

Understanding Members' Active Participation in Online Question-and-Answer Communities: A Theory and Empirical Analysis

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ABSTRACT: Community-based question-and-answer (Q&A) websites have become increasingly popular in recent years as an alternative to general-purpose Web search engines for open-ended complex questions. Despite their unique contextual characteristics, only a handful of Q&A websites have been successful in sustaining members' active participation that unlike lurking consists of not only posting questions but also answering others' inquiries. Because the specific design of the IT artifacts on Q&A websites can influence their level of success, studying such leading Q&A communities as Yahoo! Answers (YA) provides insights into more effective design mechanisms. We tested a goal-oriented action framework using data of 2920 YA users and found that active online participation is largely driven by artifacts (e.g., incentives), membership (e.g., levels of membership and tenure), and habit (e.g., past behavior). This study contributes to the IS literature by showing that active participation can be understood as the setting, pursuit, and automatic activation of goals.

KEY WORDS AND PHRASES: online question-and-answer community, active participation, habit, artifacts, incentives, goal-oriented action, system-generated data, dynamic panel data analysis

Introduction

Community-based question-and-answer (Q&A) websites have become increasingly popular in recent years as an alternative to general-purpose Web search engines for open-ended complex questions [27, 61, 82]. With their quick turnaround rate in solving open questions and their community wisdom in solving natural-

language questions, a challenge that search engines are not yet capable of meeting [61, 91], online Q&A services provide an alternative way for Internet users to acquire and share knowledge in everyday life. One of the most popular Q&A websites, Yahoo! Answers (YA), attracts an estimated 6 million unique visitors monthly in the United States alone [75]. Besides YA, there are other popular online Q&A websites in different languages such as Answers, Stack Overflow, Korea's Naver Knowledge iN, and China's Baidu Knows [94]. Despite its role in addressing a particular need in Web search, this emerging technology has attracted little attention in the Information Systems (IS) field. Consequently, we have a limited understanding of why and, more importantly, how people in these communities actively participate through not only posting questions but also actively answering others' inquiries. Meanwhile, only a handful of online Q&A websites have been successful in sustaining their members' active participation [40, 74, 100]. This research analyzes the participatory behavior of individuals in a leading Q&A community (YA) in order to provide guidelines on how website artifacts should be designed and as such, deliver insights on how to stimulate questioning and answering activities on Q&A websites.

Online Q&A communities differ in many respects from other types of online communities such as organizational knowledge management (KM), online professional communities, Wikipedia — and open source software (OSS) — types of online communities, and customer-based, firm-hosted online communities. First of all, compared with other knowledge-sharing communities, online Q&A community members are given explicit access to the number of points that they need to accumulate for promotion to a subsequent level. In doing so, Q&A communities provide a detailed road map on how to earn points for various types of participatory behaviors. Clear guidance about the points needed for the next promotion is known to enhance goal pursuit, especially when an aspirant's current status is near the borderline [16]. This unique contextual characteristic of online Q&A communities is expected to fundamentally change the dynamics of members' active participation. In particular, these communities penalize excessive knowledge seeking as a way to enhance the quality of questions. Such a unique penalty system is inevitable in maintaining the quality of their shared knowledge [27, 85]. Meanwhile, the voting mechanism in online Q&A communities is designed to reward members for quality, not quantity, contributions. Taken together, the well-defined prospect of

promotion in online Q&A communities, in conjunction with their unique system of noneconomic incentives and disincentives, presents novel and rare settings substantially different from those of other communities.

Second, whereas most online communities have specific moderators or administrators [15, 43], online Q&A communities implement decentralized control systems that mostly rely on a distribution of power based on membership levels. For example, although all members are allowed to ask, answer, and rate in online Q&A communities, the extent of such active participation is systematically limited by members' levels. Membership level is an artifact that cumulatively tracks overall activity and rewards members for their past and present efforts. In general, members with higher levels can ask, answer, and rate more frequently than lower-level members. These levels tend to facilitate self-discipline and self-driven active participation that are both essential for building a high sense of community [60]. This peer moderation system driven by the decentralized control of individual members is one of the unique properties of online Q&A communities. Such a highly structured membership system differs significantly from that of Wikipedia, wherein all members' contributions are assigned equal weight and resolution of disagreements relies heavily on implicit social norms [11]. Thus, it is important to take a careful look at how different levels of community membership regulate both seeking and sharing knowledge in such a new online environment.

Third, the main purpose of online Q&A communities is to facilitate questions and answers that arise from members' everyday lives. These members are not bound to accomplishment of certain tasks or to particular work hours. Instead, their participation is highly flexible in that it can occur anytime, anywhere within members' daily routines. Such a flexible environment is known to be conducive to routine behavior, and thereby members' participation is likely to exhibit recurrent patterns [63]. This relatively mundane nature of online Q&A communities contrasts with those of other work- or task-related communities such as organizational KM communities. As the Internet becomes pervasive and easy to access, online behavior in work- or task-related communities could eventually become routine. Thus, a routine characteristic cannot be ignored as a critical factor, especially in the context of online Q&A communities.

Numerous studies have examined knowledge seeking and contribution in such online communities as organizational KM systems [14, 47, 48, 106], encyclopedia-like general-knowledge building (e.g., Wikipedia) [6,

112], OSS [67, 72, 101], virtual idea communities [5, 15, 29, 30, 43], and online Q&A communities [17, 61, 76, 105]. Across these different contexts, researchers have mostly identified social network structures [71, 72, 80, 108] and a set of underlying psychological motives as antecedents of knowledge-sharing behavior [62, 73, 90, 98, 99]. As discussed further in the subsequent literature review, despite the vast body of work related to knowledge contribution in online communities, our understanding is quite limited regarding the incentive mechanisms, membership levels, and routine activities of members in online Q&A communities.

The purpose of this study is to develop and test a model of individuals' active participation in an online Q&A community. Because questioning and answering behaviors constitute the core activities on Q&A websites, this study is focused on understanding how frequently community members post questions and answers over time. Drawing on theories from IS and other disciplines, we propose a goal-oriented action framework that suggests that active online participation centers on the setting, pursuit, and automatic activation of goals [8, 16, 51, 52, 54]. First, we argue that online community behavior is regulated by external artifacts, such as nonmonetary incentives, that change the goal-setting process and eventually affect individual behavior [8]. Second, following the tradition of community research, our model highlights the current status of individuals' membership as a factor representing the extent to which each individual strives to achieve his or her goals [51, 52, 54]. Finally, it posits that online community behavior is also driven by goal-dependent automaticity, or habit, in addition to the deliberate setting and pursuit of goals [17, 54]. In this study, the proposed model is tested against system-generated panel data collected over eight weeks from 2920 members of YA. Overall, this study is expected to contribute significantly to IS research by offering a coherent theoretical perspective that accounts for members' active participation in online Q&A communities.

Literature Review

Online communities have revolutionized the way that people with common interests, but who are not necessarily known to one another, come together virtually to share knowledge and collaborate [26]. This phenomenon and its related research have been loosely grouped under the umbrella term of "virtual knowledge collaboration" [26, 99]. In light of the relevancy of such research to the current paper, we

attempted to review major research streams under this general concept in hopes of identifying clear research gaps that this paper aims to fill.¹ Table 1 summarizes these research streams and how our paper fills the gaps.

Insert Table 1 about here

One such research stream focuses on the use of organizational KM systems, such as electronic knowledge repositories (EKR), by organizational employees. The substantial body of literature in this stream has largely accounted for a consensus on the various motivations behind employees' knowledge-contribution and knowledge-seeking behavior, including: informational motivations and output quality (e.g., [48, 106]); collaborative sharing norms (e.g., [14, 47, 48, 99]); relational motivations and status (e.g., [9, 106]); social network characteristics (e.g., [80, 108]); and incentive mechanisms (e.g., [47, 48]). Because of the organizational context of such systems [47], however, the prior literature primarily focused on incentive mechanisms that are economic or job- or career-related [83]. By contrast, the noneconomic incentive mechanisms studied in this paper have been underexplored. Moreover, previous research has inspected the general concept of habit but failed to find a significant effect of habit on knowledge contribution (see [9]). Although He and Wei [37] explored the moderating role of habit on the intention to contribute and seek knowledge, they did not examine the cumulative effect of habit beyond that of the current behavior. They also overlooked other boundary conditions that may strengthen or weaken the effects of habit.

Research that concentrates on online discussion communities consisting of professionals employed outside the virtual environment has formed another stream. Nevertheless, this research largely shares the same inquiries as the aforementioned research stream. For instance, such research has investigated knowledge contribution as a function of network position, intrinsic motivations such as the enjoyment of helping, extrinsic factors such as identification, knowledge sharing norms, social cognitive factors, and trust (e.g., [20, 59, 62, 73, 99, 111]). A handful of other studies (e.g., [26]) focus on theorizing the foundation of the existence and efficacy of knowledge collaboration in such online communities. Not enough attention has been paid to the role of IT-artifact incentives or to the likely effect of habit on either knowledge contribution or

¹ Because of the sheer volume of existing research that can be related to virtual knowledge collaboration, it is not our intent to give an exhaustive account of the relevant literature. Nonetheless, we have strived to discuss all major streams within this broad research area that are closely related to the objective of our paper.

knowledge seeking. Furthermore, few studies explored how membership characteristics (i.e., membership levels and tenure) affect behavior in knowledge exchange.

