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Knowledge Contribution Behavior in Online Q&A Communities: An Empirical Investigation

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Abstract: As social networks and media technology combine, online Q&A communities are playing an important role in satisfying people's knowledge exchange needs. However, the combination of social networks and media technology does not mean that an exchange of knowledge will occur. Users are the critical components of an online Q&A community, and their active participation is critical for its development. Thus, it is crucial to figure out factors impacting users' motivation to participate in community activities, especially knowledge contribution. In this study, we focus on user behavior regarding knowledge contribution in social Q&A communities, and differentiate users' initial participation behavior from continued participation behavior. We collect users' activity data from a well-known Chinese social Q&A community, and the results show that identity-based trust, feedback from previous knowledge contribution, opportunities of social exposure, word-of-mouth marketing, and pressure from norms of reciprocity have a positive impact on users' continued knowledge contribution behavior.

Keywords: Social Q&A community; Knowledge contribution; Social capital; Social exchange; Social recognition

1 Introduction

Knowledge seeking is an important activity of people. Before the internet age, people could only acquire knowledge through books, newspapers, magazines and other traditional channels. With the development of information technology, especially the Internet, user-centered social media have greatly changed the ways by which people acquire knowledge. In social media, individuals are nodes connected with each other, and each node can function as a knowledge creator, knowledge consumer, and/or knowledge disseminator. Under this background, social media based on Web 2.0 appears, develops, and has gradually become an important way for people to acquire and exchange knowledge. Among the different types of social media, online social Q&A communities, where people ask, answer, and discuss questions regarding common practices or interests (Zhao, Detlor, & Connelly, 2016), provide people with channels to propose their personalized questions to the public directly.

Although different online social media may generate content in different ways, they do not generate content by themselves. Actually, users are the content producers and consumers on these platforms. Therefore, their content generation and dissemination behavior in online social media are very important for the development of social media. With the development of information technology, the competition among user-centered social media becomes fiercer. Retaining users and encouraging them to generate and disseminate more content is critical for the development of social media.

Currently, research on participation behavior in social media mainly concentrate on general social media, such as Twitter, Facebook, YouTube (Oh & Syn, 2015; Rudat & Buder, 2015; Shi, Rui, & Whinston, 2014), etc. Different from this stream of research, our study focuses on social Q&A communities where content generated are knowledge presented as discussions regarding

common practices or interests while content in general social media, such as Facebook, Twitter etc., are usually opinions, moods, or comments. Furthermore, from the perspective of different types of knowledge representation, our study is also different from another two fields of research. Firstly, our study can be differentiated from research on collective intelligence, such as open source software projects, Wikipedia etc., because although users in Q&A communities discuss questions regarding common topics, they could present their knowledge individually instead of presenting collectively into a same artifact (i.e. a software or a wiki article), avoiding the risk of collective ignorance. Secondly, our study is also different from studies on general Q&A platforms, such as Baidu Answers, Yahoo! Answers etc., for the reason that the complete social networks (users can follow not only other users but also topics and questions) and feedback mechanism (users can freely evaluate other users' answers by upvoting or downvoting, and answers are ranked by number of upvotes given by community members) make knowledge on social Q&A communities appear as accredited knowledge while knowledge on general Q&A platforms is just arranged as lists.

Moreover, existing studies do not distinguish initial contribution behavior from continuous contribution behavior. However, extant research on behavior in information systems shows that factors affecting initial behavior and continuous behavior are significantly different from each other (Venkatesh & Davis, 2000; Venkatesh, Morris, Davis, & Davis, 2003). Initial contribution behavior is mainly influenced by external factors, such as social pressure and publicity. However, continuous contribution behavior is more likely to be affected by users' previous experience and a consideration of system functions, social relations and many other aspects.

There are mainly two types of users in social Q&A communities: questioners and answerers. Questioners seek knowledge in the community by asking questions, while answerers contribute knowledge by providing answers to these questions. Questioners have inherent motivation to promote the development of the community for the purpose of acquiring more answers and knowledge. However, to maintain answerers' interests in the community, extra incentives are needed to stimulate them to contribute more knowledge (Jabr, Mookerjee, Tan, & Mookerjee, 2014). In fact, despite the large number of online communities, very few of them have succeeded in retailing users and motivate knowledge contribution (Ma & Agarwal, 2007). Online social Q&A communities can be a significant source of value for knowledge exchange, however, this value can only be realized when users take active parts in the knowledge contribution activities (Butler, 2001). Due to the "public goods" nature of knowledge in online social Q&A communities, users may lack sufficient incentives to contribute. Users can benefit from other users' contribution without contributing, which may cause the problem of under-contribution and hinder the growth of online social Q&A communities (Chen, Harper, Konstan, & Li, 2010). A natural question we can raise here is: how to motivate community members to contribute knowledge? To solve this problem, it is the common concern for both scholars and practitioners to identify factors affecting answerers' participation behavior, and accordingly encourage them to make more knowledge contribution.

Existing literature has studied factors influencing users' participation behavior in virtual communities from the perspectives of website function design (Ma & Agarwal, 2007), incentive mechanism (Jabr, et al., 2014), user motivation (Ardichvili, Page, & Wentling, 2003) and some other aspects. Many factors that affect users' knowledge contribution behavior have been identified, such as responsibility and norms (Wasko & Faraj, 2000), trust (Tsai & Ghoshal, 1998),

recognition (Constant, Sproull, & Kiesler, 1996), image motivation (Jabr, et al., 2014), self-efficacy (Hsu, Ju, Yen, & Chang, 2007; Kankanhalli, Tan, & Wei, 2005), outcome expectation (Kolekofski & Heminger, 2003), etc. Mostly, these studies adopted surveys to explore the factors influencing a user's participation behavior from psychological perspectives, while few empirical studies have adopted data of real community activities.

Hence, this study focuses on users' knowledge contribution behavior in social Q&A communities, and distinguishes users' participation behavior into initial participation behavior and continuous participation behavior. We collected first-hand user activity data in a famous Chinese social Q&A community to explore the factors influencing users' continuous knowledge contribution behavior in the community.

