemination, and guarantee constitutes part of knowledge collaboration in virtual communities. N. Diakopoulos et al. argue that user reputation-bestowing behavior helps manage comment quality.

Finally, reputation-bestowing behavior reflects users' personal preferences and social image, providing references for information push, advertising, and market forecasting. T. Lappas et al. mined user preferences through social endorsement information using topic modeling techniques, validated with Twitter and Flickr data. L.F. Lin et al. proposed a social endorsement-based diffusion mechanism to guide corporate advertising, improving user satisfaction and target delivery rates. L. Qiu et al. found experimentally that increased audience size and higher levels of online reputation-bestowing behavior positively impact market forecasting effectiveness.

Integrating these characteristics, this study defines UGC reputation-bestowing behavior in social Q&A communities as behavior encompassing public feedback, evaluation, recommendation, guarantee, and dissemination of UGC. Notably, the public nature of reputation bestowal appears not only on UGC interfaces, influencing sorting and others' perceptions, but also on endorsers' personal pages with real-time push notifications to followers. In Zhihu, "like," "favorite," and "thank" all express UGC adoption, but since "favorite" and "thank" are not publicly displayed under specific answers nor shown on users' personal homepage feeds, they cannot endorse or amplify influence. The "like" function satisfies all characteristics of reputation-bestowing behavior, making it the focus of this empirical study using Zhihu data.

Research Design and Process

3.1 Research Methodology and Approach

Grounded theory methodology (GTM) is one of the most commonly used qualitative research methods in social sciences and information science, allowing researchers to "theoretically describe the general characteristics of a topic while grounding that description in empirical observation or data." It is particularly suitable for research with limited existing studies requiring theory building. In information systems research, GTM frequently appears in studies of technological change and socio-technical behaviors in emerging fields.

This study chose GTM for four reasons: First, social Q&A community users' UGC reputation-bestowing behavior constitutes part of user information behavior, and GTM is among the most suitable methods for human-related issues. Second, few scholars have applied GTM to study UGC reputation-bestowing behavior in social Q&A communities, with most research focusing on adjacent areas like knowledge contribution or sharing behaviors. Third, GTM suits studies without pre-existing hypotheses seeking data-driven theory, which matches this research' s needs. Fourth, recent GTM studies on social Q&A community users have produced excellent substantive theories. While GTM is typically used in social research, it also applies to ubiquitous information systems, particularly those with social characteristics.

This study follows GTM' s common approach: theoretical sampling guided by emerging theory, selecting existing Zhihu questions, crawling all data using web scrapers, then expanding searches through Zhihu' s related question recommendations and linked content in crawled data to complete primary data collection. Grounded theory coding analysis of original materials then extracted research categories and explored their logical relationships to build the theoretical model framework.

3.2 Data Collection

3.2.1 Data Source Selection Social Q&A communities have proven valuable resources for professional knowledge sharing since their inception, widely accepted and used by internet users. These systems store all questions and answers as searchable databases, serving not only technical knowledge sharing but also as sources for advice and curiosity across disciplines. By the end of 2018, Zhihu announced over 220 million users (102% year-over-year growth), more than 30 million questions, and over 130 million answers, making it the world' s largest Chinese social Q&A community and an extremely rich knowledge repository.

Using Zhihu as a data source offers four advantages over traditional interviews: First, as a form of UGC, Zhihu' s Q&As are completed spontaneously by participants without requiring them to be in specific locations or situations, eliminating most contextual interference and ensuring authentic reflection of participants' thoughts. Second, Zhihu allows users to add images, videos, or external links to supplement viewpoints and enables commenting and editing of published UGC, reducing information uncertainty and misunderstandings while facilitating accurate analysis. Third, interview samples are typically limited to dozens of participants, whereas Zhihu provides massive data. Fourth, all data is permanently stored and publicly accessible, enhancing research repeatability and result verifiability.

3.2.2 Raw Data Collection To analyze UGC reputation-bestowing motivation in social Q&A communities, the author searched Zhihu in May 2019 for keywords related to this behavior (such as "like," "agree," "vote"), using a snowball sampling approach to select multiple relevant questions for a database. Since Zhihu provides related question recommendations and allows users to add links to relevant Q&As, the author adopted a strategy of collecting data while analyzing. Around the theme of user UGC reputation-bestowing motivation, over 100,000 characters of data were collected. Before final analysis, the author excluded: (1) irrelevant or content-free responses; (2) overly humorous or cryptic responses with unclear meaning; (3) responses with fewer than 20 characters. For questions with excessive answers, typically only the top 20 responses or comments were analyzed. Ultimately, 250 response records (including answer content and comments) were organized for this study, with 200 used for coding analysis and model building, and the remaining 50 reserved for theoretical saturation testing. Partial statistics for relevant questions are shown in Table 1 .

