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Continuous knowledge contribution in social Q&A communities: the moderation effects of self-presentation and motivational affordances

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Abstract

Purpose – Based on the perspectives of social capital, image motivation and motivation affordances, this paper explores the direct and moderation effects of different kinds of motivations (i.e. relationship-based motivation, community-based motivation and individual-based motivation) on users' continuous knowledge contributions in social question and answer (Q&A) communities.

Design/methodology/approach – The authors collect the panel data of 10,193 users from a popular social Q&A community in China. Then, a negative binomial regression model is adopted to analyze the collected data.

Findings – The paper demonstrates that social learning, peer recognition and knowledge seeking positively affect users' continuous contribution behaviors. However, the results also show that social exposure has the opposite effect. In addition, self-presentation is found to moderate the influence of social factors on users' continuous use behaviors, while the moderation effect of motivation affordances has no significance.

Originality/value – First, this study develops a comprehensive motivation framework that helps gain deeper insights into the underlying mechanism of knowledge contribution in social Q&A communities. Second, this study conducts panel data analysis to capture the impacts of motivations over time, rather than intentions at a

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fixed time point. Third, the findings can help operators of social Q&A communities to optimize community norms and incentive mechanisms.

Keywords Social Q&A community, Knowledge contribution, Social capital, Self-presentation, Motivational affordances

Paper type Research paper

1. Introduction

Virtual communities are moving offline gathering places to online, facilitating up the exchange of information. The increasing demand for knowledge has resulted in the emergence of question and answer (Q&A) communities, where common topics bring together people of similar interests and professional backgrounds. Users play both the roles of questioner and answerer in the communities, creating and sharing knowledge (Guan *et al.*, 2018). The earliest Q&A communities such as Google Answers and Baidu Knows are issue-oriented, and users mainly focus on exchanging knowledge and solving problems (Zheng *et al.*, 2020). Currently, due to the proliferation of social media, the significance of relationship building is increasingly emphasized by online communities (Cheng *et al.*, 2020). Q&A communities such as Quora, Stack Overflow and Zhihu have adopted social mechanisms that enable users to follow and comment on each other's questions and answers. These mechanisms augment regular Q&A systems with social networking features that help establish social linkages among users, questions and topics (Jin *et al.*, 2015). As a result, users are no longer motivated to contribute knowledge based only on their interests. They've begun to consider their community identity, recognition of their abilities and the sense of accomplishment (Chen *et al.*, 2018). At the same time, users who view participation in social Q&A communities as a way to expand interpersonal relationships also hope to make more friends through knowledge contributions and benefit from social connections (Gazan, 2015).

Different from general social media platforms (e.g. Facebook, Weibo) where social networks are generally formed by acquaintances, social Q&A communities are based on weak ties and formed by strangers who share the same interests (Jin *et al.*, 2015). In addition, general social media platforms may not have strict guidelines for content creation and feature more casual communication (Bilgihan *et al.*, 2014; Park *et al.*, 2014; Ordenes *et al.*, 2019). However, social Q&A communities, which generate knowledge presented as in-depth discussions about common practices or interests, focus more on knowledge contribution than information about facts or individuals' moods (Guan *et al.*, 2018). In social Q&A communities, members are often encouraged to provide accurate and well-researched answers to promote knowledge sharing (Gazan, 2010). Besides, social Q&A communities are distinct from issue-oriented Q&A communities (e.g. Google Answers, Baidu Knows) and open source collective intelligence websites (e.g. Wikipedia, Baidu Encyclopedia), where contribution behaviors are not necessarily influenced by social relationships between users (Harper *et al.*, 2008). Social Q&A communities have a relatively complete social network and feedback mechanism, with a focus on promoting discussion to generate a variety of perspectives (Khansa *et al.*, 2015). Previous research has noted that user behavior can vary greatly within different types of communities (Lampe *et al.*, 2010; Jin *et al.*, 2015). Given the unique nature of social Q&A communities, the present study aims to understand the motivation mechanism in this context, which is critical to maintain the vibrancy of social Q&A communities.

A stream of research (e.g. Fang *et al.*, 2018; Park *et al.*, 2014; Malinen, 2015) has documented that the survival of online communities depends on creating an ambiance that enables continuous participation of community members. However, despite the popularity of virtual social communities among Internet users, many of them fail to retain users (Malinen, 2015). With diversified channels to access information, users can easily get distracted and migrate among different communities. Among all participation behaviors, the contribution behavior is considered the key social dynamic of online communities (Ling *et al.*, 2005; Cavusoglu *et al.*, 2021), especially for social Q&A communities where high-quality and up-to-date content is essential to attract users and sustain the community. However, this issue is challenging due to the "public goods" problem inherent in social Q&A communities: users can enjoy the contribution of others without exerting any effort themselves. Previous research has noted that because contributing knowledge takes more time and effort, it is typical for social Q&A communities to suffer from the "tragedy of the commons" (Guan *et al.*, 2018). As social Q&A communities rely on knowledge contributors to generate content (Qiu and Kumar, 2017), the "public goods" nature of communities could lead to an undersupply of knowledge and may cause the failure of operation (Goes *et al.*, 2016). In addition, scholars have proposed that the sustainability of communities will at risk if not all participants contribute sufficiently, especially in communities that primarily focus on utilitarian knowledge sharing (Chen *et al.*, 2019). Stack Overflow, the global leading community for exchanging technical knowledge, reported that only 6.5% of users contributed knowledge in 2022, highlighting the significant challenge of encouraging knowledge contribution in social Q&A communities. Therefore, it is of vital importance to investigate how to effectively motivate continuous knowledge contributions of members to maintain the long-term vibrancy of social Q&A communities.

Although previous studies have developed and tested motivational models to understand the factors that influence active participation as well as continuous contribution in online communities, there are still several research gaps. First, existing studies on participation or contribution behaviors mainly focused on online review websites or general social media platforms (Chen *et al.*, 2017; Bronner and Hoog, 2011; Lee *et al.*, 2014; Rui and Whinston, 2012). Yet scholars have suggested that user motivations may vary greatly across different types of information system (Fang and Zhang, 2019). Due to unique features of social Q&A community, we postulate that members' motivation of this kind of community may be different from those in other communities (e.g. social Q&A community members are expected to provide deeper insight and are more engaged in social network). As existing literature shows mixed results on the influence of various motivations in different online communities, there is still an improvement for knowledge of contribution behavior in the context of social Q&A community. Second, given that most extant literature only examine the direct effects of several single predictors on user contribution behaviors (e.g. Chang and Chuang, 2011; Jadin *et al.*, 2013; Khansa *et al.*, 2015), the understanding of what stimulate users' determination to contributing knowledge in social Q&A communities remains limited. Additionally, there is currently a lack of research that considers the classification of various motivations and explores their collective impact on user contribution behaviors (the impacts of different motivations are usually considered in a separate manner). Thus, a comprehensive theoretical framework needs to be developed to explain the motivation mechanisms that affect continuous contribution. Third, most existing studies use questionnaires to collect data (Zhao *et al.*, 2012; Mustafa and Zhang, 2022; Zhang *et al.*, 2021), which may has a bias in self-reporting and only explores the intention or willingness to continue to participate instead of actual behavior. Besides, scholars have noted that users' motivations change over time, leading to the change in their perceptions and behaviors (Dong *et al.*, 2023; Tsai and Bagozzi, 2014). Although a few studies collect actual behavior data of users, they mostly rely on cross-sectional data, which only considers the impact of motivations at a fixed time point and does not adequately account for the potential effects of changing differences over time. Therefore, we employ a data-driven approach and collect a panel dataset to examine the impacts of motivations varying along with time.

The existing research has explored user participation and contribution behaviors from various perspectives. Based on an integrative literature review, we classified different antecedents into three categories of motivations: *relationship-based*, *community-based* and *individual-based* motivations. Regarding *relationship-based motivation*, we draw on social capital theory (Bourdieu, 1986), which defines social capital as the resources embedded in social networks and relationships among people. By focusing on the resources within relationships (Zhao *et al.*, 2012), the social capital perspective helps us understand how resources are formed in social Q&A communities and what outcomes the resources can bring. This theory is suitable for understanding knowledge contribution in social Q&A communities, as the exchange of knowledge involves social interactions among members influenced by social networks. For *community-based motivation*, we investigate how community artifacts design affects knowledge contribution behavior from the perspective of motivational affordances. Motivational affordance is the characteristic of an object or environment that makes it appealing and can trigger behavioral outcomes such as continued engagement and contribution (Hamari *et al.*, 2014). Since social Q&A communities have provided a variety of motivational affordances, it is necessary to figure out whether and how these designs work for community vibrancy. In terms of *individual-based motivation*, we turn to the perspective of image motivation, which asserts that the recognition of social image can encourage individuals' efforts and contributions. Scholars have suggested that as an approach to express self-identity and build self-image, the user profile conveys users' perception that their fellow members appreciate them for who they truly are (Pan *et al.*, 2017). Also, building of personal image can impact the establishment of social relations as well as individuals' sequent behaviors (Hsiao *et al.*, 2016; Li *et al.*, 2018). Therefore, we apply the perspective of image motivation to understand what role individual-based motivation plays in bringing knowledge growth to social Q&A communities. To sum up, this study seeks to explore the effects of three kinds of motivations on continuous knowledge contribution by developing a comprehensive theoretical framework that involves three motivation-based perspectives.