2 Theoretical Analysis and Research Hypotheses

2.1 Related Literature

2.1.1 Knowledge contribution behavior

Based on existing theories, such as the theory of social awareness (Hsu, et al., 2007), social capital theory (Kankanhalli, et al., 2005), social exchange theory (Rui & Whinston, 2012), social identity theory (Ren, et al., 2012) etc., researchers have identified many factors influencing users' participation behavior in knowledge communities. Based on the framework of Wang and Noe (2010), this paper summarizes the factors that influence knowledge sharing behavior in virtual communities into three categories: personal characteristics, network characteristics and mental motivation.

Personal characteristics

Knowledge sharing in virtual communities is non-obligatory, and users' personality and experience can play an important role in determining whether to share or not. Existing research focuses on the impact of confidence, openness, computer skills and willingness, educational background, working experience and other aspects of users' knowledge sharing behavior. For example, a study by Cabrera, Collins, and Salgado (2006) found that the more willing a user is to share his past experiences, the more likely he will exchange knowledge with others. Jarvenpaa and Staples (2000) studied factors influencing a user's knowledge sharing behavior from the perspectives of computer skills and willingness. The results showed that computer skills were significantly and positively correlated with the willingness of knowledge sharing. Constant, Kiesler, and Sproull (1994) found that employees who were better educated and had worked for longer years would be more likely to take part in knowledge sharing activities. Based on a study on user support forums, Jabr, et al. (2014) concluded that the more complete a user's personal information (such as online identity, personal label, self-presentation and other detailed information) is, the more likely he will participate in the knowledge sharing activities in the community. In addition, it is more possible for those users who are more confident about their ability of knowledge contribution and the usefulness of the knowledge they own to share knowledge in a community (Bordia, Irmer, & Abusah, 2006).

Network characteristics

Driven by Web 2.0 technology, knowledge management communities have brought in the elements of social networks and have gained great success. Research by Cross and Cummings (2004) showed that, for users in virtual communities, the quantity of social ties and the quality of interpersonal relationships were directly related to the quality and quantity of knowledge contribution, and could enhance their perception of the usefulness of the knowledge shared in the community. Jabr, et al. (2014) studied the product communities of Apple, Oracle, SAP and SUN and found that social exposure is one of the motivations for users to use the communities. Social network is an important channel for social exposure. Users are more likely to answer questions if they have more opportunity for social exposure. Feedback from other users in the social network, especially positive feedback is also important factors affecting users' continuous participating behavior in the social community. Burke, Marlow, and Lento (2009) found that users' posting behavior are influenced by their friends' posting behavior. In addition, the more feedback a new user gets for his first posting, the more likely he will continue to post. Besides, the influence of the strength of social ties on user behavior also draws the attention of many researchers. From the social network perspective, compared to strong ties, weak ties are more likely to introduce new knowledge, obtain new work opportunities (Lin & Dumin, 1986) and propagate new ideas (Campbell, Marsden, & Hurlbert, 1986). Research by Levin and Cross (2004) demonstrated that knowledge seekers in weak ties could benefit more than those in strong ties when the information reliability is the same. Research by Hansen (1999) showed that strong ties play a more significant role in knowledge transfer and trans-department flow of complex knowledge inside enterprises.

Mental motivation

Among various mental motivations influencing users' knowledge contribution behavior, belief of intellectual property, perception of benefits and costs and individual attitudes arouse extensive attention from researchers. For example, research by Constant, et al. (1994) showed that when users were convinced that they had the ownership of the contributed knowledge, they would be more willing to participate in knowledge sharing activities. Benefits and costs are widely discussed as influencing factors in studies on knowledge sharing behavior. Social exchange theory indicated that cost-benefit ratio is the main motivation for social exchange. The lower the cost-benefit ratio is, the more active people will be in social exchange and vice versa (Cropanzano & Mitchell, 2005). In enterprise knowledge and management systems, many researches have confirmed that the main purpose of users to contribute knowledge is to acquire recognition of other members, promotion opportunities and rewards. In social Q&A community, users mainly exchange attention and knowledge. They obtain attention or knowledge by exchanging knowledge with others (Rui & Whinston, 2012).

2.1.2 A review of related studies

In studies on user participation behavior in virtual communities, most user behavior models are established based on social capital theory (Kankanhalli, et al., 2005; Wasko & Faraj, 2005), social cognitive theory (Chiu, Hsu, & Wang, 2006; Hsu, et al., 2007), social exchange theory (Posey, Lowry, Roberts, & Ellis, 2010; Rui & Whinston, 2012) etc., which lays theoretical foundation for this study. However, the distinction between initial participation behavior and continuous participation behavior was ignored by most studies. Based on previous studies (Goes, Guo, & Lin, 2016; Jabr, et al., 2014), we collected data of users' participation behavior in social

Q&A communities and analyzed motivation and influencing factors of users' continuous participation behavior in social Q&A communities.

In addition, most studies on participation behavior in virtual communities adopt the method of questionnaire surveys, analyzing users' motivation of participating from subjective perspectives (e.g. Wasko and Faraj (2005), Kankanhalli, et al. (2005)) or studying the influence of outside environment on users' participation in the community. Researchers seldom pay attention to the influence of interaction between users on participation behavior. By tracking users' social behavior and interaction behavior, this paper explores users' continuous participation behavior from the perspectives of mental motivation, social activity and interaction behavior to figure out users' behavior motivation and its influence factors.

Besides, this study is different from previous studies on Facebook, YouTube, Twitter, Microblog and other general social media (Oh & Syn, 2015; Rudat & Buder, 2015; Shi, et al., 2014), in which users' contributions are mainly general information rather than knowledge. This study is also distinguished from studies on general Q&A communities, such as Yahoo! Answers and Baidu Answers, in which users' contribution behavior is not obviously influenced by social relationship between users as in the burgeoning social Q&A communities in this paper, such as Zhihu and Quora.