Another research stream examines the crowdsourcing community as a means of collectively generating digital information products, services, or knowledge [32]. Such communities include Wikipedia as an encyclopedia-style, general-knowledge example [11], and OSS as specialized-skills problem-solving examples [67]. A large body of research under this broad term concerned the success and failure of Wikipedia articles (e.g., [78]) or OSS projects (e.g., [72, 101], and see [3, 65] for a comprehensive review), but this is not our focus. Another major inquiry conceptually overlaps with those discussed above: Why do members contribute to such communities? Again, some commonly recognized drivers of active participation behavior here include social network structure and role-play in teams, intrinsic motivations (e.g., altruism, commitment), extrinsic rewards (exclusively monetary and career-related incentives), social interaction, community reciprocity norms, and community response (e.g., [21, 36, 110, 112], and see [97] for a comprehensive review). While this research enlightens our general understanding of contribution behavior in a large virtual community, it has largely overlooked how virtual incentives — such as points, levels, and statuses embedded in the systems to motivate active participation behavior — influence knowledge contribution. Moreover, although von Krogh et al. [97] emphasized social recognition and status seeking as key motivations, and although abundant theoretical and empirical work has examined such factors, their focus has been on the psychological reactions to the general concept of social recognition. They did not examine the type of social status that is explicitly represented by membership levels and accumulated points in an online virtual community.

Another related research stream examines customer-based, firm-hosted communities, including “virtual idea communities” [15]. A salient feature of such communities is their sponsorship by a host firm [15], which prompts researchers to primarily focus on two broad research questions: (1) Why do customers participate and, more important, contribute ideas in such communities? (2) How could IT artifacts help in heightening the extent of customers’ active participation? On these quests, relevant research has found that self-marketing — meaning customers’ ideas are prominently visualized in such communities and firms

recognize utilizing these ideas — and altruism are strong motives of contributions (e.g., [43, 45, 103], and see [15] for a comprehensive review of this literature). Although prior research (e.g., [15, 43, 45]) has helped us understand how customers respond to *qualitative* forms of social recognition, such as firms' verbal recognition and prominent showcasing of customers' contribution within online forums, more research is needed to examine the effects of *quantitative* forms of social status, such as virtual points and membership levels.

Finally, much research has studied online Q&A websites specifically [e.g., 27, 58, 82, 85] and helped us to understand why incentive and reputation systems are important to the success of online Q&A websites. Others have uncovered some of the motives behind members' knowledge contribution in online Q&A communities [e.g., 61, 76, 105]. Nevertheless, we still lack knowledge of how such systems influence members' actual knowledge-sharing behavior. Upon reviewing the online Q&A community literature, we have identified the following three research gaps: (1) How do nonmonetary incentives based on IT artifacts such as points, levels, and promotion influence members' participatory behavior in online Q&A communities? (2) How can a peer reputation system based on IT artifacts (i.e., gradually increased power and privileges to ask, answer, and rate as members level-up) be leveraged to motivate members' knowledge contribution in online Q&A communities? (3) How do habitual factors regulate membership behavior in online Q&A websites?

To summarize, although the vast body of research reviewed above has enriched our understanding of the underlying psychological mechanisms of virtual knowledge collaboration, we still lack a clear understanding of the implications pertaining to the IT-artifact incentive mechanisms, membership levels, and routine aspects of member behavior in online Q&A communities.

Theoretical Framework and Hypotheses

Figure 1 presents a conceptual model of individuals' participation in an online Q&A community. Our model is built on a goal-oriented action framework and posits that the setting, pursuit, and automatic activation of goals drive members' participatory behavior such as posting questions and answers. Three types of antecedent mechanisms affecting knowledge seeking and contribution are broadly identified; these are artifacts (i.e., goal

setting), membership (i.e., goal pursuit), and habit (i.e., goal internalization). This section presents the theoretical rationale for the antecedent mechanisms and proposes our research hypotheses.

Insert Figure 1 about here

Goal-Oriented Action Framework

Goals refer to specific outcomes that a person desires or expects to attain. Theories of goal-oriented actions offer a comprehensive and coherent account for purposive behavior; thus, they have been widely used in the social psychology, marketing, and IS literatures [54]. Such theories conceptualize purposive behavior as the setting, pursuit, and automatic activation of goals. Goal setting starts with a “why” question related to personal motivations behind actions (e.g., reputation in an online community). Then, a “what” question follows that determines a focal goal (e.g., upgrade in member level). In goal pursuit, a “how” question is raised to develop a detailed action plan (e.g., posting answers). Subsequently, actions are performed that lead to a certain consequence (e.g., success or failure). Whenever purposive behavior is performed, the hierarchical structure of goals mentioned earlier needs to be established consciously and deliberately. However, with repetition the actions become mentally associated with the goal hierarchy. As a result, the behavior can be performed without conscious effort because the mental structure linking goals and actions tends to be activated automatically whenever the person encounters a similar situation. This process indicates automatic activation of goals that is believed to be a main driver of habitual behavior [52, 53].

Drawing on theories of goal-oriented actions, we propose a goal-oriented action framework where individuals’ active participation in an online Q&A community is categorized as three different, yet related, types of activities, i.e., goal setting, goal pursuit, and automatic goal activation. In particular, our theoretical framework (Figure 1) states that (1) goal setting depends on the membership structure of a website, (2) goal pursuit is implied by the current status of individual membership, and (3) automatic goal activation is inferred from prior and current behavior on the website. First of all, people can have various motivations for their active participation in an online community (e.g., knowledge growth, reputation building, and enjoyment in helping others) [47, 48, 92, 99]. Because restrictions on participation are often imposed on newcomers, online

Q&A community members who want to maximize their benefits are likely to strive to get promoted. Thus, an incentive structure for membership promotion is expected to regulate the goal-setting process. Second, achieving a higher level status requires community members' planning, persistence, and commitment. Accordingly, goal pursuit is related to the current status of individual membership. Finally, members will acquire a habit with repeated visits to the same website over time [52, 53]. Hence, we contend that member behavior on a Q&A website is associated with automatic goal activation. In summary, the goal-oriented action framework provides us with a theoretical lens for understanding the complex phenomena underlying members' active participation in online Q&A communities.

Artifacts (Goal Setting)

Research suggests that individuals' behavior is shaped, modified, and regulated by the artificial design of a website [10, 62, 76]. In particular, the online community literature mostly highlights the critical role of incentives in affecting active community participation [12, 29]. This stream of research uses goal-setting research from the social psychology literature to explain how incentives reorganize a personal goal structure and ultimately affect behavior [8, 16, 51, 52, 54]. The goal-setting theory posits that people tend to perform better when goals are explicitly specified and achievable [10]. It also suggests that members participate more actively in their community activities as long as incentives are present for doing so and the requirements are reasonable. Consistent with this reasoning built on the goal-setting theory, Kraut and Resnick [55] argue that, unlike vague goals, concrete goals incite people to work harder in online communities. Further, Beenen et al. [10] found that specific numeric goals are more effective than nonspecific goals in motivating prosocial behaviors within the context of an online movie rating community. A more interesting finding of their experimental study is that if goals are set too high, members become discouraged and tend to contribute less.

The “gamification” of online communities — i.e. “the use of game design elements in non-game contexts” [24 p. 2] — has been incorporated in many applications [5]. One such game-like element that proved particularly effective in goal-oriented gameplay is game level. Leveling-up in games has been shown to force players to focus on a goal and allows them to “enjoy topical challenges, gain status and reputation, get

ego gratification, and may even land future job offers” [5 p. 204]. Applied to online Q&A communities, the goal-oriented echelon system — in which players are rewarded for their contributions to help them get promoted to higher levels — is arguably the most important incentive mechanism. Membership levels have been adapted as an incentive mechanism in the design of online Q&A communities. Given that at higher levels more privileges are accorded to members and a broader spectrum of activities is granted, members’ levels connote their power within the online community. This kind of membership privilege is an object of personal pursuit; accordingly, community members tend to strive to attain such privileges, and this striving naturally drives their active participation in community activities. Thus, clear-cut echelon systems are at the heart of most online Q&A communities, providing players with measurable and achievable milestones.

Ducheneaut et al. [25] found that in the multiplayer role-playing game, *World of Warcraft*, players spent considerably more time on the game just before their expected promotion to higher reward levels at which they would acquire more game skills and resources, allowing them to embark on harder game-specific tasks and “leveling up” in the game. After players attained their anticipated goals, Ducheneaut et al. [25] reported a noticeable reduction in their playing time. Several free-to-download mobile gaming applications use a similar clear-cut echelon system that even entices players to spend real in-app money to get promoted faster [28]. Online Q&A communities are akin to the *World of Warcraft* game in that they incite their members to work harder at contributing to the community. They do this by presenting them with periodic goals and challenges and granting them more privileges as they “level-up.” Thus, the goal-setting theory leads us to believe that individual behaviors on Q&A websites may differ according to how close members are to being promoted to higher levels of membership. Given that knowledge contribution, i.e. answering questions, requires more effort and time but helps to earn points, while posting questions entails their loss, we expect that as members approach promotion to higher levels, they are more enticed to post answers instead of

questions to get promoted. That is, the closer a member is to promotion, the more answers, but fewer questions, he or she will post. Accordingly, our first hypothesis is stated as follows:²

H1 (a): *The extent to which a member is near promotion in the current period will be negatively associated with the number of questions the member posts in the subsequent period.*

H1 (b): *The extent to which a member is near promotion in the current period will be positively associated with the number of answers the member posts in the subsequent period.*

Membership (Goal Pursuit)

Goal pursuit involves the development of an action plan, coordination of actual action, evaluation of the outcome, and, if necessary, adjustments to the plan and action [8, 16, 51, 52, 54]. First, action planning addresses the question of how to achieve the goal, and it leads to a detailed plan regarding when, where, how, and how long the person should act. Second, for successful execution of the plan, an actor needs to initiate effort and overcome obstacles. Third, after the plan's implementation, an actor will deliberately assess whether his or her goal has been achieved. Finally, if a person fails to achieve the goal, he or she will make a new plan and guide his or her subsequent action accordingly. As evident from the discussion, goal pursuit requires willpower and perseverance; for successful goal attainment, an actor should remain committed and focused on the task at hand. When applied to active online Q&A community participation, the goal-oriented action framework clearly suggests that the current status of community membership is a good indicator of how seriously members strive to achieve their goals. General-purpose Q&A communities promote the exchange of everyday knowledge across diverse areas of interest that are not necessarily technical or knowledge intensive [1]. In such communities, membership levels are believed to represent members' willpower and commitment in pursuing their goals over time in the face of problems and difficulties.³

Committed members strive to grow their community by sharing knowledge, helping others, and taking leadership roles. In Q&A websites, such prosocial behaviors are rewarded explicitly through upgrading

² It is important to note that despite their interesting observations while tracking the time players spent in the World of Warcraft, Ducheneaut et al. [25] did not perform any sophisticated analysis that shed light on the specific players' activities. We, on the other hand, differentiate between questioning and answering activities and their ramifications in terms of points rather than time spent.