Specifically, we propose two research questions (1) *How do different kinds of motivations (i.e. relationship-based motivation, community-based motivation and individual-based motivation): influence users' continuous knowledge contribution in social Q&A communities?* (2) *How do motivational affordances (community-based motivation) and self-presentation (individual-based motivation) moderate the impact of relationship-based motivation on continuous knowledge contribution?*

To address the research questions, we first review previous literature and categorize the sources of motivation into relationship-based, community-based and individual-based. We then introduce three theoretical underpinnings (i.e. the perspectives of social capital, motivational affordances and image motivation) corresponding to each of the three motivations. A research model is thus built to investigate the underlying mechanism of users' continuous knowledge contribution behaviors in social Q&A communities. Subsequently, we collect a panel dataset from Zhihu, a popular social Q&A community in China. The panel dataset includes the activity data of 10,193 Zhihu users in six consecutive periods. The negative binomial regression is applied to test our research model. Finally, we discuss how our research adds to the existing theories and advances our comprehension of the factors that drive continuous knowledge contribution in social Q&A communities.

2. Literature review and theoretical background

2.1 Knowledge contribution in social Q&A communities

Knowledge contribution in social Q&A communities is the process of creating and presenting knowledge in the form of in-depth discussions about common practices or interests (Guan *et al.*, 2018). As the result of processing and interpreting information, knowledge is subjective and valuable since it is shaped by individuals' experience, reflection and critical thinking (Zhang *et al.*, 2021). Social Q&A communities have the value of helping people access knowledge more easily (Yaari *et al.*, 2011; Autio *et al.*, 2013), yet this value can only be realized when community members actively participate in knowledge contribution activities (Lampe *et al.*, 2010; Guan *et al.*, 2018; Jin *et al.*, 2015). As the success of social Q&A

communities largely depend on the overall knowledge base, it is essential for members to provide a variety of perspectives on various topics. Extant studies have suggested that the motivation driving continuous knowledge contribution by community members differs from that of initial contribution, which is primarily influenced by external factors such as friend recommendations (Dong *et al.*, 2023). During the process of making knowledge contributions, other incentive mechanisms, such as social relationships, play a critical role in motivating future contributions (Jin *et al.*, 2015; Dong *et al.*, 2020). However, due to the special nature of knowledge shared in social Q&A communities, where users can benefit from other users' contributions without having to contribute (Chen *et al.*, 2010), social Q&A communities may face the proverbial "tragedy of the commons" dilemma (Chen *et al.*, 2019). One common issue faced by many social Q&A communities is a lack of balance between the number of users seeking knowledge and the number of users contributing knowledge (Wang *et al.*, 2022). This can bring serious problems to the community. For example, unanswered questions can accumulate, leading to frustration among users who are seeking knowledge and eventually driving them away from the community. Unanswered questions can accumulate, causing frustration for users seeking knowledge and ultimately driving them away from the community (Guan *et al.*, 2018). Therefore, one of the biggest challenges in maintaining the long-term vibrancy of social Q&A communities is how to effectively motivate continuous knowledge contribution of community members. Although researchers have examined a variety of predictors of knowledge contribution, limited attention has been paid to the joint impacts (e.g. the interaction effects) of different motivations on knowledge contribution. As the interaction between antecedents of contribution behavior might play an integral role in predicting users' continuous knowledge contribution, it is necessary to consider different kinds of motivations together. Besides, many existing studies, whether based on survey data or secondary data, have focused on the effects of predictors at a fixed time point, while ignoring the potential effects that may arise over time. Since scholars have suggested that as members' motivations may not remain stable as they involve in the community over time (Xia *et al.*, 2012), it is important to look into the potential effects of changing differences over time by conducting longitudinal research (Yan *et al.*, 2021).

2.2 Motivations for knowledge contribution

As social Q&A communities do not have regular monetary incentive system to foster knowledge contribution, scholars are concerned with what motivates users to keep contributing. Based on existing theories, such as social exchange (Lee *et al.*, 2011; Rui and Whinston, 2012), social comparison (Jabr *et al.*, 2014; Esteves *et al.*, 2021), social cognitive theory (Chiang and Hsiao, 2015; Ogink and Dong, 2019), etc., scholars have found a variety of factors affecting users' contribution behavior in online communities. While many studies only examine the effect of several single factors, a few studies have summarized the categories of behavioral motivators. For example, Jin *et al.* (2015) divided the motivations for content contribution as organization-based and individual-based. Guan *et al.* (2018) summarized personal, network and mental motivations as the predictors of knowledge sharing behavior. Yan *et al.* (2021) classified the antecedents of continuance intention as psychological, technological, social and behavioral. Based on a comprehensive review of previous literature on contribution behaviors and behavioral motivation frameworks, this paper categorizes the motivations that drive continuous knowledge contribution behaviors in social Q&A communities into three types: *relationship-based*, *community-based* and *individual-based*. Table 1 summarizes a set of factors that have been explored by empirical research about contribution in online communities.

2.2.1 Relationship-based motivation. Motivation from *relationships* has been widely discussed since social networks got popular. Social relationships, as a link connecting users,

Table 1. Selected research on user participation and contribution in online communities

Study	Platform	Methodology	Theory	Motivation types: Relationship-based	Community-based	Individual-based
This study	Online social Q&A community	Data analytics	Social capital theory, motivational affordances, image motivation theory	✓	✓	✓
Park *et al.* (2014)	Online investment community	Survey	Social exchange theory, social capital theory	✗	✗	✓ perceived knowledge, perceived usefulness
Jin *et al.* (2015)	Online social Q&A community	Data analytics	Social cognitive theory, social capital, social exchange theory	✓ receive positive feedback, number of followers	✗	✓ identity communication
Chiang and Hsiao (2015)	Online virtual community	Survey	Uses and gratification theory, social cognitive theory	✗	✗	✓ reputation, altruism, self-expression, the perception of belonging to a particular online community
Goes *et al.* (2016)	Online virtual community	Data analytics	Drive-reduction theory	✗	✓ glory-based incentives from community	✗
Khansa *et al.* (2015)	Online social Q&A community	Data analytics	Goal-setting theory	✗	✓ community membership level, points	✓ habits
Guan *et al.* (2018)	Online social Q&A community	Data analytics	Social exchange theory, social capital theory, social cognitive theory, communication theory of identity	✓ the number of followers/followees/approvals/answers	✗	✓ self-presentation information
Li and Fang (2019)	Online brand community	Survey	Attachment theory, task-technology fit theory	✗	✗	✓ satisfaction, expectation confirmation, perceived complementarity, brand attachment
Dong *et al.* (2020)	Online consumer review community	Data analytics	Status theory	✓ the following behavior from other users; the number of likes received	✓ coins awarded by the community, status-standing	✗
Kuem *et al.* (2020)	Online virtual community	Survey	Self-determination theory	✗	✗	✓ knowledge self-efficacy, self-identity verification, community identification
Chen (2020)	Online social Q&A community	Data analytics	Social exchange theory, expectation-confirmation theory	✓ commenting	✗	✓ tenure

Source(s): Author's own creation

stimulate users to become attached to the community and stay in the community (Boguñá *et al.*, 2004). Research on social networks have demonstrated that the establishment of social relations will affect users' participation behaviors, that is, the following behavior from other users will stimulate users' continuous contribution (Qiu and Kumar, 2017; Dong *et al.*, 2020). For example, based on social networking sites, consumer opinion leaders influence the information sharing behavior of Generation Y on the platform (Bilgihan *et al.*, 2014) and consumer intentions (Casaló *et al.*, 2020). The information sharing intention is more closely related to the contribution behavior in the collectivist culture (Shneor *et al.*, 2021). Users who take the initiative to observe and learn from others will also have easier access to information and demonstrate more participation behaviors (Reagans *et al.*, 2005; Chung and Cho, 2017). Commenting also positively affects users' continuous participation behaviors (Chen, 2020). In communities related to knowledge sharing, users can give helpfulness votes or "likes", which leads to a positive impact on continuous knowledge contribution (Dong *et al.*, 2020). Nevertheless, the existing literature does not provide a comprehensive study of motivations from social relationships. Most of the studies investigate only one or several factors of them. To have a better understanding of relationship-based motivation, this study draws on social capital theory, which contends that social relationships can create value for individuals as they provide resources that can be used for the achieving desired outcomes (Bizzi, 2015). Social capital refers to the resources that individuals have access to through social relations, such as reputation, recognition, norms of reciprocity, access to information, etc (Machalek and Martin, 2015). The continuous accumulation of these resources can shape individual behaviors. In the context of social Q&A communities, the accumulation of social capital is expected to generate more knowledge contributions. Based on the central thesis of social capital theory, this paper explores relationship-based motivation for continuous knowledge contribution behaviors in social Q&A communities.