2.2 Theoretical Background

2.2.1 Social Capital Theory

Social capital theory, evolved from new economic sociology, was proposed by French sociologist Bourdieu in his seminal work *The Forms of Capital* (Bourdieu, 1986). This theory has quickly become one of the most influential analytical frameworks. Bourdieu believed that social capital is the synthesis of both real and virtual resources embedded in people's lasting social networks, and its amount depends on the size of network that he could utilize effectively and the quantity of different types of capital (such as economical capital, cultural capital, symbolic capital, etc.) (Bourdieu, 1986). Social capital is found to be essential for knowledge sharing (Kankanhalli, et al., 2005). High-quality social network could enhance the scope, depth and efficiency of knowledge exchange (Lane & Lubatkin, 1998). Nahapiet and Ghoshal (1998) defined social capital in terms of three dimensions to illustrate the process of knowledge sharing in communities, that is, structural capital (the overall pattern of connections between nodes), relational capital (assets created and leveraged through relationships) and cognitive capital (resources providing shared representations, interpretations, and systems of meaning among parties). According to the above three dimensions, researchers have identified many factors that will influence people's knowledge contribution behavior: network ties (Chiu, et al., 2006; Tsai & Ghoshal, 1998), responsibility (Wasko & Faraj, 2000), norms (Coleman, 1990; Wasko & Faraj, 2000), trust (Tsai & Ghoshal, 1998), recognition (O'Reilly & Chatman, 1986), common language (Nahapiet & Ghoshal, 1998) and shared vision (Cohen & Prusak, 2001).

2.2.2 Social Exchange Theory

Homans (1958) proposed social exchange theory when studying people's social behavior in economic affairs. Based on his theory, Blau (1964) proposed that social exchange behavior would take place under the condition that others would pay something back. When others no longer pay

back anything, the person would stop carrying out that behavior. During economic exchange, people are rational and will take both the elements of benefits and costs into consideration (Emerson, 1976). In social media, it is difficult to quantify the benefits and costs of knowledge contribution, so knowledge contribution behavior in social media is exchange behavior that is long-term oriented and pays attention to common benefits in the long run (Foa, 1993). Previous studies showed that cost factors that influenced knowledge contribution behavior include: loss of knowledge privilege (Davenport & Prusak, 1998), time and energy (Orlikowski, 1992) etc.; benefit factors include: community rewards (Kankanhalli, et al., 2005), image motivation (Jabr, et al., 2014; Wichardt, 2009) reciprocity (Wasko & Faraj, 2000) and pleasure (Kankanhalli, et al., 2005) etc.

2.2.3 Social Cognitive Theory

Social cognitive theory was derived from social learning theory proposed by Miller and Dollard (1941). It proposed that people's opinions, emotion and behavior would be affected by their interactions with others (Bandura, 2001). Social cognitive theory is widely adopted in studies on individual behavior. It provides a framework for understanding, forecasting and changing people's behavior, and believes that individual behavior is affected by personal factors, behavioral factors and situational factors simultaneously (Bandura, 1986). Reciprocity and trust among people are believed to be the most important situational factors affecting knowledge sharing behavior. Self-efficiency, perceived comparative advantage, compatibility and outcome expectation are considered as the main personal factors influencing user behavior (Bandura, 1982; Rogers, 1995).

2.2.4 Communication Theory of Identity

Communication theory of identity was first proposed by Hecht (1993). This theory, emphasizing the mutual impact between identity and communication, was used to analyze identity problems from the perspective of communication (Hecht, Warren, Jung, & Krieger, 2004). It proposes that social relationships and social roles are internalized by individuals in the process of communicating with others, and individual identity is showed in the form of social behavior through communication (Hecht, 1993). Hecht, et al. (2004) defined identity as a four-dimension construct. First, individual identity is the self-cognition and self-image of individual person. It is on individual level and acts as the basis for analyzing individual characteristics. Second, presented identity is the identity individual presents or expresses, and is shown in the process of communication. Third, relational identity is part of social relationship of both sides during communication and the results of interaction and negotiation between the two sides. Fourth, group identity surpasses individual identity and is defined by the group. Presented identity and relational identity are usually used in analyzing users' participation behavior in social media, showing as self-presentation (Ma & Agarwal, 2007) and social exposure respectively (Jabr, et al., 2014; Wasko, Teigland, & Faraj, 2009).

2.3 Drivers of Knowledge Contribution

2.3.1 Identity-based trust

Many studies show that there is a positive association between customers' trust and their loyalty to the enterprises (Sirdeshmukh, Singh, & Sabol, 2002), and that customers' loyalty to

enterprises would positively influence their repeat purchase (Yi & La, 2004). Trust is widely regarded as a multidimensional concept. Based on previous studies, Hsu, et al. (2007) defined trust in terms of three levels: economy-based trust, information-based trust and identity-based trust. Among them, identity-based trust is the highest-level trust and is derived from people's mutual understanding, appreciation and support. People strengthen their mutual trust by emotional investment. In user-centered social media, users express their trust by following other users, which in turn promotes their information exchange. In addition, identity-based trust brings constant flow of information and provides opportunity for social learning from other users. Users can accumulate knowledge and skills by receiving others' answers and observing others' contribution behavior. These knowledge and skills may be applied in the future and could promote users' productivity of knowledge sharing (Reagans, Argote, & Brooks, 2005). Therefore, we define identity-based trust as emotional and informational reciprocity formed by the behavior of following in social Q&A communities. Users' relationship and identity recognition based on following would contribute to collaboration and creation of collective intelligence (Panteli & Sockalingam, 2005). Based on the above analysis, we propose the following hypothesis:

H1: The higher a user's identity-based trust is, the more likely he will contribute knowledge continuously.

2.3.2 Social feedback

Social feedback, in this paper, refers to a mechanism by which communities or users give positive feedback to other users' participation behavior. The feedback could be encouragement to users for their contribution behavior, or affirmation to the value of their contribution. In social Q&A communities, 'like' and 'thank' are two main forms for users to express their recognition of the information, and can also be treated as feedback to the knowledge contributors. The reciprocity theory, theory of reinforcement (Skinner & Ferster, 1997) and need for belonging (Baumeister & Leary, 1995) all indicate that feedback users received would influence their subsequent behavior. That is, the more positive feedback users get, the more likely they will participate in community activities continuously. This has been supported by many studies. Using empirical data from an enterprise social media, Brzozowski, Sandholm, and Hogg (2009) found that new users who got feedback would contribute more comparing to those who didn't get any feedback. Research by Macy (1991) showed that if a user's first news commentary got positive ratings, he might quickly post his second one. Rui and Whinston (2012) found that people tweeted for information and attention, and that users' information sharing behavior were greatly influenced by the number of followers. Using random-effect models, Byron and Khazanchi (2012) meta-analyzed 60 experimental and non-experimental studies that examined the rewards–creativity relationship with children or adults, and concluded that positive feedback could promote users' creativity. Based on the above analysis, social feedback can be treated as the benefits in terms of social exchange. We propose the following hypothesis:

H2: The more positive feedback a user get, the more likely he will participate in community activities continuously.