³ General-purpose online communities (e.g., YA) differ from domain-specific online communities (e.g., Stack Overflow that focuses on the computer programming domain). In domain-specific communities, although levels may still reflect commitment to some extent, they more clearly represent members' knowledge in the specific domain of focus. Therefore, the generalizability of the hypotheses and results about membership levels may be limited to general-purpose online communities. We have conceded this limitation in the Discussion section, and we thank an anonymous reviewer for pointing out this critical distinguishing feature of online communities.

of membership levels. Thus, the level of membership is a good proxy for goal pursuit in Q&A websites; put differently, high-level members are generally thought to be actively engaged in community activities. Research implies that higher level members contribute more often to the dialogue on their online forum. For example, Rafaeli and Ariel [77] proposed that community members who are committed to Wikipedia participate more in the online community than others less motivated and committed. Therefore, it is reasonable to argue that high-level members tend to identify themselves with the community and are eager to offer their time to support it. The discussion mentioned previously leads us to expect that online Q&A community members at higher membership levels will post more messages as questions and answers than lower-ranking members. Thus, we propose the following hypotheses:

H2 (a): *A member's level of membership in the current period will be positively associated with the number of questions the member posts in the subsequent period.*

H2 (b): *A member's level of membership in the current period will be positively associated with the number of answers the member posts in the subsequent period.*

Although asking and answering questions constitute two forms of contributions that are equally necessary to establish successful online Q&A communities, they are nevertheless driven by different motivations and thus are governed by different dynamics. Answerers are “information givers” or “information providers” [70 p. 2]. Oh [70] adapted the digital reference service model in [88] to online Q&A communities and identified five steps in the answering process as (1) question selection, (2) question interpretation, (3) information seeking, (4) answer creation, and (5) answer evaluation, all of which require a great amount of effort and involve a varied set of mental strategies. On the other hand, the process of asking questions does not require the same amount of willpower and perseverance that is needed to select suitable questions and research best answers, and members who solely post questions without contributing answers are often considered free riders [93]. Answering questions is proactive, whereas asking questions depends on the efforts of other community members for an answer. Upon answering a question, a member shows a higher level of initiative and exerts more effort than when the same user is asking a question. Given the importance of willpower and commitment in the answering of a question and based on the premise that community membership is a good measure of the extent of goal-orientation, we expect that the positive

impact of membership levels on Q&A participation is stronger for answers than for questions. Thus, we propose the following hypothesis:

H2 (c): *The positive impact of a member's level of membership in the current period on his or her active participation in the subsequent period is stronger for answers than for questions.*

In community research, tenure refers to the length of time a member has been in the community of interest [62, 99]. Community tenure is one of the few variables that are commonly identified as potential determinants of knowledge contribution in the community literature [99, 102]. Likewise, the notion of tenure has long been an important variable in management literature [99]. In the literature, it is specifically hypothesized as a factor that boosts a person's commitment and eventually makes one pursue a greater goal. The rationale behind this premise is that tenure generally represents accumulated investments, which in turn engage one in maintaining the status quo [89]. Despite this proposition, however, empirical results have been mixed; in many cases tenure was not significant in affecting engagement [68] and sometimes even had a negative relationship with engagement [49]. These contradictory findings imply that the impact of tenure on engagement may vary across different settings.

Similar to what occurred in management research, community research also has produced mixed results about the role of tenure. For example, Wasko and Faraj [99] found that the tenure of a member in a professional legal organization has a positive impact on the volume of his or her contribution to the organization's online bulletin board system. However, Ma and Agarwal [62] did not find a relationship between tenure and knowledge contribution in their examination of two online communities (i.e., emotional support and luxury car owner communities). Moreover, in the case of Usenet, which is a worldwide online discussion system, a large number of members were found to contribute just once [98, 102]. In the context of various general discussion websites, similar studies have found that a lack of commitment leads active members to become lurkers [10, 46, 82, 102]. These findings suggest that members' interest may subside as their initial enthusiasm wanes.

Although seemingly eclectic, the findings of the community studies suggest quite consistent patterns concerning the effect of tenure on knowledge contribution. In particular, the extent of goal pursuit tends to

increase as a member's tenure lengthens, especially when the community in question is closed and personally meaningful to the member (e.g., professional associations, local communities). In contrast, if the focal community is *open*, a number of members tend to be dormant without closing their accounts. Most online Q&A communities are open and nonbinding. Moreover, formal procedures are rarely in place for members to end their membership. As a result, although people join to satisfy their initial needs, many of them tend to lurk afterward [10, 46, 82, 102]. This reasoning leads us to suspect that in online Q&A communities, the tenure of a member is negatively associated with the extent of goal pursuit and hence with knowledge contribution. Therefore,

H3 (a): *The tenure of a member will be negatively associated with the number of questions the member posts in the subsequent period.*

H3 (b): *The tenure of a member will be negatively associated with the number of answers the member posts in the subsequent period.*

The process of answering questions has been found to be motivated by several factors. These include enjoyment, efficacy, altruism, community interest, social engagement, empathy, reputation, and reciprocity [70]. Motivation is defined as “one’s desire and energy that causes certain behaviors in task performance or learning” [70 p. 1]. Yu et al. [109] revealed similar motivations to answer questions, i.e. active learning, self-enhancement, reciprocity, reputation, enjoyment of helping others, self-protection, moral obligation, and the advancement of the virtual community. Regardless of the specific motivation, answering questions requires willpower and takes time. Selfless sharing of information not only consumes precious time, but equally important, it often involves sharing valuable (often expensive) knowledge or expertise, such as medical or legal advice, for free. Most Q&A websites are free and open communities that do not provide contributors of information with any monetary compensation. Motivation has been shown to dynamically change depending on the situation or condition [70]. Given the absence of concrete financial benefits in open Q&A websites, members’ motivation to contribute inevitably wanes over time as their tenure increases. Posing a question is less dependent on strong motivation because it consists of soliciting rather than giving. Given the differing degrees of motivation required for answers and questions, and the expectation that motivation decreases over

time in the absence of financial compensation, we expect tenure to negatively affect answering behavior more than it does question-asking behavior. Therefore,

H3 (c): *The negative impact of a member's tenure in the current period on his or her active participation in the subsequent period is stronger for answers than for questions.*

Habit (Automatic Goal Activation)

Whereas much research on online communities follows the well-established tradition of the reason-oriented action framework, some researchers are turning their attention to the role of habit in community participation [77]. In essence, this new stream of research suggests that with repeated participation, online behavior becomes ritual and eventually evolves into a routine that requires no conscious processing. Various reasons may exist for why members want to initially establish a relationship with their community (e.g., sharing knowledge, self-esteem, etc.). No matter what the original motives are, however, regular visits to a website over time could transform community participation into daily routine. Eventually, community participation becomes so tightly integrated into one's daily routine that it no longer requires conscious planning [77].

Although relatively ignored in online community research, the topic of habitual behavior has been receiving more attention in IS research [23, 44, 54]. In general, these studies show that IT adoption involves careful evaluation of the pros and cons associated with a new application but with repeated use of the same application, individuals' behavior operates within the realm of habit. Research in psychology sheds light on the nature of habitual behavior by uncovering the mental process of automatic processing [96]. According to this psychology literature, conscious behavior is characterized by the deliberate formation of mental representation connecting goals and actions. With repeated performance, this knowledge structure is formulated over and over again. As a result, it becomes hard-wired in the brain. Such a mental representation is said to be activated automatically without conscious decision making when situated in a familiar environment. Because habitual behavior is automatic behavior guided by the internalization of repeated goal-setting processes, it is also called goal-dependent automaticity [8, 16, 51, 52, 54].

Online environments have essentially no limitations with respect to time and place. Thus, in the online world, individuals typically have more opportunities to perform the same behavior than they do in its

offline counterpart. As a result, online environments tend to be conducive to habit, which is implied by the reported high level of correlation between past use and future use. For example, Kraut et al. [56] showed that past use of e-mail is highly correlated with subsequent e-mail use. Similarly, in a study of online news use, Kim et al. [54] found that a significant relationship exists between past use and future use of online news. These findings suggest that online behavior is easily woven into daily life, and accordingly, past behavior becomes the best predictor of future behavior. Likewise, individuals' use of a Q&A website is expected to be routine with little deliberate planning required. More specifically, just as people nowadays often use search engines to look for information, they also could habitually rely on a Q&A website to answer their questions. If this is the case, we can expect that current questioning behavior will be positively associated with subsequent questioning behavior. In addition, we conjecture that answering behavior on a Q&A website can be viewed as something similar to social chatting and thus, eventually will be integrated into daily life. Then, current answering behavior is expected to be correlated with subsequent answering behavior. Thus, we propose the following hypotheses:⁴

H4 (a): *The number of questions posted by a member in the current period will be positively associated with the number of questions the member posts in the subsequent period.*

H4 (b): *The number of answers posted by a member in the current period will be positively associated with the number of answers the member posts in the subsequent period.*

As discussed earlier, habitual behavior results from a knowledge structure formulated over time with repeated activation of the same mental representation. To accurately assess the extent of habit, researchers need to look not only at current participation but also at prior cumulative participation over time. The entire history of past use has rarely been analyzed for the study of habit in IS. Nevertheless, Kim [51] analyzed three-wave panel data on postadoption use and found that prior use has a direct impact on subsequent use beyond the effect of current use. The study's findings illustrate that habit is accumulated incrementally and routine behavior is the culmination of the entire history of past behavior. The previous discussion suggests that subsequent active community participation in terms of questioning and answering behaviors is a function not only of current participation but also of prior participation over time. Thus,

⁴ Our hypotheses predict the existence of habitual patterns that will lead actors to corresponding Web pages when faced with certain situational cues. Yet it is important to note that composing questions and answers always requires conscious thought.