2.2.2 Community-based motivation. Motivation from *communities* usually comes from financial incentives (Burtch *et al.*, 2018) and the design of artifacts (Khansa *et al.*, 2015). Because the contribution behavior we focus on in this paper is spontaneous answering behavior from users (which is not motivated by financial incentive), we mainly discuss the design of artifacts in the community. By designing artifacts, information systems can stimulate users' motivation, interest and enjoyment, which will lead to users' continued participation and contribution behaviors (Hamari *et al.*, 2014; Chen *et al.*, 2018). Lee *et al.* (2011) have found that social rewards given by communities have a positive impact on users' willingness to provide information. Some researchers have investigated the artifacts of membership in online communities and found that the longer a user has been a member, the more content he/she contributes (Khansa *et al.*, 2015; Goes *et al.*, 2016; Chen, 2020). Under the gamification design, levels (Khansa *et al.*, 2015), points (Denny *et al.*, 2018) and badges (Moro *et al.*, 2019) are found to stimulate users' determination to contribute content. Badges awarded to users by platforms not only represent gratitude for their contribution, but also are recognition of their professional knowledge (Li *et al.*, 2012), which will stimulate users' satisfaction and sense of accomplishment, encouraging them to contribute more content. However, Goes *et al.* (2016) argued that the positive impact of honor-based incentives on user contributions is only temporary. Therefore, it is still unclear whether the design of community artifacts will have a long-term effect to promote continuous knowledge contributions from users. We expect to solve this problem from the perspective of motivational affordances.

2.2.3 Individual-based motivation. Motivation from *individuals* generally come from intrinsic motivation, which is usually related to personal feelings and emotions (Ryan and Deci, 2000; Wu and Gong, 2020). Individuals will motivate themselves to work hard to seek the sense of accomplishment and responsibility (Tietjen and Myers, 1998). When it comes to continuous behaviors in online communities, some previous studies have proven that users stay in a community because of perceived enjoyment (Hsiao *et al.*, 2016; Hamari *et al.*, 2020) and attachment (Chiang and Hsiao, 2015; Li and Fang, 2019). Social identity has been verified to be an important intrinsic motivation to influence user engagement behavior on social media, because identity presentation allows others to learn about one's interests, experiences, attitudes, etc. For example, Jabr *et al.* (2014) found that the more detailed a user's personal information (such as online identity, personal label, self-presentation and other detailed information) is, the more likely he/she will participate in the knowledge sharing activities in the community. Based on self-determination theory, Kuem *et al.* (2020) have concluded that users' self-identity verification has a powerful impact of motivation on engagement and contribution in online communities. In the context of social Q&A communities, few studies have confirmed the actual impact of identity presentation on continuous knowledge contribution behaviors. As such, this paper considers self-presentation of identity as a motivation from individuals and discusses its role on user behavior.

2.3 Social capital theory

The concept of social capital was first proposed by Bourdieu (1986), who believed that social capital is a collection of resources related to the membership of a group. Portes (1998) suggested that social capital is the ability of individuals to get resources in the network through their membership, and it is an asset contained in the relationship among individuals. The accumulation of social capital can lead to several positive consequences such as increasing the efficiency of action, encouraging cooperative behavior within the groups and engaging in citizenship behavior (Fang *et al.*, 2018). Nahapiet and Ghoshal (1998) divided social capital into three distinct dimensions: structural capital, cognitive capital and relational capital. Structural capital represents the configuration of linkages between individuals within a social network. Cognitive capital refers to the shared perspective or understanding that individuals possess within a social network. Relational capital reflects the quality and nature of the relationships between individuals, often characterized by trust or reciprocal exchange. Based on the three dimensions, scholars have identified a number of factors that influence user online behaviors, such as social interaction ties (Xiong *et al.*, 2018; Wang *et al.*, 2022), trust (Tsai and Ghoshal, 1998; Liu *et al.*, 2014), norms of reciprocity (Guan *et al.*, 2018), recognition (O'Reilly and Chatman, 1986) and shared understanding (Chang and Chuang, 2011).

Since knowledge sharing is achieved through the interaction of users in the community, it is essentially a socialization process (Pan *et al.*, 2015), and social capital is believed to facilitate the effective operation of knowledge sharing in this process (Wasko *et al.*, 2009; Li *et al.*, 2014). Interactions are generally considered to increase social capital (Zhao *et al.*, 2012; Ellison *et al.*, 2014; Zhang *et al.*, 2017), and a social Q&A community is a favorite place for content sharing and knowledge exchanging, as such, social Q&A community is beneficial for promoting social capital accumulation. Social capital is considered as a key resource in social systems and has been shown to be related to knowledge sharing among community members (Chang and Chuang, 2011; Yan *et al.*, 2019). Social capital theory can be used to explain users' motivation for knowledge contribution in social Q&A communities by understanding how social relationships and influence their behaviors (Wang *et al.*, 2022). Social capital largely influences users' participation and contribution behaviors in the social Q&A community through interpersonal relationships motivation. Therefore, we apply social capital theory to better understand the influence of *relationship-based motivation* on users' continuous knowledge contribution behavior in social Q&A communities. Specifically, the dimension of structural capital is used to investigate the role of social exposure and social learning, because the structural dimension describes the extent to which individuals in a network are connected with each other (Guan *et al.*, 2018; Wang *et al.*, 2022). The dimension of cognitive capital is adopted to examine the effect of peer recognition as the cognitive dimension is generally represented by shared language or mutual understanding (Chang and Chuang, 2011) and is often associated with cognitive benefits acquired in the social network (Ogink and Dong, 2019). The dimension of relational capital is employed here to examine the role of knowledge seeking since the relational dimension is characterized by trust and norms of reciprocity (Guan *et al.*, 2018; Yan *et al.*, 2019). More details will be discussed in section 3.

2.4 Motivational affordances

An affordance describes the general actionable properties of an object that can satisfy individuals' particular needs (Gibson, 1977). The term of motivational affordances refers to the possibilities for satisfying the motive of the individual after achieving the goals enabled by the affordance (Zhang, 2008). Motivational affordance in social networking is a characteristic of information systems. By designing artifacts, information systems can stimulate users' motivation, interest and enjoyment, which in turn will lead to users' continued participation and contribution behaviors (Hamari *et al.*, 2014; Khansa *et al.*, 2015; Chen *et al.*, 2018). Zhang (2008) suggested that the overarching goal of the information systems design is to support the motivational needs of users. Online communities provide a variety of motivational affordances, such as levels (Goes *et al.*, 2016; Dong *et al.*, 2020), comments (Chen *et al.*, 2018), gamification design (Denny *et al.*, 2018), etc. The general principle of motivational affordances in information systems design is that motivational affordances can invoke intrinsic motivations, such as interest and enjoyment that further promote behavioral outcomes such as continued engagement and contribution (Hamari *et al.*, 2014). For example, Moro *et al.* (2019) have confirmed that the gamification design in online review sites can bring users a sense of honor and thus promote their review writing behaviors.

Previous research has discussed the influence of motivational affordance on user participation behaviors on social media platforms (Li *et al.*, 2018; Zhou *et al.*, 2019), online shopping websites (Burtch *et al.*, 2018), online learning communities (Wu and Chen, 2017) as well as healthy communities (Khurana *et al.*, 2019). However, there is a scarcity of research on motivational affordance in the context of social Q&A communities. Also, as different users perceive the affordance in various ways, the same technological capability could be used very differently (Chen *et al.*, 2019). For example, the number of "likes" received by an answer may be viewed by some users as a kind of achievement, while other users may regard them as a sense of recognition of their expertise. Thus, understanding the motivational affordances underlying an information systems design requires researchers to apply an affordance perspective (Suh and Wagner, 2017). As a result, in this paper, we aim to explore the role of motivational affordances, i.e. *motivation from communities*, on users' continuous contribution behaviors in social Q&A communities.

2.5 Image motivation

Image motivation is typically defined as the desire to be liked and appreciated by oneself and others (Jabr *et al.*, 2014). Image motivation theory is often used to explain that recognition of social image can encourage individuals' efforts and contributions. Ariely *et al.* (2009) proposed that image motivation is the key factor that stimulates people to perform prosocial behaviors and provide public goods, which will help them gain appreciation and respect from others. Image motivation is one of the internal incentives that drive individuals to make positive contributions (Ali and Ahmad, 2009; Danish and Usman, 2010). Self-expression and improvement can enhance this internal belief by building a personal image (Barasch and Berger, 2014; Qiu and Kumar, 2017). People hope that their social image remains positive and that their behaviors would be recognized. Such social recognition will significantly increase one's willingness to contribute (Soetevent, 2011; Tonin and Vlassopoulos, 2013).

As online communities become more developed, users now have the option to display their personal information (profile) to attract more attention. To a large extent, the user profile expresses users' self-identity and conveys members' perception that their fellow members appreciate them for who they truly are (Pan *et al.*, 2017). Hsiao *et al.* (2016) and Li *et al.* (2018) indicated that the building of personal image and self-identity facilitate the establishment of social relations when examining the influence of social images on participating behaviors in social media. The shaping of self-image is believed to increase the sense of belonging to the community, therefore increasing sustained participation behaviors (Zhou *et al.*, 2019; Kuem *et al.*, 2020). Users of social Q&A communities can also choose to have their personal information (education, industry, professional experience, etc.) displayed on their homepages. They may help identify members of similar experience and facilitate the effective exchange of information. Nevertheless, little research in social Q&A communities has focused on the impact of personal information presentation on users' participation and contribution behaviors. Hence, based on image motivation theory, we take personal information presentation as *motivation from individuals* to study its impact on users' continuous contribution behaviors in social Q&A communities.