2.3.3 Social exposure

Different from traditional enterprise communities, social Q&A communities do not have specific reward and punishment mechanism to promote reciprocal behavior. Social capital, embedded in people's social networks, is an important factor affecting users' continuous knowledge contribution behavior (Nahapiet & Ghoshal, 1998). According to social capital theory,

social capital originates from the process of social interactions, and is expected to produce social resources in the future. The core of social capital is the social network formed among people (Coleman, 1990). The size of social network reflects the attractiveness and popularity of the users. Moreover, social network could help users to promote influence and increase exposure in the community. Studies on operation management of virtual communities show that attraction and communication ability of users are important factors determining the success of the community. It could increase activeness and satisfaction of users in the community (Hagel & Armstrong, 1997). Social ties are widely used to measure the relationship of members in social communities. Social ties have different forms in different virtual communities. For example, in technical forums, social ties are formed when users involve in a same topic discussion; but in social networking services, they appear as relations of friendship among users. However, no matter what type it presents, social ties could influence users' participation behavior (Bouty, 2000; Wasko, et al., 2009) and activeness of the community (Tsai & Ghoshal, 1998). Social cognitive theory is widely used to illustrate the influence of social ties on user behavior. It proposes that user behavior is rational choices made by users after evaluating the consequences of their behavior. Users are more likely to participate in activities that are believed to produce   consequences within expectation (Paul, Hong, & Chi, 2012). In social Q&A communities, content contributed by users is spread through social networks. To some degree, the scope of social exposure reflects users' potential benefits. The larger the scope of social exposure is, the more information rational person would contribute. Based on the above analysis, we propose the following hypothesis:

H3: The more social exposure users get in social Q&A communities, the more likely he is to continuously contribute knowledge.

2.3.4 Norms of reciprocity

Different from enterprise knowledge communities, where users know each other well, and knowledge contributors could gain not only appreciation from friends online but also rewards offline, such as bonus, and promotion opportunity (Bock, Zmud, Kim, & Lee, 2005; Kim, 2002), participants in online Q&A communities, gathered by common interests and hobbies, are generally strangers to each other, and voluntarily participate in community activities. On the one hand, knowledge seekers cannot determine who will answer their questions or the quality of the answers. On the other hand, knowledge contributors cannot guarantee that they could get a reward. Theory of reciprocity could be used to explain users' long-term participation behavior in social Q&A communities. Norms of reciprocity are regarded as core characteristics of social exchange, and could be used to illustrate various relations in communities (Lee, Kim, & Kim, 2006). According to the view of knowledge market by Davenport and Prusak (1998), reciprocity is an important factor influencing users' knowledge sharing behavior. Research by Wasko and Faraj (2000) also shows that users' knowledge sharing behavior in social networks are influenced by the rule of reciprocity in the community. In this paper, norms of reciprocity are regarded as a belief in mutual help, that is, users' current contributions would be rewarded in the future, and users' current rewards should be followed by subsequent contributions. In social Q&A communities focusing on knowledge exchange, knowledge contributors who share their knowledge expect that they could get help from others when they need knowledge in the future. In this sense, one type of the benefits of knowledge contribution is reciprocity, which is consistent with social exchange theory (Emerson, 1976). For users who get answers from others, they should also help other users by answering questions at appropriate time. Therefore, according to social exchange theory and

theory of reciprocity, both users' knowledge seeking behavior and the positive feedback they obtained would influence their knowledge contribution behavior. Based on the above analysis, we propose the following hypotheses:

H4a: The more a user searches for knowledge, the more likely he is to contribute knowledge.

H4b: The more feedback a user gets for his questions, the more likely he is to contribute knowledge.

2.3.5 Identity communication

Identity is a user's evaluation of his own ability, quality, motivation and roles. The answers to "Who am I?" form people's individual identities (Ma & Agarwal, 2007). Identity communication reflects an individual's effort to express and present one's identity to others with the goal of achieving a shared understanding.

Self-presentation theory proposed by Goffman (1959) believes that people want to make their own identity clear enough to others before working together. Only when consensus is reached by both sides, will they feel that they are recognized and have a sense of belonging and presence in the community. Researchers have proposed three reasons to explain the importance of identity communication in virtual communities.

First, a clear identity helps users to obtain information more effectively. According to detailed possibility model, if the source of information is reliable enough, users' perception of the usefulness of the information will be higher and they are more willing to spend time and effort processing the information (Sussman & Siegal, 2003). Otherwise, if the identity of the information contributor is unclear, it will be difficult to process and adopt the information, making the efficiency of knowledge exchange lower. Second, from the perspective of relationship construction, it is much easier for people who are from similar social organizations or share similar interests, values, and experiences to build relationship. Effective identity communication can help community members to find out users with similar identity and establish their relationships (Stutzman, 2006). Third, effective identity communication can promote knowledge contribution. Research on participation behavior in virtual communities showed that users help strangers not only because of altruism but also for reputation, mutual benefits as well as self-esteem (Bock, et al., 2005).

Many studies have shown that the recognition from other community members can encourage a user to participate in the community activities. Therefore, establishing one's online identity provides significant motivation for knowledge contributors not only by helping them enhance their reputations and self-esteem, but also by amplifying the possibility of future reciprocation. What's more, social exposure is essential for identity communication. Under the same degree of social exposure, those who show more self-presentation information will be more popular. Similarly, if the amount of feedback they obtained is the same, those who show more complete self-presentation information will get a higher level of recognition. Based on the above analysis, we propose:

H5a: Individuals who disclose more self-presentation information will contribute more knowledge to online social Q&A communities.

H5b: The more self-presentation information a user discloses, the more strongly social exposure will impact on his continuous knowledge contributing behavior.