- H5 (a): *The number of questions posted by a member in the prior periods will be positively associated with the number of questions the member posts in the subsequent period.*
- H5 (b): *The number of answers posted by a member in the prior periods will be positively associated with the number of answers the member posts in the subsequent period.*

Interaction between Membership and Habit

We previously proposed that habit, at least in part, would drive active community participation. Although this prediction addresses general behavioral patterns likely to be exhibited in online Q&A communities, several reasons exist to suggest that such behavioral patterns vary with respect to current membership status. For example, Rafaeli and Ariel [77 p. 255] have argued that committed members participate in community activities “as part of ceremonies and rhythms of their personal life.” In other words, such rituals by committed members are more likely to be transformed into strong habits [77]. Further, Heidemann et al. [38] showed that as individuals become more involved in the activities of their online community, their “participation becomes more automatic” (p. 13) and their “habit effect strengthens” (p. 12). Heinonen [39] also noted that increased perceived familiarity with the online community creates a sense of habit and a status quo that in turn is expected to perpetuate habitual behavior, whether through soliciting or contributing answers. A higher membership level indicates a higher level of involvement and, in turn, a higher degree of familiarity. Therefore, the reasoning described earlier leads to a conclusion that habitual patterns will be more evident among higher ranking members than among lower level members. Thus, we hypothesize that as a person’s rank increases, the relationship between current and subsequent contributions will be stronger. For the same reason, the effect of past contributions and subsequent contributions is expected to be stronger with a higher level of membership.

- H6 (a): *The impact that the number of questions posted by a member in the current period has on the number of questions the member posts in the subsequent period will be stronger with an increase in the person’s membership level in the current period.*
- H6 (b): *The impact that the number of answers posted by a member in the current period has on the number of answers the member posts in the subsequent period will be stronger with an increase in the person’s membership level in the current period.*
- H7 (a): *The impact that the number of questions posted by a member in the prior periods has on the number of questions the member posts in the subsequent period will be stronger with an increase in the person’s membership level in the current period.*

H7 (b): *The impact that the number of answers posted by a member in the prior periods has on the number of answers the member posts in the subsequent period will be stronger with an increase in the person's membership level in the current period.*

In addition to membership level, tenure is another variable believed to reflect the extent of goal pursuit [99]. Prior research has found that the longer a member's tenure, the more likely his or her excitement levels will dwindle because of boredom or disappointment, leading in turn to a decrease in commitment and to an eventual end of active participation [69]. The negative effect of tenure on the continuance of active participation has also been observed in virtual communities [113]. In open Q&A communities without monetary rewards, members tend to lose willpower the longer their membership. In fact, when members experience negative feelings such as boredom, lack of excitement, or lack of motivation, they become less committed to contributing knowledge to their online communities. This contrasts with newer members who are kept motivated by the initial excitement of joining the community. As the degree of members' commitment diminishes with time, rational evaluation of the benefits vs. costs of participation replaces routine participation and dissolves the knowledge structure that drives repeated behavior. For this reason, routine contributions will be stronger for those who most recently joined an online community. Thus,

H8 (a): *The impact that the number of questions posted by a member in the current period has on the number of questions the member posts in the subsequent period will be weaker with an increase in the tenure of the member.*

H8 (b): *The impact that the number of answers posted by a member in the current period has on the number of answers the member posts in the subsequent period will be weaker with an increase in the tenure of the member.*

H9 (a): *The impact that the number of questions posted by a member in the prior periods has on the number of questions the member posts in the subsequent period will be weaker with an increase in the tenure of the member.*

H9 (b): *The impact that the number of answers posted by a member in the prior periods has on the number of answers the member posts in the subsequent period will be weaker with an increase in the tenure of the member.*

Methodology

Research Setting

Launched in 2005, YA was the first worldwide English-language Q&A website [87]. YA remains an open online community without a membership fee or service charge. Since the start of the service, YA has been one of the largest Q&A websites in terms of the number of visitors [75, 104]. Because of the relative stability of its membership base and service offerings, compared with newer websites, YA was chosen as the target

system of this study. To promote active participation and reward contributions, YA maintains a complex system of points and levels, ranging from Level 1 to Level 7. A level is assigned based on the total number of points that a member has earned since his or her initial subscription. For example, a member gets one point a day by logging in to YA. In addition, a member can earn two points by answering a question and one by voting for an answer. The highest reward, which is worth 10 points, is given for a best answer. Meanwhile, the act of posting a question is penalized with a loss of five points, although three points can be recouped if a questioner chooses a best answer for the question. Such a point system is deliberately devised to encourage answering and discourage the proliferation of freeloaders. Typically, some restrictions exist in terms of how many questions, answers, and votes one can post per day, but those restrictions are gradually removed as members move up the membership ranks.

Data Collection

Data for this research were gathered from the YA website over eight weeks by a Web crawler. We first collected about 3330 resolved questions covering various topics that were asked over a six-month period. Then we tracked the weekly activity of the users who asked these questions. Some of these users had hidden profiles (i.e., they had chosen to hide their answers and questions and other user information for security purposes). After filtering out users with hidden profiles, we ended up with a sample of 2920 users whose data we subsequently collected over the aforementioned eight weeks. Although the usernames that users select are random and often anonymous, each user is identified internally by a user ID that uniquely characterizes his or her profile Web page on YA. We were able to track users' activities and behaviors using these built-in YA IDs. Figure 2 gives a snapshot of a typical YA profile Web page. A profile Web page includes information about when a specific user became a YA member. It also tracks the user's membership level, total number of points, and the points gained during the prior week. In addition, the profile Web page includes up-to-date information about the total number of questions and answers that the user has contributed. Given the large number of users that we needed to monitor and whose information we needed to mine, we used a software program to automate the data collection process and extract weekly information about all selected users.

Weekly data cover a long enough span and have been shown to emulate habitual behavior well [52, 53], especially for leisure activities that are more likely to be carried out during leisure time.

Insert Figure 2 about here

Measures and Variables

To study users' activity levels and behaviors, we focused on the number of questions and answers that each user contributed during the period under consideration. Our dependent variables were questions this week ($Q_{This,i,t}$) and answers this week ($A_{This,i,t}$), where $i = 1, 2, \dots, 2920$ denotes a particular user and $t = 1, \dots, 8$ a particular week. We computed these two variables by subtracting the total number of questions (answers) as of last week from those as of the current week.

Our first independent variable, $Level_{i,t-1}$, measures user i 's level as of the previous week. As mentioned previously, Level 7 is the highest level achieved by users on the YA portal. To get to that level, though, a user must have banked at least 25,000 points. At that level, users are considered active members of the YA community and are allowed to contribute unlimited answers and ratings and thus, are given advanced status and control. We measured a user's tenure as the number of weeks that he or she had been a member, as of the prior week. YA members who achieved a given level quickly are more active contributors to the YA community than those who took longer to achieve the same level. We controlled for users' tenure by using the variable $NumWeeks_{i,t-1}$ that we computed as users' membership duration, as of the prior week.

A key variable in our models is users' closeness to getting promoted, a status represented by the variable percent till promotion ($PctPromo_{i,t-1}$) that helps us elucidate users' incentives to participate in the YA community. This variable is especially relevant in online Q&A communities such as YA in which members can easily set their goals in terms of points and levels and in which promotion is achievable through more active participation. Users are provided from the beginning with a clear-cut system of membership levels, and they thus have an idea of how many points they need to bank to earn promotion to the next level. Instead of computing an absolute difference between the points required to reach the next level and the current total

points of a user, we chose to express $PctPromo_{i,t-1}$ as the proportion of points required for promotion relative to the point difference between the next level and the prior level, as of last week.

The cumulative independent variables, as of the prior week, are crucial to measuring users' habit. These variables are total questions ($QTill_{i,t-1}$) and total answers ($ATill_{i,t-1}$), the percentage of questions that earned stars ($PctStarsTill_{i,t-1}$), and the percentage of answers selected as best answers ($PctBestTill_{i,t-1}$), as of the previous week. We also included two interaction effects. First, the interactions between levels last week, $Level_{i,t-1}$, and questions and answers during last week, $QThis_{i,t-1}$ and $AThis_{i,t-1}$, on the one hand, and questions and answers as of last week, $QTill_{i,t-1}$ and $ATill_{i,t-1}$, on the other. The second consisted of the interactions between $NumWeeks_{i,t-1}$ and $QThis_{i,t-1}$ and $AThis_{i,t-1}$, on the one hand, and $QTill_{i,t-1}$ and $ATill_{i,t-1}$, on the other.

Table 2 details the variables and their descriptions; Table 3 provides the variables' descriptive statistics and pairwise correlations. Figure 3 plots the distribution of users' weekly question and answer contributions as a function of their levels, as of the previous week. Figure 3 indicates that, on average, higher level users post more answers than lower level users. The figure also reveals that, for users above Level 2, users' answer contributions, on average, exceed their question contributions. On the other hand, the number of questions that users ask is relatively stable across user levels.