2.6 Summary

Based on an extensive review of previous literature on contribution behaviors and behavioral motivation frameworks (e.g. Jin *et al.*, 2015; Guan *et al.*, 2018; Yan *et al.*, 2021), this paper distinguishes three categories of motivation: *relationship-based motivation*, *community-based motivation* and *individual-based motivation*. Due to the primary and unique nature of social Q&A communities that distinguish them from conventional Q&A communities, social characteristics play a critical role in shaping user behaviors within these communities. As discussed earlier, social capital embedded in social relationships is essential in influencing the operation of social Q&A communities. We therefore adopt social capital theory to better understand *relationship-based motivation* for users' knowledge contribution behaviors. Although existing literature has examined several social factors that influence user contribution, few studies have considered different kinds of motivations from an integrated perspective, especially in the context of social Q&A communities. In addition, a key limitation of previous studies is that they give disproportionate attention to the direct effects of several motivational factors and neglects the role of moderation effects. The antecedents that affect knowledge contributions in social Q&A communities can be complex and not solely determined by social characteristics. As a result, we also incorporate *community-based* and *individual-based motivations* in our research. We adopt the perspectives of motivational affordances and image motivation to understand of these motivations. Although social capital theory has been used to identify various motivational factors in virtual community contexts, inclusion of two other perspectives extends social capital theory to explain how different motivations may collectively influence knowledge contribution in the social Q&A community context. By considering different kinds of motivations, we develop a comprehensive theoretical framework that helps gain deeper insights into the underlying mechanism of knowledge contribution. Besides, much of the existing literature uses questionnaires to analyze the motivation of user contributions, which has a bias in self-reporting and only explores the willingness to continue to participate rather than the actual behavior. To fill this gap, we employ a data-driven approach and track users' actual behavior to investigate the underlying mechanism of continuous contribution behaviors in social Q&A communities.

3. Research model and hypotheses

3.1 Social learning

Social learning in social Q&A communities can be explained from the perspective of the structural capital dimension, which refers to the connections and relationships that exist between members in the social network. In social Q&A communities, users with similar interests or knowledge domains can establish connections through the following mechanism. This mechanism allows individuals to accumulate knowledge by observing the contributions of others who share their interests, while embodying the social learning process (Jin *et al.*, 2015). According to social capital theory, people accumulate social capital in the process of social learning (Chamlee-Wright, 2008). This pattern of interaction facilitates the flow of knowledge as it increases the number of social interaction ties, which makes knowledge more accessible in social Q&A communities and also leads to the accumulation of structural capital. The structural dimension of social capital theory emphasizes the quality of relationships between members within a social network, which can be enhanced through social learning. Preceding research reports that social learning plays a critical role in driving an individual's participation behavior in online communities. For example, Jin *et al.* (2015) found that individuals accumulate knowledge by observing the contributions of other members and users with more social learning opportunities will contribute more knowledge to the communities. Shi *et al.* (2021) suggested that observing similar others' successes might enhance the observer's self-efficacy and confidence in that they can accomplish it as well and therefore is positive to knowledge contribution. The following mechanism in social Q&A communities increases the closeness of user connections within communities and provides opportunities for social learning. As scholars believe that individuals with more social learning opportunities are more likely to write attractive content to gain the attention of others (Fang *et al.*, 2018), we believe that social learning can facilitate knowledge contribution in social Q&A communities. Therefore, we propose the following hypothesis.

H1. Social learning positively affects users' knowledge contribution in social Q&A communities.

3.2 Social exposure

The networks and connections in social Q&A communities can help users increase exposure and thus expand influence. The scope of social exposure reflects the potential benefits of users; the greater the scope of social exposure, the larger the impact on the community (Guan *et al.*, 2018). The impact of social exposure can be explained from the structural dimension of social capital theory, which focuses on the patterns of social relationships that enable the flow of resources. It has been suggested that the core of social capital is the social ties formed among people (Coleman, 1990). Being an important channel for social exposure, ties in social network has been found to be associated with a greater probability of knowledge flow (Singh, 2005). In social Q&A communities, posts created by users spread through social networks. Guan *et al.* (2018) argued that users are more likely to answer questions if they have more opportunity for social exposure. Social media platforms have widely adopted the following mechanism in order to enhance their interactivity and bring their users closer to each other. When a community member is followed by others through the following mechanism, it increases their chances of social exposure, leading to the accumulation of structural capital. Structural capital generates network stickiness that keeps users stay in these social networks, actively contributing knowledge to maintain interactions (Li and Ku, 2018; Wang *et al.*, 2022). Additionally, social exposure has been linked to fulfillment (Porter and Donthu, 2008) and self-efficacy (Hocevar *et al.*, 2014), which are generally believed to facilitate engagement behaviors in online communities (Kuem *et al.*, 2020). Furthermore, since people are more inclined to act in accordance with their own interest, the greater the scope of social exposure, the more content people contribute (Kuang *et al.*, 2019). Collectively, it is reasonable to assume that the more social exposure a user gain in social Q&A communities, the more likely he/she is to contribute knowledge continuously. We therefore hypothesize the following.

H2. Social exposure positively affects users' knowledge contribution in social Q&A communities.

3.3 Peer recognition

Online communities typically use feedback mechanisms to show peer recognition for other users' contribution behaviors (Dong *et al.*, 2020). The dimension of cognitive capital is employed to examine the role of peer recognition. According to social capital theory, cognitive capital reflects the shared values, beliefs and understanding in the social network (Nahapiet and Ghoshal, 1998). The knowledge shared by users on social Q&A communities is a result of their personal thoughts and information processing, largely incorporating individuals' subjective opinions. Shared understanding in social Q&A communities can be reflected through the feedback mechanism, where users can click "like" for the answers they appreciate. The number of "likes" received by an answer contributor will be displayed on their profile as a symbol of peer recognition (Jin *et al.*, 2015). In other words, peer recognition in social Q&A communities is based on shared understanding and structural capital is accumulated through this process, influencing users' subsequent behavior. Shared understanding provides positive feedback, creating a conducive community atmosphere and promoting user creativity (Ogink and Dong, 2019). Previous studies on social platforms have found that peer recognition indicates value recognition from others, and users who receive more positive feedback have higher self-esteem (Burrow and Rainone, 2017; Elder *et al.*, 2022). Some scholars have suggested that a positive community atmosphere (where many answers receive "likes") creates social capital and increases users' contributions to the community (Rechavi and Rafaeli, 2012). Other scholars have found that users' contribution behavior is mainly determined by the amount of attention and recognition they receive from other participants (Rui and Whinston, 2012). We suppose that users who gain more peer recognition have share more common perceptions with others, thus accumulating more cognitive capital in the social network, leading to more knowledge contributions in the community. Based on the above analysis, we propose the following hypothesis.

H3. Peer recognition positively affects users' knowledge contribution in social Q&A communities.

3.4 Knowledge seeking

Knowledge seeking in social Q&A communities manifests as people asking questions in order to obtain knowledge (Harper *et al.*, 2009). The dimension of relational capital is employed to examine the role of knowledge seeking. Relational capital is a dimension of social capital that looks at the level of trust, reciprocity and mutual obligations that exist between people and how these factors affect social behaviors (Lee *et al.*, 2020). This dimension highlights both the emotional and instrumental aspects of social relationships in knowledge seeking. Emotional aspects include feelings of trust and reciprocity, which can foster a sense of community and encourage members to help others. Instrumental aspects, on the other hand, include the practical benefits of social connections and the access to knowledge. From this perspective, knowledge exchange in social Q&A communities is mutual (Wiertz and Ruyter, 2007), with users not only seeking knowledge from other members, but also making contributions to the community. Just as some literature suggested, asking behaviors should be distinguished from answering behaviors (Phang *et al.*, 2009). When an individual actively seeks out knowledge from others in social Q&A community, he/she is more likely to build stronger relationships with other members; thus, relational capital is accumulated. The accumulation of relational capital can lead to a sense of obligation to contribute back to the community and share their own knowledge in the pursuit of reciprocity (Guan *et al.*, 2018). On the other hand, if an individual is not actively seeking knowledge, he/she may be less likely to feel a sense of reciprocity and social capital might not accumulate, leading to a reluctance to contribute. Ahmed and Srivastava (2017) pointed out that after users develop the habit of using a Q&A community, they will habitually to seek answers from the community. Park *et al.* (2014) have demonstrated that the intention to seek knowledge is positively related to information sharing behavior in online communities. We suppose that users who actively participate in the community hope that they will not only be able to share knowledge but will also find answers from the community when they have questions, and users who ask more questions will also contribute more answers out of reciprocity. Therefore, we propose.

H4. Knowledge seeking positively affects users' knowledge contribution in social Q&A communities.