3.2.3 Theoretical Sampling Criteria Grounded theory is a manual process that explicitly incorporates human judgment. This study adopted the classic grounded theory design method—constant comparative analysis (CCA)—which requires assigning codes or categories to each data line and continuously comparing these codes with related codes throughout the document. Coding continues until core categories and concepts emerge and all possible categories are exhausted, forming a progressive coding process from original statements to concepts to categories.

To reduce individual subjective bias, this study employed multiple independent coders: five doctoral students in information science were invited to participate. The 200 responses for coding were shuffled and numbered A1-A200, with different allocation schemes ensuring each response was coded by two different people. When coders agreed, the code was confirmed; disagreements were resolved through group discussion. After initial theory formation, the remaining 50 responses were used for saturation testing to ensure comprehensive coverage.

3.3 Category Extraction and Model Building

3.3.1 Open Coding Open coding involves repeatedly selecting raw data, integrating similarities, and refining semantics to form a progressive coding process from original statements to concepts to categories. Following Strauss and Corbin' s three-step open coding procedure, this study divided original propositions into events, developed concepts based on content and theoretical categories, and formed conceptual groups that evolve into more prescriptive categories.

The study first deconstructed original text, conducted word-by-word analysis to extract elements, and used keywords from the raw data when naming concepts. Initial coding yielded 33 first-level concepts: answer viewpoint alignment, clear exposition, readability, answerer personal preference match, knowledge gain, unique perspective, answerer sincerity, content guarantee, answerer motivation, conformity, bookmarking, moderate tone, accidental operation, momentary emotion, diffusion propagation, content-question alignment, trusted person influence, answerer reliability, online image shaping, social return, empathy arousal, monetary benefit, answer usefulness, adequate effort, answer authenticity, memory evocation, answer entertainment value, detailed evidence, resonance, logical structure, habit, interpersonal interaction, and answer professionalism. Table 2 shows examples of these concepts with corresponding raw data.

3.3.2 Axial Coding To enhance analytical meaning, second-level concepts underwent rigorous comparison and refinement. Axial coding identifies and builds relationships among concepts and subcategories, which may be causal, similar, characteristic, functional, or structural. Through repeated analysis, a more abstract hierarchical level—categories—was formed. Based on compliance principles and data context, this study analyzed data revealing connections among concepts and examined underlying contexts and causal relationships.

The 33 first-level concepts were further integrated by merging those with similar connotations, resulting in 11 second-level concepts: answer content factors, answer narrative factors, answerer factors, monetary benefit, social benefit, knowledge benefit, altruism, others' influence, accidental operation, emotional factors, and habit, as shown in Table 3 .

3.3.3 Selective Coding Selective coding integrates and organizes categories into a larger theoretical framework explaining relationships among categories and creating final theory. This stage requires synthesizing all categories around core categories representing the research theme while ensuring no new concepts, dimensions, or relationships emerge.

The selective coding results are shown in Table 5 , identifying core categories: UGC information (including content and narrative factors), UGC information source (answerer factors), social influence, perceived usefulness (encompassing personal benefits—monetary, social, knowledge, emotional—and social benefits), and facilitating factors (habit and accidental operation).

3.3.4 Saturation Testing To test conceptual model saturation, the 50 reserved test samples underwent open, axial, and selective coding again. Results showed all emerging concepts were already contained in Table 5, with no new logical or causal relationships among categories. This indicates the conceptual model' s categories are sufficiently rich, confirming theoretical saturation.

Analysis and Discussion

4.1 Model Construction

Observing the selective coding results, this study combined the Information Acceptance Model (IAM) and Unified Theory of Acceptance and Use of Technology (UTAUT) to construct a theoretical model of user UGC reputation-bestowing behavior motivation in social Q&A communities.

IAM posits that information content quality (central route) and information source credibility (peripheral route) directly affect information recipients' perceived usefulness. Information quality refers to relevance, timeliness, accuracy, and completeness, reflecting message content characteristics. Information source credibility refers to trustworthiness or provider expertise. Perceived usefulness indicates the degree to which information is considered valuable and helpful. UTAUT suggests user adoption is influenced by performance expectancy, effort expectancy, social influence, and facilitating conditions.

Based on coding analysis and theoretical saturation testing, the theoretical model framework is shown in Figure 2 [Figure 2: see original paper]. The model reveals that users' UGC reputation-bestowing behavior is influenced by reputation-bestowing willingness and facilitating factors. Reputation-bestowing willingness is affected by perceived usefulness and social influence, while users' judgment of perceived usefulness is influenced by UGC information quality, information source, and social influence.

4.2 Model Factor Explanation

4.2.1 Information Quality UGC information is the most fundamental component in social Q&A communities, primarily referring to answers posted by users. Users browse and register in these communities mainly to view, post, comment on, and vote on UGC. As information-demand-centered platforms, the quantity, quality, and influence of UGC are crucial determinants of site scale and longevity.