Insert Table 2, Table 3, and Figure 3 about here

Figure 4 illustrates the distribution of users' weekly contributions relative to their tenure. In Figure 4, tenure intervals range from fewer than 20 weeks to more than 160 weeks. The figure shows that those who have been YA members the longest tend to ask fewer questions than newer members. Except for users who have been YA members for fewer than 20 weeks, Figure 4 also reveals that, regardless of their tenure, users answer more questions than they ask. Although answers consistently outnumber questions, the number of answers decreases slightly with user tenure. The initial findings revealed in this section seem to support our hypotheses that newer and more engaged members contribute more to YA and exhibit stronger habits of contribution. In the next section, we rigorously test these hypotheses and conduct various robustness checks.

Insert Figure 4 about here

Model Development

We formally tested our models using techniques of multiple panel data analysis, including the ordinary least square (OLS) or pooling panel data model, the fixed effect model (FEM), the generalized least squares (GLS) based random effect panel data model (REM), and the one-way and two-way generalized method of moments (GMM) panel models. Doing so allows us to conduct various robustness checks to select the model best fitted to our data. In the OLS panel data model, pooling repeated observations on the same user contradicts an assumption of independence; if this assumption is erroneous, this could result in serial correlation of the model's residuals. The poolability test (or Chow test) checks for such serial correlation. The Chow test's null hypothesis states that all coefficients specific to each term are equal. The FEM allows individual-specific effects to be correlated with the explanatory variables and treats the individual error components as a set of parameters that need to be estimated using OLS. On the other hand, the REM is used when the individual error components are not correlated with the regressors, but nevertheless, result in correlation across composite error terms. The REM uses GLS estimation instead of OLS and is only preferred over the FEM when individual specific effects are certainly unrelated. Given this strong assumption, the FEM is generally preferred over the REM. The Hausman test is conducted to decide whether an FEM or REM is more appropriate. The Hausman test does not test if the individual effects are literally random but rather if these effects are correlated with the regressors [66]. In the Hausman test, the test statistic is asymptotically distributed as χ^2 under the null hypothesis that the regressors are not correlated with the error terms.

Our data have unbalanced panels (cross-sections of YA users) in which users are observed in a given week over eight weeks. Given that our models relate dependent variables in the current week to multiple independent variables during and as of the prior week, our data are best characterized as the dynamic panel data models given in Equations (1) and (2).

$$\begin{aligned} QThis_{i,t} = & \beta_1 QThis_{i,t-1} + \beta_2 AThis_{i,t-1} + \beta_3 NumWeeks_{i,t-1} + \beta_4 PctPromo_{i,t-1} + \beta_5 Level_{i,t-1} \\ & + \beta_6 QTill_{i,t-1} + \beta_7 ATill_{i,t-1} + \beta_8 PctStarsTill_{i,t-1} + \beta_9 PctBestTill_{i,t-1} \\ & + \beta_{10} (NumWeeks_{i,t-1}) * (QThis_{i,t-1}) + \beta_{11} (NumWeeks_{i,t-1}) * (QTill_{i,t-1}) \\ & + \beta_{12} (Level_{i,t-1}) * (QThis_{i,t-1}) + \beta_{13} (Level_{i,t-1}) * (QTill_{i,t-1}) + \mu_i + \nu_{i,t} \end{aligned} \quad (1)$$

$$\begin{aligned}
A_{i,t} = & \gamma_1 A_{i,t-1} + \gamma_2 Q_{i,t-1} + \gamma_3 \text{NumWeeks}_{i,t-1} + \gamma_4 \text{PctPromo}_{i,t-1} + \gamma_5 \text{Level}_{i,t-1} \\
& + \gamma_6 \text{ATill}_{i,t-1} + \gamma_7 \text{QTill}_{i,t-1} + \gamma_8 \text{PctStarsTill}_{i,t-1} + \gamma_9 \text{PctBestTill}_{i,t-1} \\
& + \gamma_{10} (\text{NumWeeks}_{i,t-1}) * (A_{i,t-1}) + \gamma_{11} (\text{NumWeeks}_{i,t-1}) * (\text{ATill}_{i,t-1}) \\
& + \gamma_{12} (\text{Level}_{i,t-1}) * (A_{i,t-1}) + \gamma_{13} (\text{Level}_{i,t-1}) * (\text{ATill}_{i,t-1}) + \eta_i + \omega_{i,t}
\end{aligned} \tag{2}$$

for $i = 1, 2, \dots, 2920$ and $t = 1, \dots, 8$. The β_i 's and γ_i 's are the coefficients' estimates, respectively, for the current week's question and answer contributions. μ_i and η_i account for the individual cross-sectional effects, i.e., user characteristics, and the error terms, $v_{i,t}$ and $\omega_{i,t}$, control for the idiosyncratic effects.

Estimating dynamic models poses more challenges than estimating static models because the lagged dependent variable in dynamic models is likely to be correlated with the user-specific effect. Because of that, it has been argued that OLS estimators, whether obtained via fixed or random effects, give inconsistent estimates with dynamic panel data models [7, 13, 41]. For panels with a limited number of weeks and a large number of users, Arellano and Bond [7] suggested using the GMM model in first differences. First-order differencing removes the cross-sectional effects and makes the model estimable by using instrument variables. The first-order differencing has the potential to introduce another bias if the differenced error term is correlated with the differenced lagged dependent variable. In this case, the least squares estimator, whether obtained by using an FEM or REM, is inconsistent. Using instrument variables offers a possible solution. To test the consistency of the GMM estimators, we conducted the Sargan test and the Arellano and Bond's serial correlation tests [7]. The Sargan test checks the validity of the GMM instruments and the overidentifying restrictions under the null hypothesis that the instruments are not correlated with the residuals and are valid. Arellano and Bond's serial autocorrelation tests are conducted under the null hypothesis that the errors in the first-difference regression do not exhibit first- or second-order serial correlation.

Data Analysis and Results

Results of Research Hypotheses

The Chow test (p-value = 0.000) confirmed, and understandably so, the presence of individual-specific effects

in both equations.⁵ The results of the Hausman test favored the alternative hypothesis that the FEM model is preferred over the REM model for both equations. The modified Wald test revealed groupwise heteroskedasticity ($p < 0.001$), and the Wooldridge test revealed serial autocorrelation ($p < 0.001$) in the fixed-effect panels, indicating that the FEM is invalid. The Wooldridge first-difference test for serial correlation in panels was not rejected, suggesting that the one-step and two-step GMM models are possibly valid alternatives. The Sargan test results in Table 4 provided evidence ($p > 0.1$) that the two-step GMM model's overidentifying restrictions are valid, thus showing a preference for the two-step GMM model over the one-step counterpart for both equations. Consequently, hereafter we will present the detailed findings of the two-step GMM estimation results for question-and-answer contributions, as shown in Table 4.

First, as expected, members who are closer to being promoted asked fewer questions ($\beta_4 = 0.201, p < 0.001$) but appeared more involved with answering other users' questions ($\gamma_4 = -2.909, p < 0.001$), confirming hypotheses H1 (a) and H1 (b), respectively. Also, highlighted in the results is the significant effect of membership levels on users' question-and-answer contributions. Particularly, members with more advanced standing as of the prior week were found to post more questions ($\beta_5 = 0.075, p < 0.001$) and answers ($\gamma_5 = 2.345, p < 0.001$) moving forward, confirming hypotheses H2 (a) and H2 (b), respectively. We further conducted a one-sided z-test [22, 34] to investigate the validity of Hypothesis H2 (c) in which we conjectured that the effect of membership level, as a proxy for members' goal-orientation, is more pronounced with answer contributions than with question contributions. The z-test led to a $z = 22.7$ ($p < 0.001$), confirming that the coefficient estimate for users' level of membership for answers ($\gamma_5 = 2.345, p < 0.001$) is significantly larger than the question counterpart ($\beta_5 = 0.075, p < 0.001$), a confirmation that validates Hypothesis H2 (c).

Insert Table 4 about here

Our findings also confirmed that members with longer tenure contribute fewer questions ($\beta_3 = -0.002, p < 0.001$) and answers ($\gamma_3 = -0.013, p < 0.001$), validating hypotheses H3 (a) and H3 (b), respectively. Another z-test yielding a $z = -11$ ($p < 0.001$) also revealed that the coefficient estimate of user tenure for

⁵ We do not show results pertaining to specification tests and the pooled OLS, FEM, and REM models because of the page limit. These results will be available upon request from interested readers.

answers ($\gamma_3 = -0.013, p < 0.001$) is significantly more negative than that for questions ($\beta_3 = -0.002, p < 0.001$), which confirms Hypothesis H3 (c).

The habit of asking questions appears to carry through in the near future ($\beta_1 = 0.034, p < 0.001$) and on a cumulative basis ($\beta_6 = 0.006, p < 0.001$), confirming hypotheses H4 (a) and H5 (a), respectively. Similarly, more answers are expected from members who have been frequent answerers during the prior week ($\gamma_1 = 0.017, p < 0.001$) and cumulatively as of last week ($\gamma_6 = 0.002, p < 0.001$), as such validating hypotheses H4 (b) and H5 (b), respectively.

Our results also confirmed that the higher a user's membership level, the stronger the relationship between his or her question contributions in the prior and current weeks ($\beta_{12} = 0.069, p < 0.001$), as suggested in Hypothesis H6 (a). Similarly, the more advanced a member's standing, the stronger the relationship between last week's number of answers and this week's ($\gamma_{12} = 7.216, p < 0.001$), thus confirming Hypothesis 6 (b). However, these results were only validated partially for cumulative question-and-answer contributions. In the case of questions, the relationship between current contributions and cumulative past contributions, as of the prior week, appears to be stronger with higher membership levels ($\beta_{13} = 0.051, p < 0.01$), confirming Hypothesis H7 (a). However, in the case of answers, the relationship between current contributions and cumulative past contributions, as of the prior week, was not found significant ($p > 0.01$). Thus, Hypothesis H7 (b) was not supported.