3.5 Motivational affordances

Motivational affordance in online communities is designed primarily to improve user experience and motivate user participation (Hamari *et al.*, 2014). Specifically, it can provide positive feedback for users, which will increase the intrinsic motivation of members (Deci *et al.*, 1975) and encourage interaction outcomes such as continued involvement and contribution (Chen *et al.*, 2018). Social media platforms have offered different types of motivational affordances such as points, levels, tags and status to better support social interactions (Oeldorf-Hirsch and Sundar, 2015; Dong *et al.*, 2020). For instance, most virtual communities have employed different forms of status hierarchy systems which distinguish members by awarding them with improved status-standings for their community participation and contributions (Dong *et al.*, 2020). The status-standings can be seen as "an individual's relative standing in a group based on prestige, honor and deference" (Willer, 2009). And the motivational affordance of status-seeking has been proven to lead to greater contributions (Khansa *et al.*, 2015) and better performance within communities (Kilduff *et al.*, 2016). Different from peer recognition, motivational affordance is officially given by the community and can be more formal and objective. As an incentive from community, motivational affordance can increase the interaction between community and users, stimulating user attachment to the community (Khansa *et al.*, 2015) and gives users a sense of accomplishment as well as responsibility, encouraging them to undertake social responsibility and share information with other members (Lee *et al.*, 2014). In conclusion, we predict that motivational affordances will promote users' continuous knowledge contribution in social Q&A communities. We therefore propose the following.

H5a. Motivational affordance positively affects users' knowledge contribution in social Q&A communities.

Previous discussions have suggested that social exposure motivates continuous knowledge contributions, and we further assume that the strength of this motivational impact can be influenced by motivational affordance. To be more specific, members who are highly motivated by motivational affordance have a stronger social responsibility and demonstrate greater sense of obligation (Lee *et al.*, 2014). Take professor badge (one form of motivational affordance in social Q&A community) for example, as a sign of professional, it helps users confirm their professional identity (Cavusoglu *et al.*, 2021). When users with professor badges obtain social exposure, they tend to believe that the professional knowledge they contribute attracts more attention of others, thus boosting their willingness to keep contributing. Meanwhile, users with more professor badges would receive greater scope of social exposure, and so their expertise is witnessed by more people, thus the user might feel more fulfilled (Jabr *et al.*, 2014; Guan *et al.*, 2018). As such, we predict that motivational affordance will strengthen the impact of social exposure in motivating continuous contribution. We therefore propose the following.

H5b. Motivational affordance positively moderates the influence of social exposure on knowledge contribution in social Q&A communities.

For peer recognition, the situation is similar. Under the same degree of peer recognition, those who have more professor badges tend to feel that the professionalism of their content is more recognized by the community (Feng *et al.*, 2022). This provides an important source of motivation for knowledge contributors, which not only helps them improve their reputations and self-esteem, but also amplifies the possibility of future contribution (Guan *et al.*, 2018). Thus, we expect that more motivational affordance gained by users would lead to greater effect of peer recognition on knowledge contribution behaviors. Based on the above analysis, we propose.

H5c. Motivational affordance positively moderates the influence of peer recognition on knowledge contribution in social Q&A communities.

3.6 Self-presentation

Self-presentation, also known as impression management, refers to the deliberate display of oneself in accordance with one's own desires (Liu *et al.*, 2016), i.e. a series of behaviors performed by an individual to communicate with others with the aim of establishing, maintaining or enhancing the image of oneself in the minds of others (Zhao *et al.*, 2008). On social platforms, users can create their own profiles and display them to the public as a means of self-presentation, which allows others to learn about one's interests, experiences, attitudes, etc. This is especially common in knowledge communities, where identity presentation can be seen as one's image building to show his/her ability to share expertise (Fedushko *et al.*, 2018). Previous studies found that self-presentation positively affects user's self-image viewed by others, thereby promoting social interactions between users (Ko, 2013; Zhao *et al.*, 2018). Zhou *et al.* (2019) believed that self-image improves the sense of belonging and satisfaction, thereby increasing the willingness of SNS users to continue using it. Kuem *et al.* (2020) argued that self-identity verification reflects the extent of self-confidence of community members, which motivates active participation behaviors. Dong *et al.* (2020) used the count value of items displayed by the focal user as the extent of self-disclosure and verified that this individual characteristic facilitated users' contribution behavior in the virtual community. Therefore, it is safe to assume that there is a positive correlation between self-presentation and knowledge contribution behaviors. Consequently, we expect that.

H6a. Self-presentation positively affects users' knowledge contribution in social Q&A communities.

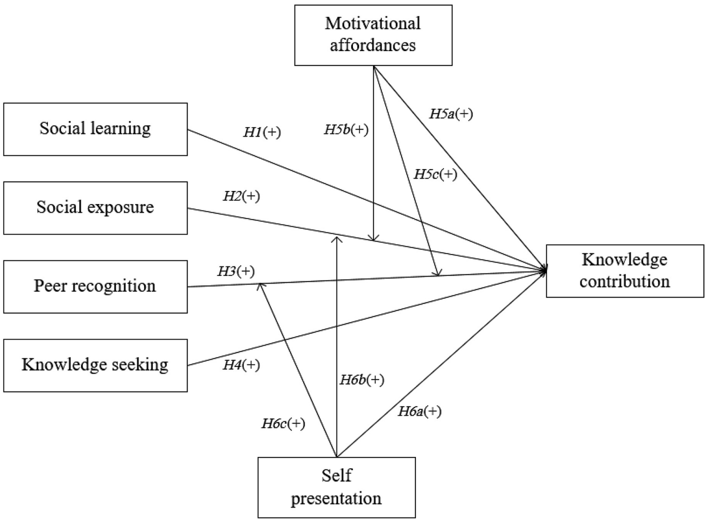
As mentioned, self-presentation plays a significant role in communities. We posit that it also strengthens the impact of social exposure on contributions. Compared to the instantaneous interpersonal and social interaction offline, the relatively safe social environment provided by online communities gives users maximum control over their self-presentation (Walther, 2007). A clear self-presentation helps users acquire information more effectively (Zhao *et al.*, 2008). If the source of information is reliable enough, users' perceived usefulness of the information will increase, and users may be more willing to spend time and effort processing it (Srivastava and Kalro, 2019), which will result in higher efficiency of knowledge exchange. In online communities, users help others not only for altruism, but also for reputation, reciprocity and self-esteem (Bock *et al.*, 2005). Self-presentation provides important motivation for knowledge contributors, not only by helping establish their online identity and enhance their self-esteem, but also by amplifying the possibility of future reciprocation (Guan *et al.*, 2018). Therefore, at the same level of social exposure, the more detailed the user self-presentation information is, the more likely they will contribute knowledge in the community. Thus, we propose.

H6b. Self-presentation positively moderates the influence of social exposure on knowledge contribution in social Q&A communities.

We also expect self-presentation to moderate the impact of peer recognition on users' knowledge contributions. A user's identity communication will not only be displayed in his personal homepage, but also be passed on to others in the same community by knowledge contribution behaviors. In addition, users can improve their self-presentation by disclosing more personal information. Complete self-presentation information indicates users' intention to improve their popularity with the help of community activities (Bareket-Bojmel *et al.*, 2016; Liu *et al.*, 2016). At the same level of peer recognition, those who show more self-presentation information will be more popular and receive more positive feedback (Guan *et al.*, 2018), pushing them to contribute more. Based on the above analysis, we propose.

H6c. Self-presentation positively moderates the influence of peer recognition on knowledge contribution in social Q&A communities.

Figure 1 shows our research model in this study.



Source(s): Author's own creation

Figure 1. Research model of continuous knowledge contribution

4. Methodology

4.1 Research context

We chose Zhihu, China's largest social Q&A community, as the research context of our study. Established in 2011, Zhihu is an online Q&A platform where users can ask questions, answer and exchange opinions. New topics, questions and answers are created on Zhihu every day. Zhihu users can interact with each other through actions such as clicking "likes", leaving comments and sending private messages. By the end of 2021, Zhihu has an average monthly active user base of 103.3 million and a cumulative total of 420 million Q&A content.

Figure 2 is an example of a Zhihu user's homepage, which contains basic personal information, such as location, career, professional experience, education background, etc. A user can follow others to form social networks, and in this way, the person being followed by the focal user becomes his/her followee. Once the followee posts something new, the content will be automatically pushed to his/her followers (Dong *et al.*, 2020). The records of questions and answers contributed by the user are also listed. The answers may receive "likes" from other users and the total number of "likes" received is displayed on the user's homepage. In addition, the community recognizes the professionalism of the user's answers by awarding them professor badges, which are also displayed on his/her homepage.

We randomly selected 10,193 users on Zhihu and used Python 3.8 to collect users' personal information, contribution content and interaction data from May 9, 2020, to July 24, 2020. Because our study focuses on the behavior of continuous knowledge contribution, only active members who continuously contributed knowledge are chosen for analysis. To capture this sample, we set a 15-day time unit so that the whole timeline was divided into five stages. In our context, a 15-day period is a moderate time unit to study user contribution behavior, because a very short time period may not capture the activity of some active yet at that specific time infrequent knowledge contributors (Jabr *et al.*, 2014). Likewise, if the time unit is

Figure 2.
A screenshot of a Zhihu User's homepage

Source(s): Author's own creation

too long, important information about changes in user behavior may not be captured (Dong *et al.*, 2020). The final dataset comprises the dynamic behavioral data of 10,193 users across five time periods. The software STATA 14 is used to test the proposed hypotheses.