When bestowing reputation, users evaluate information quality across two dimensions: content factors and narrative factors. Content factors involve semantic judgment: viewpoint alignment, unique perspectives, usefulness, question relevance, detailed evidence, internal logic, professionalism, and knowledge expansion. Narrative factors involve writing quality: clarity, readability, moderate tone, entertainment value, and adequate length.

4.2.2 Information Source UGC information source refers to the posting user. In this study, it means users who answer others' questions. Social Q&A communities typically provide verification pathways for user identity, education, and work experience, which some users leverage to enhance credibility. The platform' s reputation system also displays users' historical behaviors and achievements. When bestowing reputation, users consider whether answerers match personal preferences, demonstrate sincerity, and appear reliable. Preference matching involves alignment with users' characteristics, interests, and emotions. Answerer sincerity refers to the attitude displayed in responses, with research showing politeness affects reputation-bestowing decisions. Answerer reliability involves judgments about trustworthiness, verified credentials, achievements, or existing social relationships.

4.2.3 Perceived Usefulness As autonomous agents, social Q&A community users weigh expected risks and benefits before making behavioral decisions. This trade-off constitutes perceived usefulness—the expected benefits from UGC reputation-bestowing behavior.

Personal Benefits: Monetary, Social, Knowledge, and Emotional. Personal benefits refer to expected gains from behavior, including material and spiritual rewards. Monetary benefits involve economic returns, either through "water army" activities boosting specific UGC or premium users leveraging their influence for compensation. Social benefits include online image shaping, relationship maintenance, and reciprocity. Since reputation-bestowing behavior is visible to followers, endorsed UGC becomes part of one' s online image. Users may also bestow reputation for interpersonal relationship purposes or as reciprocation. Knowledge benefits involve using the "like history" function to bookmark content for future learning. Emotional benefits involve expressing interest, identification, or resonance through reputation bestowal.

Social Benefits. Social benefits refer to expected societal gains from behavior.

In this context, they include guaranteeing UGC content quality, motivating answerers, and diffusing high-quality UGC. With hundreds of millions of answers of varying quality, users view reputation bestowal as a way to vouch for content, express appreciation, and help disseminate quality information.

4.2.4 Social Influence Network users' information behavior is often environmentally influenced, whether in virtual or real contexts. Data reveal that social Q&A community users' reputation-bestowing behavior is affected by trusted others' endorsements and conformity psychology. The social nature of these platforms means users have offline trust relationships that can be bidirectional or unidirectional. When user A sees trusted user B endorse certain UGC, A may follow suit. Additionally, real-time display of reputation counts can trigger conformity, leading users to endorse already-popular content without even viewing it.

4.2.5 Facilitating Factors Facilitating factors primarily involve habit and accidental operation. Some users exhibit "habitual liking," endorsing viewed or even unviewed UGC. Others accidentally trigger voting buttons during browsing. However, these factors represent a relatively small proportion of all cases.

4.3 Summary

Overall, social Q&A community users' UGC reputation-bestowing behavior can be viewed as a response triggered by UGC perception, comprising three stages: information reception, internal judgment, and reaction. Upon encountering information, users may have clear goals or simply browse casually, with varying participation levels and expectations. Personal traits like curiosity and learning motivation also differ. Regardless of intent, a "noticing stimuli" process occurs, with stimuli originating from information, environment, or others' behaviors, followed by information evaluation and judgment.

After collecting, analyzing, and organizing information, users' reputation-bestowing willingness may lead to actual behavior, though facilitating factors like accidental clicks or habitual liking can also directly impact behavior.

Conclusion and Future Directions

This study used GTM to explore user motivations for UGC reputation-bestowing behavior in social Q&A communities, providing references for user relationship management, behavior guidance, and future scale/questionnaire design. The findings indicate that reputation-bestowing behavior is primarily influenced by reputation-bestowing willingness, which is determined by social influence and perceived usefulness of UGC information. Perceived usefulness is mainly affected by information quality, information source, and social influence. A small subset of users also exhibits accidental operations or "inertial liking."

To properly guide UGC reputation-bestowing behavior and promote community and internet information autonomy, platforms should enhance users' perceived usefulness of proper reputation bestowal by publicizing its role in community building, awarding virtual points and badges to active users, and recommending users who frequently endorse high-quality UGC as follow-worthy. Conversely, platforms should emphasize risks of irresponsible behavior by cracking down on "paid likes" and "water armies," restricting or penalizing users who indiscriminately bestow reputation, and publicly announcing enforcement actions as deterrents.

This study has limitations. First, it primarily uses Zhihu as a data source, but social Q&A communities include not only comprehensive platforms like Zhihu but also specialized ones such as Avvo (law and medicine), Stack Overflow (programming), and MathOverflow (mathematics). Whether behavioral motivations differ across community types and whether these findings apply to other contexts requires further research. Second, IAM and UTAUT suggest that user attention, demographics (gender, age), and experience may moderate relationships between perceived usefulness and behavioral intention. This study did not segment samples by population characteristics, representing a future research direction on potential motivational differences among user groups.

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