H5c: The more self-presentation information a user discloses, the more strongly user feedback will impact on his continuous knowledge contributing behavior.
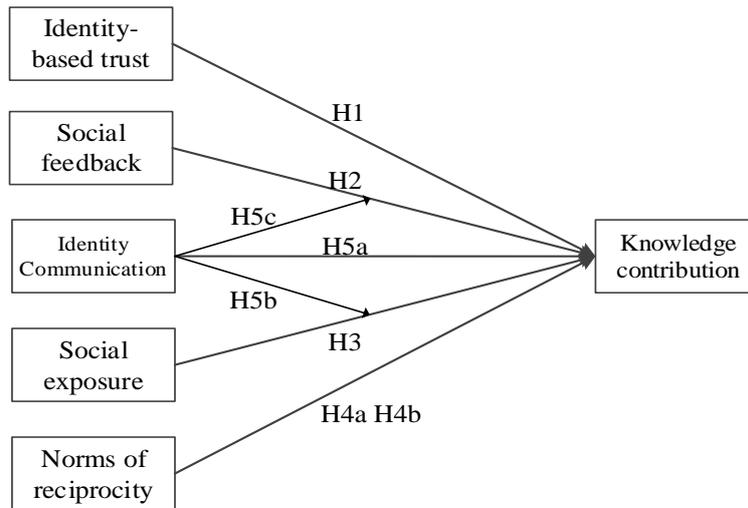
Figure 1 summarizes our research hypotheses.

Figure 1. Research model of continuous knowledge contribution

3 Research Context

We collected the data from one of the most popular Chinese social Q&A communities: Zhihu. Established in 2010, Zhihu is an online Q&A community where users ask personalized questions and share their expertise, experience and opinions. In March 2013, Zhihu was open to the public for registration. Within one year, the number of users rapidly soared from 400,000 to 4,000,000. By March 2015, the number of users reached 17,000,000 and altogether 3,500,000 questions involving more than 100,000 topics were generated. With a large number of high-quality questions and answers generated every day, Zhihu is gaining more and more popularity.

In Zhihu, users establish their social network by following others and being followed by others. Besides other users, community users can also follow topics and questions. For a community user, the information related to the activities of other users within his social network and the topics and questions he follows will be pushed to him by feed flow. Figure 2 is the personal homepage of a Zhihu user, showing his personal information, interactive information and feedback information. Whether and how to show personal information, such as education background, work experience, addresses and occupation etc., are entirely up to the users themselves. Interactive information, including the number of questions they proposed, answers they offered, users they follow and followers they have, reflects their activeness and will be updated by the platform as users participate in the community activities. The feedback information, evaluated by the number of approval and thanks, is about the feedback they got from other users in the community.

Figure 2. A snapshot of a user's homepage

We chose 3000 users randomly and recorded all their activities in this community. We followed all their activities by a Java program every week from Oct. 26th, 2014 to Feb. 1st, 2015, recording their personal information, interactive information and feedback information. The processes are as follows: first, we constructed the URL address of user's personal homepage according to the user name. Second, we downloaded the personal homepages with HttpClient software package. Third, we analyzed the data with Jsoup software package to get the user information. These three steps were repeated until we got all the information of the 3000 users in each period. Finally, all the data were stored in a MySQL database.

4 Methodology

4.1 Variable Description and Measurement

4.1.1 Dependent Variable

In Zhihu, users usually take part in discussions by proposing or answering questions. As answerers, registered users can answer any questions freely, making knowledge contribution and encouraging more users to take part in the discussion at the same time. Therefore, in this paper, we evaluate users' knowledge contribution by the number of answers they have offered. This number reflects how much knowledge they have contributed to the community.

4.1.2 Independent Variables

Identity-based trust. In Zhihu, the trust relationship based on identity means how much a user recognizes the identities of other users in the community. Users express their recognition by following the information source. The number of sources followed reflects the user's extent of recognition of other users' identities in the community. Therefore, we use the number of users a member follows as the index to measure the identity-based trust. The more people a user follows, the higher his trust based on identity is.

Social exposure. Zhihu tries to gather users who share similar interests together to improve the efficiency of communication and accelerate the speed and accuracy of information spreading. Zhihu adopts feed flow to push information from the source to its followers through the social

networks in the community. Therefore, social networks are the most direct and effective channels for information spreading. When a user posts a new question, or offers a new answer to a question, all the content will be pushed to his followers. The number of followers represents the number of audiences a user has. Therefore, we use the number of followers to measure the possibility of a user's social exposure. The more followers a user has, the higher degree of social exposure the user has.

Social feedback. In Zhihu, users have two ways to express their feedback to other users' answers: approving and thanking. The approval and thank will be pushed to the questioner by notification and will be presented in his personal homepage. Since users usually approve the usefulness of the answers when expressing their gratitude, the correlation coefficient of the two measurements is usually high. Therefore, we use the number of approvals to measure how well a user is recognized by other users in the community.

Norms of reciprocity. Mutual benefit, or reciprocity, is the basis of social exchange. In Zhihu, users keep exchanging knowledge and switching roles between knowledge contributors and consumers. Under norms of reciprocity, if people want to gain more, they need to give more. That is to say, if people want to get more answers to their own questions they need to provide more answers to other users' questions. In social community, the number of questions reflects the demand for knowledge exchange, while the quantity and quality of the answers reflect the outcome of knowledge exchange. Therefore, this paper adopts the number of questions and the feedback to these questions, i.e. the number of answers, as the factors influencing knowledge contribution on the premise of norms of reciprocity.

Identity communication. Like most social media, Zhihu encourages users to disclose as much personal information as possible and shows the information in users' personal homepages. We use the term "self-presentation" to indicate users' personal information disclosure behavior. Self-presentation information makes users differ from other users and build up their personal brands. The more self-presentation information a user discloses, the clearer his identity communication is. In Zhihu, there are 10 items of personal information a user can choose to disclose: sina microblog link, tencent microblog link, current situation, personal introduction, occupation, address, company name, title, education. In this paper, we adopt the degree of completeness of a user's self-presentation information to measure his identity communication. The value of the self-presentation information ranges from 0 to 10.

According to the above definition and measurement of variables, the variables used in study are shown in Table 1.