Finally, a user's tenure was shown to significantly affect the relationship between past and present contributions for both questions and answers. In particular, the relationship between the number of questions in the prior week and the current week was found to be weaker for longtime members ($\beta_{10} = -0.208, p < 0.001$), as conjectured in Hypothesis H8 (a). Also, the relationship between current and past cumulative question contributions, as of the prior week, was found significantly weaker for longtime members ($\beta_{11} = -0.431, p < 0.001$), as posited in Hypothesis H9 (a). By the same token, the longer an answerer has been a member, the weaker the relationships between past and present answer contributions in the short term, as conjectured in Hypothesis H8 (b) ($\gamma_{10} = -3.524, p < 0.001$), and cumulatively as conjectured in Hypothesis H9 (b) ($\gamma_{11} = -0.494, p < 0.001$).

Summary of the Results

We performed dynamic panel data analyses using various models and showed that the two-step GMM model fits best for explaining the determinants of YA users' question-and-answer contributions and active participation behaviors. Except for H7 (b), all hypotheses have been supported.

Hypothesis H7 (b) posits that the relationship between the cumulative number of answers posted, as of the prior week, and the number of answers contributed during the subsequent week is stronger for users at higher membership levels. To find a plausible rationale for the lack of support for H7 (b), we produced Figure 5, which plots the effect of cumulative answers according to users' membership levels. Figure 5 seems to suggest a sudden decrease in the effect of cumulative answers when users are promoted from Level 4 to Level 5. To understand the reasons behind this sudden drop, we conducted an ad-hoc analysis in which we applied the two-step GMM model on three subsamples: (1) members within levels 1 to 4 only (subsample 1), (2) members within levels 5 to 7 only (subsample 2), and (3) members within levels 4 to 5 only (subsample 3). The results in all subsamples are generally consistent with all of our hypotheses, except for one very interesting finding. H7 (b) is supported in both subsample 1 ($\gamma_{13} = 1.33, se = 0.11, p < 0.001$) and subsample 2 ($\gamma_{13} = 0.15, se = 0.06, p = 0.025$), but it is not supported in subsample 3 ($\gamma_{13} = -0.28, se = 0.01, p < 0.001$). Such findings are intriguing and very surprising because we did not expect these behavioral patterns to suddenly deviate from their predicted path at a certain midpoint in a continuous membership career. Consequently, we encourage future research to further investigate this question.

Insert Figure 5 about here

Discussion

The objective of this study was to examine individuals' active participation in online Q&A communities. We proposed a goal-oriented action framework by integrating relevant theories and tested it against data collected from 2920 users of YA over eight weeks. Our findings, based on dynamic panel analysis, indicate that as expected, active online participation is largely driven by artifacts (e.g., incentives), membership (e.g., membership level and tenure), and habit (e.g., past behavior). Specifically and in line with prior research [18,

29, 57], participation was found to change significantly in response to the way a website offers incentives. In addition, we found that active participation increases at higher membership levels but decreases with longer tenure. Finally, we found that habit had a significant impact on subsequent participatory behaviors, and such habitual effects strengthened further with higher membership levels but weakened with longer tenure. Overall, the findings of this study suggest that active online participation is influenced not only by the current status of membership (i.e., membership level and length of tenure) but also by habitual and technical factors often ignored in past research. This study contributes significantly to the IS literature by showing that online community behavior can be understood as the setting, pursuit, and automatic activation of goals.

Theoretical Contributions

Online community behavior is complex in nature and involves a variety of underlying causal mechanisms. Although numerous factors have been identified as the antecedents of online community behavior (e.g., [9, 37, 62, 79, 93]), an overarching framework that ties them together seamlessly has been lacking. Given the existence of this gap, and especially given the repeated emphasis in the literature that an online community is goal-directed virtual space [93, 99], an important contribution of this study to IS research is a goal-oriented action framework. Our theoretical framework incorporates the setting, pursuit, and automatic activation of goals, which account for, respectively, artifacts, membership, and habit driving active online community participation. In the course of developing this framework, we highlighted the critical role of personal goals in regulating individual behavior. More specifically, we propose the following arguments: (1) Incentives represent an artificial mechanism capable of manipulating the goal-setting process; (2) the current status of membership results from the insistent pursuit of a member's goal; and (3) habit is goal-directed automaticity acquired through repeated visits to a website. Compared with the bulk of research on online communities that has been mostly silent on the role of IT artifacts in inducing member behavior, our conceptual framework contributes significantly to this literature by showing how a certain IT-enabled rewards system *changes* members' active participation in the desired direction. In addition, this framework seamlessly incorporates automaticity, which is rarely discussed in online community research [9, 37], into a conceptual model. Taken

as a whole, the present study suggests the opportunity to study members' active participation in online Q&A communities through the powerful lens of goal-oriented action.

Compared with the large volume of community research devoted to members' subjective perceptions ([14, 20, 79, 93, 99], to name just a few), few investigations address how a certain website design actually modifies members' active participation [42]. With this in mind, our study stands as an important attempt to propose and test the way that active online participation changes according to the design mechanism of incentives. Furthermore, recall that a complex system of points and levels is an element that characterizes open, free Q&A websites. Our study is particularly meaningful in this sense because it provides a detailed account of how knowledge seeking and knowledge contribution evolve differently according to a particular incentive structure. Specifically, our findings indicate that online members post more answers but fewer questions when they are about to be promoted. Membership promotion requires total points to accumulate and pass certain threshold levels; thus, such findings are intuitive in light of the fact that incentive points are awarded to those who post answers, but points are deducted from those who post questions [82, 85]. We infer from these findings that an artificial system of rewards serves indeed as an incentive to perform prosocial behaviors. Moreover, although Jabr et al. [42] tested the effects of various forms of incentives on knowledge contribution, they did not theorize the differential effects of such incentives on knowledge contribution and knowledge seeking in the same theoretical framework. In other words, although the researchers have realized that knowledge contributors is a scarce resource and that incentive motivations should differ between knowledge contributors and knowledge seekers, they did not further consider the benefits to the community by having a penalty points system that discourages excessive knowledge seeking. Overall, the present study contributes significantly to the study of IT design mechanisms by offering a solid conceptual framework and empirically confirming its efficacy specifically in the online Q&A environment in which an artificial incentive mechanism is a critical design feature [85].

Several important findings are noteworthy regarding the impact of membership on active online participation. In particular, this study shows that a user's membership level has a powerful impact on knowledge sharing and knowledge seeking. These findings indicate that higher level members not only

contribute more knowledge to the community but also attempt to facilitate discussion by raising more questions. Such active participation in both knowledge sharing and knowledge seeking seems to result from their strong identification with the online community [62, 77]. Although much research shows that membership ranking is connected with knowledge contribution, our study is among the first to demonstrate that it can also promote knowledge seeking. Another significant finding related to membership is the negative relationship between longer lengths of tenure and active online participation, which is exactly the opposite of the findings of prior research [99]. Our study provides a theoretical account for why, in an open — as opposed to a closed — community, the time elapsed since membership registration is negatively associated with active online participation. We believe that the distinction made in our classification between open and closed communities has the potential to resolve contradictory findings about the effects of tenure that have been recorded in the knowledge management and community literatures.

Not all studies that have examined knowledge contribution have also studied knowledge seeking (e.g., [1, 50, 61, 76, 84, 86, 95, 105]). This is counterintuitive, given that these online Q&A communities are sustained through both receiving and providing answers [85]. This study contributes to the literature by theoretically and empirically showing the fundamental difference in posting questions and answers in the context of active online Q&A participation. First, given that answering questions helps to earn points but posting questions entails a loss of them, our results reveal that members closer to promotion tend to post answers instead of questions. Second, we also have shown that given the relatively lesser degree of effort and willpower needed to ask a question compared with answering it, the level of membership, as a proxy for the extent of goal-pursuit, is a stronger driver of active user participation and even more so for answers than for questions. Third, our findings also reveal that because of the stronger motivation needed to justify the time and effort spent in answering questions, compared with asking them, and because motivation was shown to dwindle over time, the negative effect of tenure on active user participation is stronger for answers than for questions. Interestingly, the results of this study indicated that our model was relatively more effective in explaining answering (Adjusted $R^2 = 52\%$) than questioning (Adjusted $R^2 = 31.5\%$). We believe that the difference in explained variance is, to some extent, attributable, as discussed earlier, to distinctly different

mechanisms involved in posting questions and posting answers. Overall, our study extends previous work by clarifying the systematic difference between knowledge seeking and knowledge sharing. The inferences acquired from this study are expected to be critical for a complete understanding of the intricacies associated with active member participation in online Q&A communities.

Although much research has focused on identifying the psychological determinants of active participation in online communities (e.g., [43, 62, 79, 93]), little attention has been paid to the dynamics of actual behavior that unfolds over time [42]. More specifically, our knowledge is limited regarding the habitual aspect of active online community participation [37]. Unlike offline communities, online communities allow members to interact with each other virtually anytime, anywhere. Thus, habit seems to be an important determinant of online community behavior. As hypothesized, our findings indicate that the act of posting questions or answers exhibits patterns of highly habitual behavior. In particular, this study shows that future behavior is influenced not only by current behavior but also by prior behavior. These findings strongly suggest that members gradually acquire over a long period the habit of participating in their community. Although He and Wei [37] tested the effect of habit in their model of knowledge-sharing behavior, their focus was the moderating effect of habit on the significance of intention to share knowledge based on a one-time cross-sectional observation of member perceptions, rather than examining member behavior over a relatively long period of time. Thus, to the best of our knowledge, our study is the first to demonstrate the longitudinal implications of habit in the context of active online community participation. Meanwhile, another important finding of this study is the moderating role of membership in determining the strength of habit. Specifically, we found that habitual patterns are more evident for members with a higher membership level and shorter tenure than for those with a lower membership level and longer tenure. Even though habitual behavior is generally well documented in IS research, our knowledge is limited, especially regarding the boundary conditions under which habit (i.e., past behavior) has a stronger or weaker effect in the broad context of online communities. This study extends the body of knowledge in the field of online Q&A communities by revealing individual differences in habitual patterns according to membership levels and tenure.