4.2 Variable description and measurement

Table 2 shows the variables in the study. There is one dependent variable: knowledge contribution; four independent variables: social learning, social exposure, peer recognition and knowledge seeking; and two moderating variables, motivational affordances and self-presentation. Each variable are measured as follows.

4.2.1 Dependent variable. Knowledge Contribution. Users on Zhihu can contribute by asking or answering questions. Since a question can be answered repeatedly on Zhihu, the platform has a very large number of answers. Compared with asking questions, users answer questions more frequently. Following previous studies (Khansa *et al.*, 2015; Goes *et al.*, 2016; Kuang *et al.*, 2019), our dependent variable *knowledge contribution* was measured by the number of answers provided by the focal user in the given period.

4.2.2 Independent variable. Social learning. Social Q&A communities are places where users share and acquire knowledge (Zhao *et al.*, 2016). Users can follow others to expand their learning sources and improve their knowledge system. On Zhihu, a user can follow other members and obtain information from his/her followees. The more people a user follows, the more information he/she gets from others in the community (Jin *et al.*, 2015). Using the same measurement from Dong *et al.* (2020), we employ the number of followees of the focal user to represent *social learning*.

Social exposure. Social exposure in online communities reflects users' attraction to the community and interaction among the community members (Wasko and Faraj, 2005). On Zhihu, information will be automatically pushed from the source to its followers. The number of followers represents the number of audiences a user has, and the more followers a user have, the higher degree of social exposure he/she has (Guan *et al.*, 2018). Following previous research (Guan *et al.*, 2018), we use the number of followers of the focal user to measure *social exposure*.

Peer recognition. Peer recognition reflects a user's perception that his/her contribution has received acknowledgement from other users (Jabr *et al.*, 2014; Jin *et al.*, 2015). Users post

Variable	Measure item	Description
Dependent variable		
Knowledge contribution	$answer_{it}$	The number of answers provided by user i during the time period t
Independent variables		
Social learning	$followees_{it}$	The number of followees of user i from registration to the time period t
Social exposure	$followers_{it}$	The number of followers of user i from registration to the time period t
Peer recognition	$likes_{it}$	The number of likes for user i's answers from registration to the time period t
Knowledge seeking	$question_{it}$	The number of questions asked by user i from registration to the time period t
Moderating variables		
Motivational affordances	$professorBadge_{it}$	Dummy variable equals to 1 if user i receives professor badges during time period t, or 0 otherwise
Self-presentation	$selfPresentation_{it}$	The number of personal information items for user i from registration to time period t

Source(s): Author's own creation

Table 2.
Variable description

answers hope to receive response or recognition from other members (Chen *et al.*, 2018), which is usually expressed by "likes", usefulness votes, etc. (Burrow and Rainone, 2017; Aghakhani *et al.*, 2021) In Zhihu, answer contributors can receive "likes" from other users, which reflects the recognition to the content they contribute. Therefore, we use the number of likes that the focal user has received to reflect *peer recognition* to a user.

Knowledge seeking. Knowledge seeking in social Q&A communities is an important way for users to acquire information (Wu and Korfiatis, 2013). By simply browsing answers, users have access to a large amount of information. However, it is hard to collect the records of browsing behavior from the community. A more direct form of knowledge seeking is through proposing questions. You can get answers to informational or conversational questions by raising questions in social Q&A communities (Harper *et al.*, 2010). Therefore, we use the number of questions asked by the focal user to measure *knowledge seeking*.

4.2.3 Moderating variable. Motivational affordances. Under the gamification design, badges are often regarded as motivational affordances to stimulate user participation in online communities (Moro *et al.*, 2019; Zhang *et al.*, 2020; Cavusoglu *et al.*, 2021; Esteves *et al.*, 2021). On Zhihu, professor badges will be awarded by the platform to those contributors who provide high quality answers. We use whether the focal user has received professor badges in the given period to indicate *motivational affordances*. This variable is a dummy variable.

Self-presentation. Self-presentation in online communities refers to users' personal information disclosure behavior (Guan *et al.*, 2018). Users on Zhihu can choose to display five types of personal information, including location, career, professional experience and education. The more items of personal information a user display, the clearer his/her identity is (Bock *et al.*, 2005). Guan *et al.* (2018) used the degree of completeness of a user's information disclosure to measure his/her identity-presentation. Following the previous study by Guan *et al.* (2018), we use the number of personal information items to measure the focal user's degree of self-presentation. The value of this variable ranges from 0 to 5.

4.3 Data analysis

The final dataset included 10,193 users and the statistics summary of users is shown in Table 3. Table 4 presents the correlation coefficient matrix of the variables. The correlation coefficients among the variables are less than 0.6. To assess any potential multicollinearity, we calculated variance inflation factor (VIF) scores for all independent variables. The VIF values for all these independent variables range from 1.03 to 1.36, below the rule-of-thumb value of 10 (Billings and Wroten, 1978). Thus, multicollinearity is not considered a problem.

In our study, the independent variables, dependent variables and moderator variables are all non-negative integers. Poisson regression and negative binomial regression are often used in analyzing count data. The difference is that the negative binomial regression does not assume equal mean and variance, but introduces a parameter to correct the over-dispersion, when the variance is larger than the mean (Gardner *et al.*, 1995). As shown in Table 4, the mean and

Table 3.
Descriptive statistics

Variable	Mean	Variance	Min	Max
$answer_{it}$	7.592	43.92	0	69
$followees_{it}$	218.6	486.5	0	15,731
$followers_{it}$	29,317	356,457	0	37,208,168
$likes_{it}$	4,332	22,213	0	1,157,240
$question_{it}$	13.20	64.97	0	2,684
$professorBadge_{it}$	0.105	0.306	0	1
$selfPresentation_{it}$	2.763	1.450	1	5

Source(s): Author's own creation

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	VIF
(1) $answer_{it}$	1.000							
(2) $followees_{it}$	0.113	1.000						1.25
(3) $followers_{it}$	0.112	0.033	1.000					1.33
(4) $likes_{it}$	0.569	0.115	0.184	1.000				1.36
(5) $question_{it}$	0.126	0.219	0.056	0.082	1.000			1.03
(6) $professorBadge_{it}$	0.218	0.130	0.110	0.359	0.095	1.000		1.08
(7) $selfPresentation_{it}$	0.090	0.147	0.058	0.105	0.061	0.232	1.000	1.17
Mean VIF								1.20

Source(s): Author's own creation

Table 4. Correlation matrix

variance of the dependent variable are quite different. Therefore, we use the negative binomial regression model to analyze our data. The negative binomial probability function is as follows:

$$pr(Y = y_{it}|\lambda, \theta) = \frac{\Gamma(y_{it} + \theta)}{\Gamma(y_{it} + 1)\Gamma(\theta)} \left(\frac{\theta}{\theta + \lambda}\right)^{\theta} \left(\frac{\lambda}{\theta + \lambda}\right)^{\lambda_{it}} \tag{1}$$

There are two parameters in the negative binomial distribution: θ and λ. Parameter θ captures the over-dispersion in the data. When θ = 0, negative binomial regression is the same as the Poisson regression. Parameter λ is the expected value of the distribution. We conduct logarithmic transformation of $followee_{it}$, $follower_{it}$ and $likes_{it}$ because these three variables are highly skewed (Racherla and Friske, 2012; Rui and Whinston, 2012). Since our study explores moderators in the research hypotheses, the hierarchical regression model is used to explore the main effects and moderation effects respectively (Angst and Agarwal, 2009; Billings and Wroten, 1978). The main effects regression model is as follows:

$$\begin{aligned} 1n(\lambda(x_{it})) = {} & \beta_i + x_{it-1}\beta + \varepsilon_{it} + \beta_0 + \beta_1 Ln(followees_{it-1}) + \beta_2 Ln(followers_{it-1}) \\ & + \beta_3 Ln(likes_{it-1}) + \beta_4 question_{it-1} + \beta_5 professorBadge_{it-1} \\ & + \beta_6 selfpresentation_{it-1} + \varepsilon_{it} \end{aligned} \tag{2}$$

where β is a vector of regression coefficients of covariates; ε_{it} is the error term. The regression model including moderation effects is expressed in Equation (3).

$$\begin{aligned} 1n(\lambda(x_{it})) &= \alpha_1 + x_{it-1}\alpha + \varepsilon_{it} \\ &= \alpha_0 + \alpha_1 Ln(followees_{it-1}) + \alpha_2 Ln(followers_{it-1}) + \alpha_3 Ln(likes_{it-1}) + \alpha_4 question_{it-1} \\ &\quad + \alpha_5(professorBadge_{it-1}) + \alpha_6(selfpresentation_{it-1}) \\ &\quad + \alpha_7 professorBadge_{it-1} \times Ln(followers_{it-1}) \\ &\quad + \alpha_8(professorBadge_{it-1}) \times Ln(likes_{it-1}) \\ &\quad + \alpha_9 selfpresentation_{it-1} \times Ln(followers_{it-1}) \\ &\quad + \alpha_{10}(selfpresentation_{it-1}) \times Ln(likes_{it-1}) + \varepsilon_{it-1} \end{aligned} \tag{3}$$

Then we use STATA to run the negative binomial regression analysis and the results of the two data regression models are shown in Table 5. Model 1 only contains independent