Table 1 Variables definition and description

Variable	Measure item	Description
Dependent variable		
Knowledge contribution	$answer_{it}$	The number of answers provided by user i during period t
Independent variables		
Identity-based trust	$followee_{it}$	The number of followers of user i from registration to current period t
Social exposure	$follower_{it}$	The number of followers of user i from registration to current period t
Social feedback	$ansBeenVoted_{it}$	The number of useful votes to user i 's

		answers during period t
Norms of reciprocity	$question_{it}$	The number of questions asked by user i during period t
	$quesBeenAnswered_{it}$	The number of answers obtained by user i during period t
Identity communication	$selfPresentation_{it}$	The number of personal information items for user i from registration to current period t

4.2 Data Processing and Descriptive Statistics

According to the research hypotheses, there is a temporal and logical precedence relationship between factors that influence users' knowledge contribution and their knowledge contribution behavior. The independent variables and dependent variable in this paper were observed separately in two consecutive periods to avoid the problem of endogeneity. We observed independent variables from October 26 to December 6, 2014 and dependent variable from December 6, 2014 to February 3, 2015.

We proposed to analyze factors influencing users' knowledge contribution, and only the data that have changed in the two consecutive periods can be used to explain the changes in user behavior. Therefore, "zombie" users without any changes for all the overserved variables in the two periods should be eliminated. The final data set included 1,599 users, and descriptive statistics of the variables were presented in Table 2. We conducted logarithmic transformation for $followee_{it}$, $follower_{it}$ and $ansBeenVoted_{it}$ because these three variables are highly skewed (Rui & Whinston, 2012).

Table 2 Descriptive statistics

variable	min	max	mean	variance
$answer_{it}$	0	74	2.503	40.904
$followee_{it}$	0	5961	122.4	108509.8
$follower_{it}$	0	547200	4109	821389816
$ansBeenVoted_{it}$	0	31599	183	1614367.7
$question_{it}$	0	89	0.716	11.63
$quesBeenAnswered_{it}$	0	1125	6.799	1717.799
$selfPresentation_{it}$	0	9	3.765	5.913

Table 3 shows the correlation coefficient matrix of the variables. It indicates that there are positive correlations between the number of answers and all the other variables. In addition, the correlation coefficients among the variables are all less than 0.6, indicating that we don't need to worry about the problem of multicollinearity (Billings & Wroten, 1978).

Table 3 Correlation matrix

variable	V0	V1	V2	V3	V4	V5	V6
V0 $answer_{it}$	1.000						
V1 $ln(followee_{it})$	0.152	1.000					
V2 $ln(follower_{it})$	0.214	0.568	1.000				
V3 $ln(ansBeenVoted_{it})$	0.221	0.139	0.341	1.00			
V4 $question_{it}$	0.082	0.013	0.018	0.036	1.00		
V5 $quesBeenAnswered_{it}$	0.214	0.137	0.192	0.187	0.527	1.00	

V6 *selfPresentation*$_{it}$	0.130	0.304	0.365	0.095	-0.001	0.059	1.00

4.3 Analytical Method

The dependent variable, knowledge contribution, is measured by the number of answers provided by a user during a given period. All the values of the dependent variable are non-negative integers. Poisson regression and negative binomial regression are widely used when dependent variables are count variables (Baltagi, 2008). They differ from ordinary least square regression in the assumptions of conditional mean and variance of dependent variable. Poisson regression assumes that the conditional mean is equal to the variance. Negative binomial regression models do not assume the equality of mean and variance and introduce a parameter to account for the over-dispersion problem when the variance is larger than the conditional mean in the data. As is shown in Table 3, the mean and variance of the dependent variable are quite different. Therefore, we adopt the negative binomial regression model to explore users' knowledge contribution behavior in online social Q&A communities. The negative binomial probability function is as follows:

$$\Pr(Y = y_{it} \mid x_{t-1}) = \frac{\Gamma(y_{it} + \theta)}{\Gamma(y_{it} + 1)\Gamma(\theta)}\left(\frac{\theta}{\theta + \lambda_i}\right)^{\theta}\left(\frac{\lambda_i}{\theta + \lambda_i}\right)^{y_{it}} \tag{1}$$

There are two parameters in the probability equation: θ and λ_i. θ captures the over-dispersion in the data. When $\theta=0$, negative binomial regression is the same as the Poisson regression; $\lambda_i=exp(x_{it-1}\beta)$, since moderators exist in the research hypotheses, we adopt the hierarchical regression model to explore the main effects and moderating effects respectively (Angst & Agarwal, 2009; Billings & Wroten, 1978). The main effects regression model is as following:

$$
\begin{aligned}
\ln(\lambda(x_{it-1})) &= \beta_0 + x_{it-1}\beta + \varepsilon_{it} \\
&= \beta_0 + \beta_1 Ln(followeesNum_{it-1}) + \beta_2 Ln(followersNum_{it-1}) \\
&\quad + \beta_3 Ln(answerBeenVoted_{it-1}) + \beta_4 question_{it-1} \\
&\quad + \beta_4 questionBeenAnswered_{it-1} + \beta_5 selfPresentation_{it-1} + \varepsilon_{it}
\end{aligned} \tag{2}
$$

Where β is a vector of regression coefficients of covariates; ε_{it} is the error term with $\varepsilon_{it}i.i.d.N(0,\sigma_t^2)$. The regression model including moderating effects is expressed as equation (3). Following the suggestions by Aiken, West, and Reno (1991), we centralize the independent and moderating variables in the moderating effect regression model.

$$
\begin{aligned}
\ln(\lambda(x_{it-1})) &= c_i + x_{it-1}\beta + \varepsilon_{it} \\
&= c_i + \beta_1 Ln(followeesNum_{it-1}) + \beta_2 Ln(followersNum_{it-1}) \\
&\quad + \beta_3 Ln(answerBeenVoted_{it-1}) + \beta_4 question_{it-1} \\
&\quad + \beta_4 questionBeenAnswered_{it-1} + \beta_5 selfPresentation_{it-1} \\
&\quad + \beta_6 selfPresentation_{it-1} \times Ln(followersNum_{it-1}) \\
&\quad + \beta_7 selfPresentation_{it-1} \times Ln(answerBeenVoted_{it-1}) + \varepsilon_{it}
\end{aligned} \tag{3}
$$