Methodological Implications

We have chosen to test our model using system-generated data. Such data are suited for representing an individual's behavior with a minimum of subjective bias [19, 42]. Our empirical design follows the same approach of a growing body of recent literature in the marketing and IS fields (e.g., [19, 42, 63, 64]). Such research has begun to recognize the unique advantages of this approach. In marketing research for instance, Chen et al. [19] collected objective data from Amazon.com to study consumers' purchase behavior as influenced by various social factors. In IS, both Ma, Kim, and Kim [64] and Ma, Khansa, Deng, and Kim [63] used system-generated data to test behavioral models in the online environment. Specifically, our paper adopted the way that Ma, Kim, and Kim [64] measured habitual behavior in the online gambling context. The authors demonstrated that objective data not only facilitated rigorous testing of an integrated model of a particular form of human behavior online (i.e., online gambling behavior), but also allowed researchers to reflect different levels of habitual behavior [64]. More closely related to the research context of this paper are Chiu et al. [20], Ren et al. [81], Tsai and Bagozzi [93], and Jabr et al. [42]. Specifically, Ren et al. [81] relied exclusively on system-recorded data in measuring different aspects of active member participation in the virtual community. More recently, system-generated data enabled Jabr et al. [42] to investigate the effects of IT artifacts on active participation behavior in several online communities. Thus, we believe that this research, together with a growing body of management literature, especially in IS, serves an important initial attempt to unveil the largely overlooked potential of system-generated data. Such an attempt may better support future research on online knowledge communities that aims to "faithfully capture the complex, dynamic interrelationships between initial and long-term knowledge-sharing decisions" [20 p. 1884].

Practical Implications

This study demonstrates that community members' desire to get promoted noticeably changes their active participation. More specifically, we found that they are more likely to show prosocial behaviors, i.e., posting more answers but fewer questions, when their total points are near the cutoff point for the next higher level. Considering that website managers determine these artificial cutoff points, our findings hint at the type of

controls that practitioners can use to further facilitate knowledge contribution. As an example, we expect that members generally will be more active participants if a redesign lessens the difference between membership levels. The rationale for this inference is that a shorter interval makes it easier to get promoted, which is likely to motivate members to contribute more. Under such a shortened interval for promotion, practitioners also need to carefully lower the incremental award of privileges for each promotion in order to avoid certain negative effects, e.g., making it too easy to reap the kind of privileges to which only elite members are entitled. In this way, practitioners can create more opportunities for members to feel a sense of achievement and thus solidify their commitment to the community.

We found that in an open Q&A website like YA, the tenure of members is negatively associated with participatory behaviors. In conjunction with the prevalence of a power law distribution in online communities, our findings clearly indicate the difficulty of engaging newcomers and turning them into long-term active participants. Nevertheless, if an online community is to succeed, it is essential that practitioners turn newcomers into regular visitors. One way to achieve this goal is to help members develop a habit of participation before their initial curiosity wanes. As mentioned earlier, people tend to be more active when the incentive of promotion is in sight. Thus, if a website is designed in such a way that novices can easily attain the second level, they may become habituated to visiting the website while striving to reap the relatively instant reward [10]. In general, practitioners are advised to take advantage of the power of habit and the artifacts discussed in this study as means to keep newcomers from lapsing into inactivity as their initial enthusiasm fades.

Limitations and Future Research

Several limitations of this study warrant mention. First, our study relied exclusively on objective data that could sometimes be not the most effective means for capturing theoretical notions such as artifact, membership, and habit.⁶ Second, our model nicely integrates various goal-oriented action theories and is shown to perform adequately. Nevertheless, some factors other than those shown in our model could affect active online community participation. Third, the present study was focused on a single Q&A website and a

⁶ We thank an anonymous reviewer for pointing out this important concern about our data collection method.

certain type of community member. Any attempts to over-generalize its findings should be made with care. Fourth, our assumption about tenure is that in an open, free community, one's commitment will wane with experience. Future research should look deeper at the effect of tenure on online participation when different types of members are involved. Fifth, our model may have limited generalizability to other types of online communities, i.e., *domain-specific* Q&A communities (e.g., Stack Overflow) and organizational knowledge-management systems. Last but not least, we started our data collection process from collecting a large sample of resolved questions, rather than unresolved questions. Further, we were not able to analyze the participatory behavior of members with hidden profiles. More studies are needed to gauge the implications in both respects.

Several directions can be identified for further research. First, our findings suggest that when their total points are near the threshold of their imminent promotion to the next level, members are more likely to commit to answering others' questions and, at the same time, refrain from asking as many questions as they usually do. Our study showcases, at a very preliminary stage, how a better designed artificial system can successfully induce more prosocial behavior. Clearly, however, more research is needed to innovate different and effective design mechanisms (i.e., incentive mechanisms, decentralization of member powers and responsibilities, peer moderation systems) and to understand what implications for member behavior these designs have when applied in a real setting. As discussed from the outset, a critical problem this research aims to address is the lack of success of many online Q&A websites in leveraging IT artifact designs to encourage active member participation. Therefore, there is a pressing need for future research to investigate how to better design various IT artifacts to foster active participation among members in online Q&A communities.

Second, a fertile avenue for further research appears to be the use of both subjective and objective measures in a single study. Each type of data has its own advantages and disadvantages, but few studies take advantage of the richness that a dual approach brings to online community research. For example, much research suggests that psychological motives play an important role in prosocial behavior in the context of online communities [15, 36, 43, 57]. Thus, it would be interesting to examine how psychological motives, which can be measured through survey questionnaires, interact with the antecedents in our model to influence prosocial behavior. Similarly, we assume in this study that membership results from several identity-related

factors such as self-identity verification [62] and community identification [4]. It would be interesting to test whether the membership level of a member truly mediates the impacts of those identity-related factors on online community behaviors. Thus, we believe that leveraging research traditions on both sides will open up a fuller and richer understanding of online community behaviors.

Conclusions

Online Q&A communities have become increasingly popular as a complement to search engines, especially when unstructured and complex problems are involved. Despite the important role of Q&A websites as alternative information sources, little research in the IS area has addressed individuals' use of such websites over time. Drawing on relevant theories from IS and other disciplines, this study develops a goal-oriented action framework that explains how members post questions and answers in their community. We analyzed a collection of system-generated data and found that behaviors of online community participants are driven by the setting, pursuit, and automatic activation of goals. Although the present study is focused on an online Q&A community, our approach shown here is expected to be reasonably applicable to other types of online communities. We hope that more research attention will be given to the way people embrace online communities in everyday life and that our proposed framework will help guide researchers in such endeavors.

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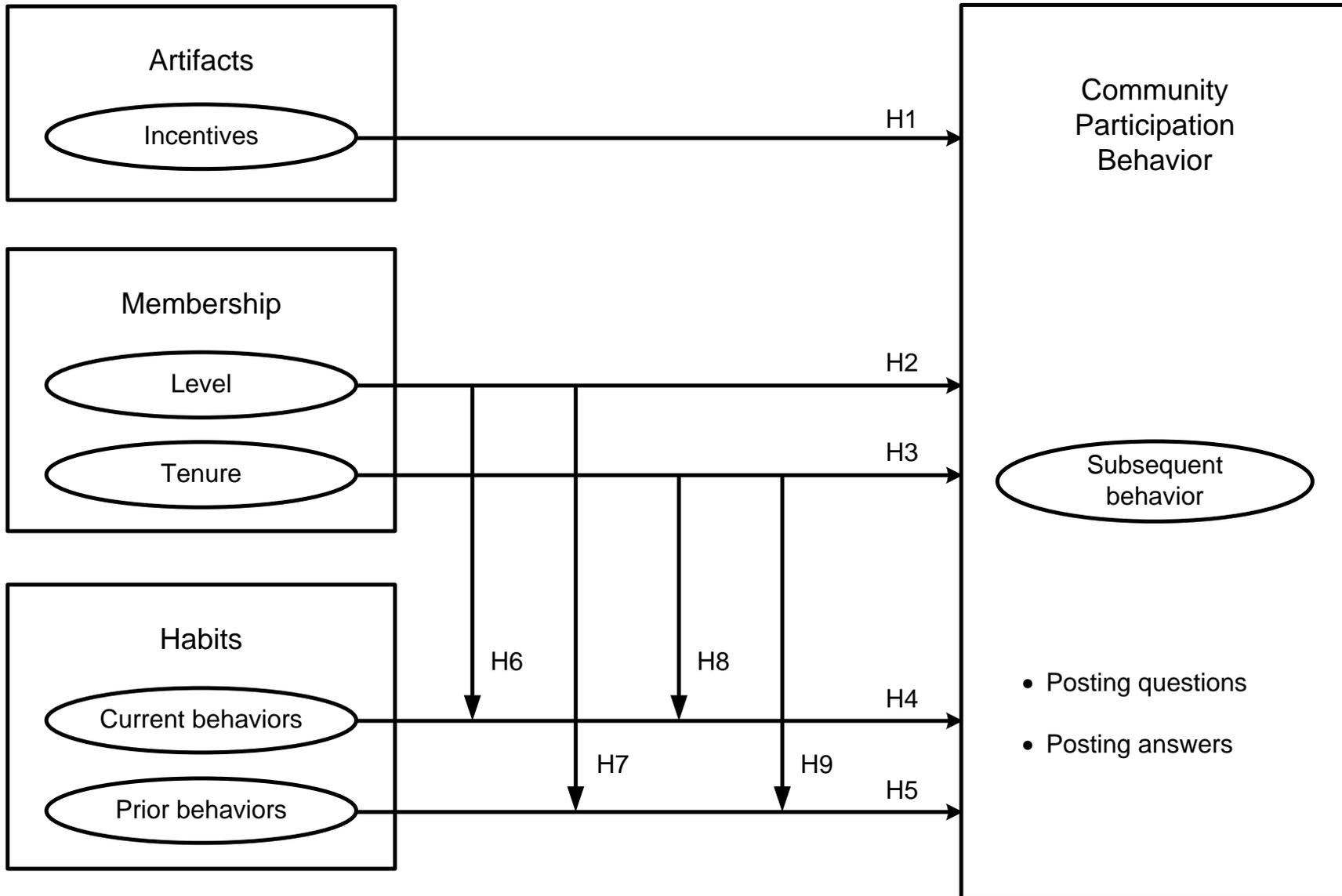
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Figure 1 Conceptual Model