Table 5.
Results of negative binomial regression

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ln(followee$_{it}$)	0.394***	0.378***	0.388***	0.384***	0.382***	0.380***
	(55.95)	(52.96)	(54.78)	(53.37)	(52.97)	(52.54)
ln(follower$_{it}$)	−0.347***	−0.340***	−0.333***	−0.398***	−0.396***	−0.354***
	(−46.99)	(−44.49)	(−42.76)	(−24.90)	(−24.68)	(−21.33)
ln(likes$_{it}$)	1.515***	1.515***	1.530***	1.747***	1.747***	1.750***
	(217.30)	(214.38)	(211.47)	(121.83)	(121.67)	(118.33)
question$_{it}$	0.00250***	0.00253***	0.00248***	0.00257***	0.00256***	0.00259***
	(16.94)	(17.30)	(17.04)	(17.34)	(17.36)	(17.49)
professorBadge$_{it}$		−0.158***	0.242*		0.0766	0.132
		(−9.10)	(2.33)		(0.70)	(1.22)
selfPresentation$_{it}$		0.0359***		0.171***	0.164***	0.195***
		(10.34)		(17.56)	(16.36)	(18.45)
professorBadge$_{it}$ × ln(follower$_{it}$)			0.0345		0.0125	−0.427***
			(0.97)		(0.34)	(−5.63)
professorBadge$_{it}$ × ln(likes$_{it}$)			−0.146***		−0.0489	0.364***
			(−4.48)		(−1.46)	(4.31)
selfPresentation$_{it}$ × ln(follower$_{it}$)				0.0273***	0.0277***	0.0142**
				(5.25)	(5.23)	(2.61)
selfPresentation$_{it}$ × ln(likes$_{it}$)				−0.0986***	−0.0962***	−0.0966***
				(−20.01)	(−19.16)	(−18.68)
professorBadgeit × selfPresentation$_{it}$ × ln(follower$_{it}$)						0.116***
						(6.16)
professorBadge$_{it}$ × selfPresentation$_{it}$ × ln(likes$_{it}$)						−0.112***
						(−4.97)
_cons	0.728***	0.651***	0.685***	0.341***	0.344***	0.255***
	(42.69)	(36.24)	(38.45)	(11.39)	(11.48)	(8.10)
AIC	470745.6	470562.4	470633.9	469783.6	469776.9	469684.3
BIC	470789.8	470624.3	470704.6	469854.3	469874.1	469799.2
Log likelihood	−235367.8	−235274.2	−235308.9	−234883.8	−234877.4	−234829.2

Note(s): *t* statistics in parentheses
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$
Source(s): Author's own creation

variables, and Model 2 adds the direct effects of the moderating variables. Model 3 and Model 4 consider the moderation effects of motivation affordances and self-presentation respectively. Model 5 takes all variables into account. Model 6 considers the three-way interaction. According to the values of Akaike information criterion (AIC), Bayesian information criterion (BIC) and Log Likelihood, Model 5 has a better model fit compared with Model 2. The regression coefficients represent the effects of the independent variables on the dependent variable. Standard deviance and significance are also included.

4.4 Results

From Table 5, we can see that all the variables are directly related to knowledge contribution behaviors with the most significance levels in Model 2, except that $follower_{it}$ and $professorBadge_{it}$ are opposite to our expected signs.

Hypothesis 1 analyzes the effects of social learning on continuous contribution behaviors. In social Q&A communities, social learning refers to learning the knowledge contributed by others. This means that users can have more resources to observe and study to improve their productivity. In our study, the number of followees is used to represent social learning. The regression result of Model 2 shows that the coefficient of $followee_{it}$ is significantly positive ($\beta = 0.378, p<0.001$). Therefore, Hypothesis 1 is supported, which means that the more social learning a user contributes, the more likely he/she is to contribute knowledge continuously.

Hypothesis 2 analyzes the influence of social exposure on continuous knowledge contribution behaviors. Social media enables everyone to create content and build their own social networks. A user getting more attention means that he/she is more likely to be exposed, and accordingly he/she will have more influence in the community. Our study uses the number of followers to measure the degree of social exposure and expects the impact to be positive. However, the regression result of Model 2 shows that the coefficient of $follower_{it}$ is significantly negative ($\beta = -0.340, p<0.001$). Therefore, Hypothesis 2 is not supported.

Hypothesis 3 analyzes the influence of peer recognition on continuous contribution behaviors. In social Q&A communities, one of the references to evaluate the professionalism of answers is how much they are recognized by other users. The more users recognize the answer and the closer the answer is to public expectations, the more professional the contributor will be considered. Our study used the number of “likes” received by the user to represent peer recognition. The regression result of Model 2 shows that the coefficient of $likes_{it}$ is significantly positive ($\beta = 1.515, p<0.001$), that is, the more peer recognition a user receives, the more likely he/she is to participate in knowledge contribution. Therefore, Hypothesis 3 is supported.

Hypothesis 4 analyzes the influence of knowledge seeking behaviors on continuous contribution behaviors. In social Q&A communities, answering and questioning are both regarded as contributions. Users ask questions in the community to seek information, and this further stimulates them to continue to contribute answers due to reciprocity. In this paper, the number of questions is used to represent knowledge seeking behaviors. The regression result of Model 2 shows that the coefficient of $question_{it}$ is significantly positive ($\beta = 0.00253, p<0.001$). Therefore, Hypothesis 4 is supported.

Hypothesis 5a, 5b and 5c analyze the influence of motivational affordances on continuous contribution behaviors. Community incentive mechanisms are important in social Q&A communities. The users’ intrinsic motivation also comes from the community’s recognition of their contributions. The more professional the user is recognized by the platform, the more likely he/she is to continue to contribute. Our study used professor badges to represent motivational affordances. Opposite to our expectation, the regression result of Model 2 shows that the coefficient of $professorBadge_{it}$ is significantly negative ($\beta = -0.158, p<0.001$). Therefore, H5a is not supported. Model 5 shows that the moderation effects of $professorBadge_{it}$ on social exposure ($\alpha = 0.0125, p > 0.05$) and peer recognition to contribution ($\alpha = -0.0489$, $p > 0.05$) are not significant. This means that the more the community recognizes the professionalism of users, the greater but not significant the impact of social exposure on contribution behaviors. Meanwhile, the impact of peer recognition on contribution behaviors is negative and insignificant.

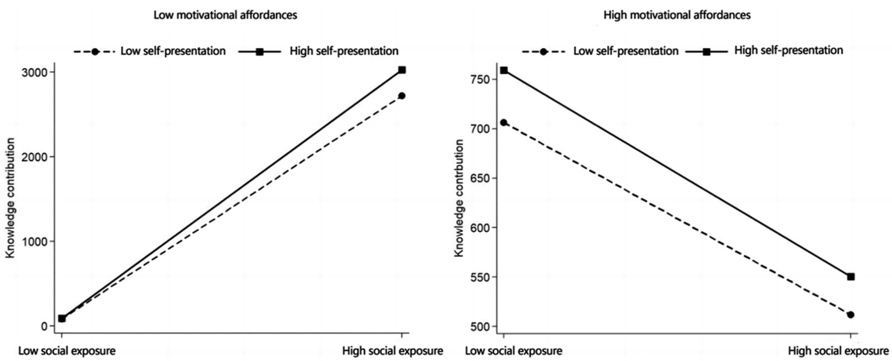
Hypothesis 6a, 6b and 6c analyze the influence of self-presentation on continuous contribution behaviors. Users on social media may disclose their own identity information to attract others. In online Q&A communities, users who disclose detailed self-information want to build a good image and are therefore more likely to continue contributing answers. In this paper, we used the degree of disclosure of user information in personal homepage to represent self-presentation. The regression result of Model 2 shows that the coefficient of questions is positive and significant ($\beta = 0.0359$, $p<0.001$). Therefore, Hypothesis 6a is supported. In Model 5, the moderation effect of self-presentation on social exposure to continuous contribution behaviors is also significantly positive ($\alpha = 0.0277$, $p<0.001$). Hypothesis 6b is also supported. Contrary to hypothesis 6c, the moderation effect of self-presentation on peer recognition to continuous contribution behaviors is significant, but the effect is negative ($\alpha = -0.0962$, $p<0.001$). Hypothesis 6c is not supported.

Moreover, three-way interaction (motivational affordances × social exposure × self-presentation) was revealed ($\alpha = 0.116$, $p<0.001$) in this study. To further understand this result, we divided the results into two-way conditions depending on motivational affordances (see Figure 3). The results of the test show that when users receive low motivational affordances, the relationship between social exposure and knowledge contribution is positive, but high self-presentation performs better than low self-presentation. However, when users receive high motivational affordances, those who have high self-presentation perform a higher level of knowledge contribution, but the relationship between social exposure and knowledge contribution is negative.

Three-way interaction (motivational affordances × peer recognition × self-presentation) was revealed in Model 6 ($\alpha = -0.112$, $p<0.001$). We also examined the interaction effects among motivational affordances, peer recognition and self-presentation. The results indicate that peer recognition and knowledge contribution are positively related regardless of motivational affordances, but users with high self-presentation tend to make more contributions.