5 Results

We used a software package based on R, pscl, which is widely used for count variable regression analysis (Zeileis, Kleiber, & Jackman, 2008), to estimate the model parameters. Table 4 shows the results of two count data regression models. Model 1 only focuses on the main effects, while Model 2 accounts for the moderating effects based on Model 1. According to the values of

Log Likelihood, AIC and BIC, Model 2 has a better model fit than Model 1. Similar to the linear regression model, the effects of the independent variables on the dependent variable is indicated by the regression coefficients. The positive (negative) sign of the regression coefficient indicates that the independent variable has positive (negative) impact on the dependent variable. Since count regression techniques model the log of incident counts, the coefficients can be interpreted as follows: for a one-unit change in the independent variable, the log of the dependent variable is expected to change by the value of the regression coefficients. "Coef.", "Std. Err." and "Sign" in Table 4 stand respectively for regression coefficient, standard deviation and significance. We can see from table 4 that all the variables except $quesBeenAnswered_{it}$ are positively correlated to users' knowledge contribution behavior at different significance levels.

Table 4 Results of negative binomial regression

Variable	Model 1			Model 2		
	Coef.	Std. Err.	Sign	Coef.	Std. Err.	Sign
(Inception)	7.240e-01	5.427e-02	***	7.156e-01	5.412e-02	***
$ln(followee_{it})$	9.894e-02	4.396e-02	*	1.100e-01	4.409e-02	*
$ln(follower_{it})$	9.271e-02	2.589e-02	***	9.426e-03	4.365e-02	**
$ansBeenVoted_{it}$	2.185e-04	5.435e-5	***	8.623e-04	1.782e-04	***
$question_{it}$	1.366e-01	1.815e-02	***	1.407e-01	1.808e-02	***
$quesBeenAnswered_{it}$	1.227e-03	1.520e-03	NS	6.923e-04	1.522e-03	NS
$selfPresentation_{it}$	6.697e-02	2.398e-02	**	1.070e-02	4.108e-02	·
$selfPresentation_{it} \times follower_{it}$	--	--	--	1.878e-02	8.421e-03	*
$selfPresentation_{it} \times ln(ansBeenVoted_{it})$	--	--	--	1.260e-04	3.336e-05	***
Theta	0.2412	0.0128	--	0.2431	0.0129	--
Log Likelihood	-5491.286			-5484.953		
AIC	5507.286			5504.953		
BIC	5491.286			5484.953		
***p<0.001; **p<0.01; *p<0.05; ·p<0.1; NS: not significant						

Hypothesis 1 investigates the impact of identity-based trust on continuous knowledge contribution behavior in social Q&A community. In this paper, identity-based trust in knowledge communities is defined as the recognition of the knowledge contributed by other users in the community. This type of recognition is manifested as the quantity of information channels established by the relationship of following. In this paper, the number of users one follows is adopted to represent the user's identity-based trust. The regression result of Model 1 shows that the coefficient of $followee_{it}$ is positive and significant at the level of 0.05 (β=9.894e-02, p<0.05). Therefore, hypothesis 1 is supported, namely, the more users one follows, the more likely he will participate in knowledge contribution.

Hypothesis 2 investigates the impact of social exposure on users' knowledge contribution behavior. In social media, people are in the center of social network set up by themselves. Because of the pushing mechanism, the more social ties a user has, the more influential he is in the community. The number of followers, which reflects the sum of the ties pointing to a user, indicates not only the user's popularity but also the potential extent of his social exposure, namely, the spreading scope of the information generated by the user under the information pushing

mechanism based on feed stream. The regression results of Model 1 show the number of followers has a positive effect on knowledge contribution behavior (β=9.271e-02，p<0.001), i.e., the more exposed a user is to the community, the more knowledge he will contribute. Therefore, hypothesis 2 is supported.

Hypothesis 3 investigates the impact of social feedback on users' knowledge contribution behavior. In social Q&A community, social feedback is defined as the feedback one user received for his or her previous knowledge contribution behavior. In this paper, we adopt the number of approval to represent the feedback a user gets for his or her answer. When users approve someone's answer, they express not only their recognition for the content of the answer, but also their appreciation for the user's hard work. The regression result of Model 1 shows that social feedback has a positive effect on users' knowledge contribution behavior (β=2.185e-04, p<0.001), i.e., the more feedback a user receives, the more likely he will contribute knowledge continuously. Therefore, hypothesis 3 is supported.

Hypothesis 4 investigates the impact of norms of reciprocity on the users' knowledge contribution behavior. In social Q&A community, users can play the roles of both knowledge seeker and knowledge contributor. When a user turns to others for help or gets help from others, he is constrained by norms of reciprocity. The regression result of Model 1 shows that a user's earlier knowledge seeking behavior have a positive effect on his subsequent knowledge contribution behavior (β=1.366e-01, p<0.001). Therefore, hypothesis 4a is supported. However, the number of answers one gets to his questions doesn't have significant impact on his subsequent knowledge contribution behavior. The reason may be that usually there are many answers to one question but only one or a few of them will be adopted by the knowledge seeker. So, the number of answers cannot reflect the information support one gets within the community. Therefore, hypothesis 4b is not supported.

Hypothesis 5 examines the impact of identity communication on the users' continuous knowledge contribution behavior. Identity communication is measured by the number of the information items a user chooses to disclose to show others his identity and features in the community. A user's identity communication will not only be presented in his personal homepage, but also be passed on to other users in the same community by the knowledge seeking or contribution behavior. Users can improve their identity communication by disclosing more personal information and involving more in the community activities. Model 1 shows positive association between the completeness of identity communication and users' knowledge contribution behavior (β=6.697e-02, p<0.01). Therefore, hypothesis 5a is supported, namely, the more personal information a user discloses, the more knowledge he will contribute to the community. The regression results of Model 2 show that identity communication has significantly positive moderating effects on social exposure (β=1.878e-02, p<0.05) and social feedback (β=1.260e-04, p<0.001), i.e., the more personal information a user discloses, the greater the impact social exposure and social feedback have on knowledge contribution behavior. Therefore, hypothesis 5b and 5c are supported.