5. Discussion

Continuous knowledge contribution behavior is vital to ensure the long-term vibrancy of social Q&A communities. This paper investigates how different kinds of motivations jointly affect



Source(s): Author's own creation

Figure 3. Three-way interaction among motivational affordances, social exposure and self-presentation

knowledge contribution in social Q&A communities and presents empirical results from a popular social Q&A community in China. Regarding relationship-based motivation, firstly, the results show that social learning positively influences users to contribute answers continuously. This finding is consistent with the results of previous studies (Dong *et al.*, 2020; Jin *et al.*, 2015). Community members follow others to observe and study their behaviors in the social environment. This process increases social interaction ties and leads to the accumulation of social capital, which in turn facilitates users' contribution behavior. Secondly, in contrast to previous studies (Kuang *et al.*, 2019; Qiu and Kumar, 2017), our study found that social exposure is an important factor in influencing users' contribution behaviors, but in a negative way. One possible explanation is that users with a larger follower base may be more focused on improving the quality of their answers to retain their followers. Creating high-quality answers requires more time and effort than providing short or superficial answers, which may result in a decrease in the number of contributions within a specific time period. Alternatively, users with more followers may feel that they are already recognized and may lack the motivation to contribute further to gain more attention. Thirdly, peer recognition has significantly positive effect on users' knowledge contribution behaviors. Positive feedback from social interactions improves users' self-confidence and stimulates them to increase productivity. This conclusion is consistent with the study by Guan *et al.* (2018), in which they found that if the user's answers received more votes, he/she would contribute more in the future. Finally, knowledge seeking behavior is proved to have a positive impact on users' contribution behaviors. From the perspective of relationship capital, users benefit from asking questions and are more likely to help others by contributing answers. This result reinforces the conclusions of some studies (Khansa *et al.*, 2015) and rejects that knowledge-seeking behaviors will reduce the perception of personal self-efficacy and reduce contribution behaviors (Kuang *et al.*, 2019).

As for community-based motivation, in contrast to our hypothesis, motivational affordances have a significantly negative effect on users' knowledge contribution behaviors, and there is no significant moderation effect of social exposure and peer recognition on contribution behaviors. This result is somewhat inconsistent with some of the current research under gamification design (Khansa *et al.*, 2015; Zhang *et al.*, 2020). One plausible explanation for the decrease in the number of contributions after users received professor badges is that they may feel that they already achieved the highest level of recognition and therefore do not need to put in as much effort as before. Just as pervious research (e.g. Lepper *et al.*, 1973) has documented that giving explicit and expected rewards can in fact dampen those users' motivations to contribute. Alternatively, users who have received professor badges may be more committed in providing well-considered answers to demonstrate their professionalism. This process may lead to a decrease in the number of contributed answers, as more time is required to provide high-quality answers. Besides, this could also be caused by social attributes. In communities with large user bases, members care more about peer recognition and less about platform recognition, and contributors can gain greater incentive from other users' recognition (Chen *et al.*, 2019). Thus, professor badges may not necessarily serve to influence knowledge contribution behaviors due to the nature of social Q&A communities.

In terms of individual-based motivation, self-presentation has a positive effect on users' knowledge contribution behaviors. It plays a positive moderating role between social exposure and contribution behaviors but a negative moderating role between peer recognition and contribution behaviors. As extant studies have found, self-presentation can represent the sense of identity and stimulate users to contribute continuously (Ma and Agarwal, 2007). The result of moderation effect on social exposure to contribution behaviors is consistent with the conclusions of previous studies (Guan *et al.*, 2018). When the number of followers is at the same level, users with more self-information disclosed are more likely to contribute answers. However, when it comes to the number of "likes", we have the opposite conclusion. It is possible that the more identity information users disclose, the more they approve of themselves. As a result, they may consider it unnecessary to win recognition from others.

Finally, we found that, as hypothesized, self-presentation is revealed to moderately affect the relationship between knowledge contributions and social exposure. The interaction of self-presentation and peer recognition has the same influence on knowledge contributions regardless of the motivational affordances. However, under different levels of motivational affordances, the interaction influences knowledge contributions in different ways. Specifically, users who are not motivated by the community will contribute more knowledge under high social exposure, while users who are highly motivated by the community will be the opposite. Recognition from the community is scarcer than peer recognition. The reason may be that recognition from the platform will bring great sense of accomplishment to the user. Being satisfied with what they have achieved, the user may make fewer contributions in the future. This research is important for further exploration of the factors affecting continuous contribution behaviors and shows the direct impact of social capital related factors on these behaviors and the importance of incentives from users themselves and the community.

6. Theoretical and practical implications

6.1 Theoretical implications

This study offers several important implications for theoretical contributions. First, the findings broaden the social Q&A community related literature by considering different types of motivations for knowledge contribution. While previous research has extensively explored the motivation for content contribution, the ways in which different types of motivations interact and influence user contributions have not been fully investigated (Jin *et al.*, 2015). Since the interaction between antecedents of contribution behavior might play an integral role in predicting users' continuous knowledge contribution, it is necessary to consider different kinds of motivations together. We advance this knowledge base by distinguishing the sources of motivations and empirically identifying variables that explain how different kinds of motivations (i.e. motivations from relationships, communities and individuals) affect users' ongoing contributions in social Q&A communities. As such, our findings provide a comprehensive view of the factors that are crucial to the social dynamics of Q&A communities, broadening the existing literature in this field.

Second, our study extends social capital theory, which regards social capital as the intangible resource hidden in the social network. We extend the application of this theory to social Q&A communities and incorporate its three dimensions to better understand the impact of social learning, social exposure, peer recognition and knowledge seeking on continuous knowledge contribution. While previous research has utilized social capital theory to study user participation in virtual communities, there has been a dearth of studies that employ actual behavior data to examine the influence of social capital on social Q&A communities. Specifically, we emphasize the importance of social capital in explaining relationship-based motivations' influence on knowledge-contributing behavior in social Q&A communities. From a social capital perspective, various social capital accumulates with social interaction in the community and facilitates continuous knowledge contribution. Additionally, we explore the moderating roles of motivational affordances (community artifact design) and self-presentation (personal information disclosure) on the relationship between social capital factors and knowledge contribution as social Q&A communities also serve as platforms to gain recognition and express identity. By combining the perspective of motivational affordances and image motivation, this study bridges and extends the applicability of social capital theory to social Q&A community context.

Third, while much of the research on user participation behaviors has centered on general social platforms and capture user behavior data (typically utilize survey) at a fixed time point, few studies choose social Q&A communities as the research context and conduct dynamic panel dataset to study the periodic activity process. Our research employs empirical data obtained from China's biggest social Q&A community and constructs a dynamic panel dataset to analyze users' contribution behaviors over time. We posit that a data-driven approach to explore the impacts of motivations of continuous contribution varying along with time would be more persuasive.

6.2 Practical implications

Our study not only contributes to the existing literature on social Q&A communities, but also provides valuable insights for practitioners aiming to build vibrant and successful communities. Firstly, as suggested by the empirical results, it is crucial for operators of social Q&A communities to prioritize the "social aspect" of the community when designing the system. By connecting more users through social networks, trust, reciprocity and sense of accomplishment can be fostered, which can lead to the establishment of positive relationships among community members and stimulate knowledge contributions. Additionally, the community itself can strengthen the interaction between contributors and other members by implementing user feedback mechanisms such as thanks, comments, attention, mood and other mechanisms. Operators can also encourage users to follow more people to increase their learning opportunities and show appreciation for answers by liking or following contributors. These can help build a thriving social Q&A community that benefits both its members and the wider community.

Since the results suggest that users may be more concerned about peer recognition on the platform and less interested in incentives from the community, community-awarded badges may not be a good incentive for more contributions. While professor badges can be a useful way to recognize and reward users who provide high-quality content, the potential downsides should also be considered. Thus, it is important to design incentive mechanisms thoughtfully to ensure that they do not have unintended negative consequences. Community managers may consider incentive features (such as levels) that are easier to access. In this way, users' sense of accomplishment can be stimulated more effectively. What's more, operators of social Q&A communities should also find out appropriate forms for members to display their information to attract more users so that knowledge contributors can better motivated. In other words, operators of social Q&A communities may encourage users to disclose more information to better build self-identity, enhance their sense of belonging and maintain their long-term relationship with the community. Overall, it is recommended that operators of social Q&A communities use the relevant factors of social capital discussed in this research to facilitate users' continuous participation and contribution, so as to prevent novices from falling into inactivity when their initial enthusiasm fades.

7. Limitations

This study also has some limitations. Firstly, while we use the number of answers provided by a user to measure his/her knowledge contribution, it is essential to acknowledge that the quality of answers is also significant. Peer researchers are expected to overcome this limitation by considering both the quantity and quality of knowledge contributions to draw more valid conclusions. Secondly, although we collected data on users' actual interaction and contribution behaviors in social Q&A communities, we have not explored the psychological mechanisms. Future research can delve into the mechanisms that underlie how social capital influences knowledge contribution behavior. Thirdly, there may be potential endogeneity issues due to the possible linkages between variables. Future research may address this potential threat by using instrumental variables. Lastly, the data used in this paper were collected from a Chinese social Q&A community, and most of its members are Chinese. Findings in different cultural environments are recommended to validate our results.

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