6 Discussion and Conclusions

Based on a continuous track of users' behavior in a social Q&A community, we explore the factors affecting users' continuous knowledge contribution behavior from the perspectives of

social capital theory, social exchange theory, social identity theory and social cognitive theory. The main results are as follows:

Firstly, social exchange is an important factor influencing users' continuous knowledge contribution in social Q&A communities. In online knowledge communities, users are both knowledge producers and consumers. As a knowledge producer, he engages in the topic discussions and gives his own opinions; as a knowledge consumer, he seeks answers from other users by asking questions. Although there are no explicit measures for each user's contribution or material incentives for prompting users to contribute content, social Q&A communities don't fall into "tragedy of the commons". On the contrary, they are attracting more and more attention from people and have accumulated plenty of content contributed by users. This "abnormal" phenomenon can be well explained by norms of reciprocity. Knowledge exchange based on norms of reciprocity is an important factor affecting users' continuous knowledge contribution behavior. A user who frequently seeks for knowledge is more likely to contribute knowledge to others, indicating users contribute because they hold the expectation that they can get response to their own questions in the future, i.e. users contribute because of reciprocity. This conclusion is consistent with the study by Chiu, et al. (2006), where they found that norms of reciprocity have a positive impact on quantity of knowledge sharing based on a survey of 310 members of a professional virtual community.

However, those whose knowledge seeking behavior get more answers do not have higher motivation to contribute knowledge. This is inconsistent with common sense and previous qualitative study: "If I gain some knowledge I feel it only right to give back and help someone else" (Wasko & Faraj, 2000, p. 165). The main reason may be that the number of answers cannot reflect the information support one gets within the community. Study by Teevan, Morris, and Panovich (2011) have proved that compared to quantity, quality is more important factor that affect users' behavior in social media. Apart from exchange of knowledge, exchange between knowledge and attention is another important form of social exchange in social media. As the amount of information generated by users becomes larger and larger, "attention" has become a type of scarce resource. Social media succeed by setting up a flat platform for information dissemination and an effective feedback mechanism. Insightful views can be spread quickly and obtain feedback in time. These feedback is not only rewards for users' knowledge contribution behavior, bus also an important component for building a user's personal brand in the community.

Secondly, social exposure has significantly positive effect on users' knowledge contribution behavior in social Q&A communities, where users can express their own opinions freely. These opinions spread via social networks established by users themselves in the form of following, and the value of the contribution is determined by the dissemination direction and scope. According to social cognition theory, high social exposure can promote users' outcome expectation of their knowledge contribution behavior (Chiu, et al., 2006). That is to say, users expect that their knowledge contribution be seen by more people so as to enlarge their influence. Under the expectation of high social exposure, users are more willing to contribute their knowledge. This result is consistent with research in other fields. For example, in a study on online product reviews, Goes, Lin, and Au Yeung (2014) found that as users became more popular, they would produce more reviews; Based on a study on user support forums, Jabr, et al. (2014) found that under feedback based recognition mechanism, social exposure has a positive impact on users' posting behavior.

Thirdly, social identity has significantly positive effect on users' knowledge contribution behavior. What's more, identity communication, as an important aspect of social identity, has positive moderating effects on social exposure and social feedback. In user-centered social media, identity-based trust is defined as users' recognition for other users' identity and professional skills. Since users in social Q&A communities can follow other users they are interested in without their approval, the number of users they have followed embodies the extent to which they recognize other users in the community. On the one hand, this relationship of recognition brings users a steady flow of information, increases their opportunities to observe, learn and improves their ability of contributing knowledge; on the other hand, other users' contribution behavior can exert pressure on the user under the norms of reciprocity. Therefore, identity-based trust promotes users' knowledge contribution behavior.

Apart from identity-based trust, self-presentation information is another way for users to express their social identity. Complete self-presentation information indicates users' intention to improve their popularity with the help of community activities. The more complete the self-presentation information is, the clearer social identity users have towards the community and the more likely they will participate in the community activities. Moreover, the degree of completeness of self-presentation information has positive moderating effects on the relationships between social exposure, social feedback and continuous knowledge contribution behavior. The more personal information a user chooses to disclose, the more influence social exposure and social feedback will have on users' continuous knowledge contribution behavior.

This paper not only enriches the application of the above-mentioned theories in social Q&A communities, but also has some practical implications for the community practitioners. First, social Q&A communities should be clearly defined as a place for the exchange of attention and knowledge. Community practitioners should also figure out the forms for users to contribute their attention, motivate free riders to follow other users, which will in turn motivate knowledge contributors to some extent. In addition, knowledge communities should improve the user feedback mechanism, enforcing the interactivity between knowledge contributors and "free riders" by the mechanisms of approving, thanking, replying, commenting, following and so on. Moreover, the interaction results need to be presented visually to all the community members.

Secondly, social media should strengthen the identity-based trust relationships among users. In social Q&A communities, users are faced with the problem of information overload. Machine learning has been widely used to precisely recommend content to solve the problem. Social Q&A communities can also adopt the method of machine learning to provide users with more precise information. Finally, based on ensuring users' information security, social Q&A communities should encourage users to disclose more personal information, enforcing their sense of belonging and maintaining their long-term relationships with the community. Besides, self-presentation information of a user is important information source for experts, community practitioners to recognize him. Therefore, if users disclose more self-presentation information, it will be easier for expert recommendation and knowledge recommendation, which increase users' chances of social learning and social exchanging.

However, our study also has some limitations. First, this study is based on archival data that we get from users' daily activities instead of experiments. So, all the relationships we have identified are, strictly speaking, just associations instead of causal relationships, which may be more helpful in explaining and changing users' behavior. Second, our study employs the number

of a user's answers to represent his knowledge contribution, which may be over-simplified. Because users resort to online Q&A communities for high-quality answers that are important and helpful for decision making (Harper, Raban, Rafaeli, & Konstan, 2008), that is to say only those valid and responsive answers constitute true knowledge contribution (Lou, Fang, Lim, & Peng, 2013). In future research, we will take both the quality and quantity of knowledge into account and adopt controlled experiments to gain more valid conclusions.

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