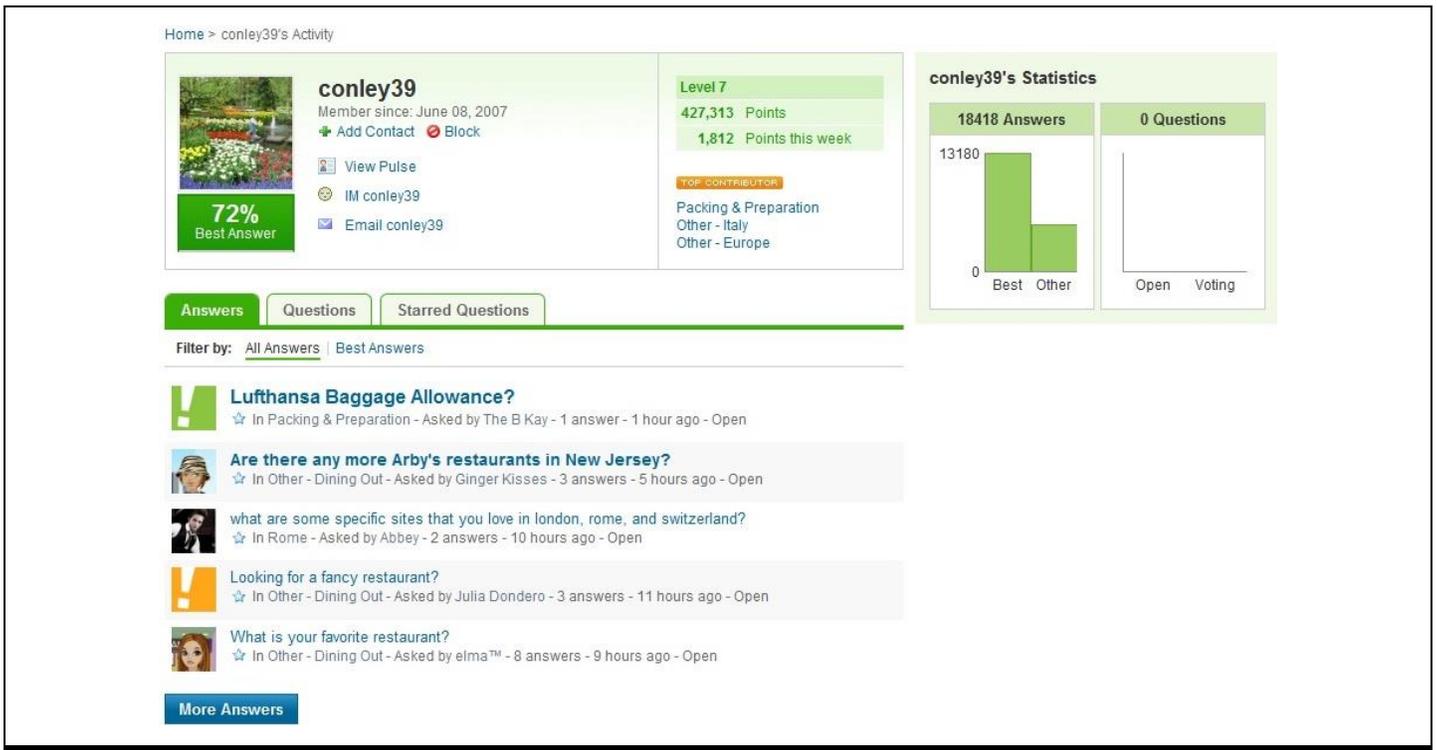


Figure 2. Sample Yahoo! Answers Profile Web Page

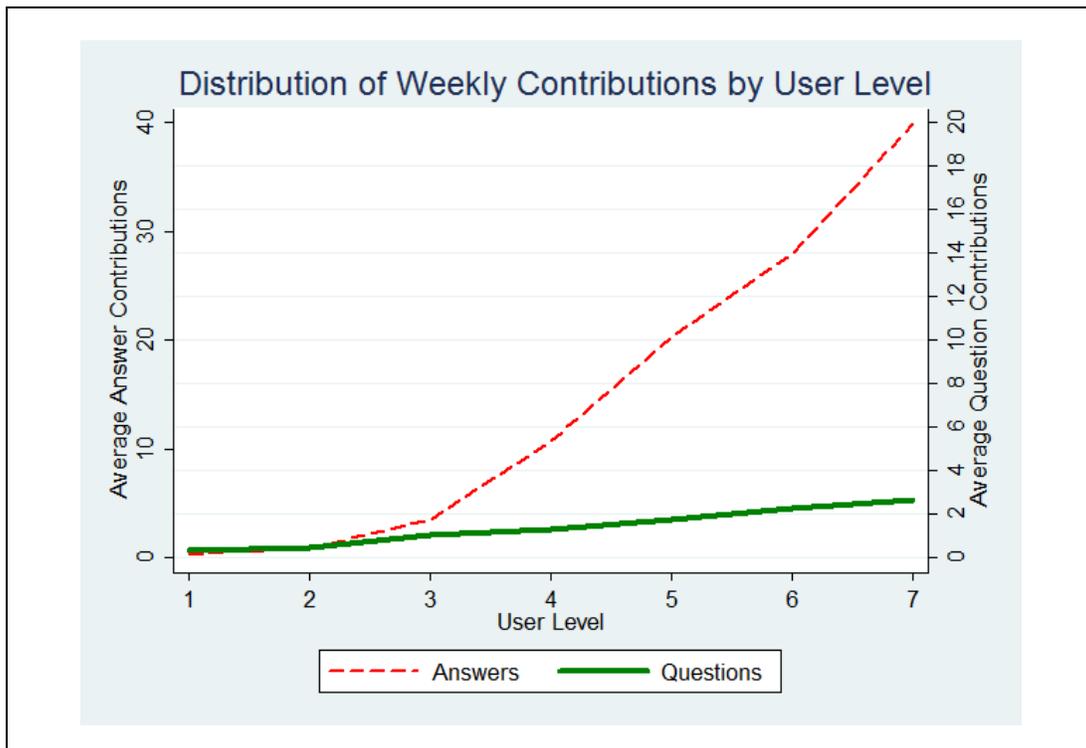


Figure 3. Average Weekly Number of Answers and Questions by User Level

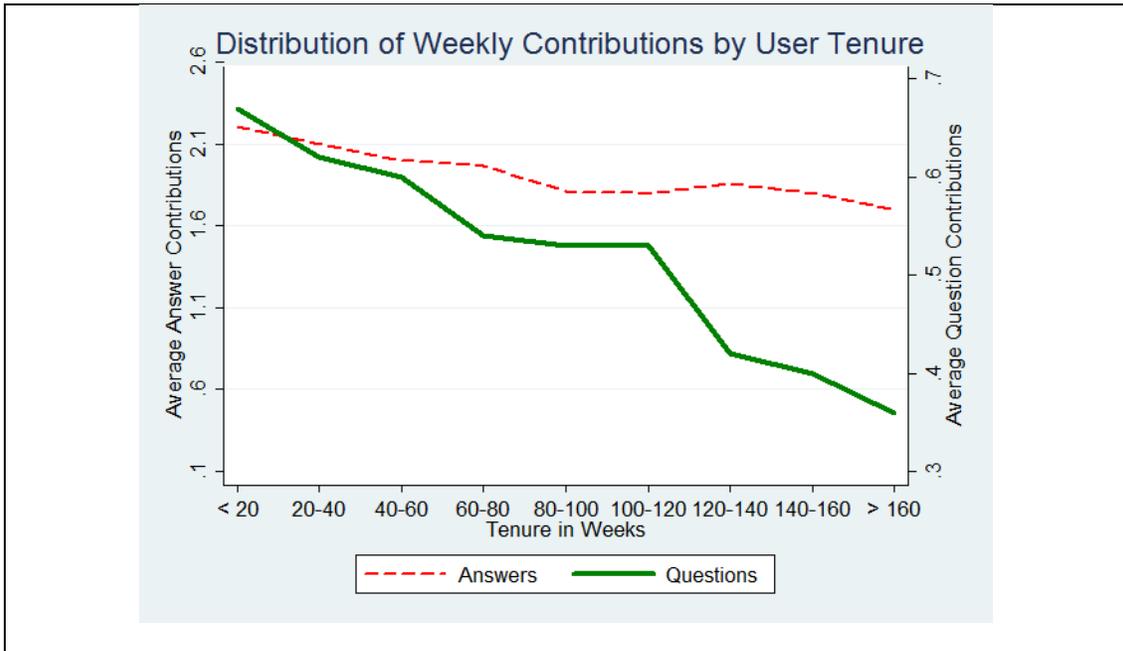


Figure 4. Average Weekly Number of Answers and Questions by User Tenure

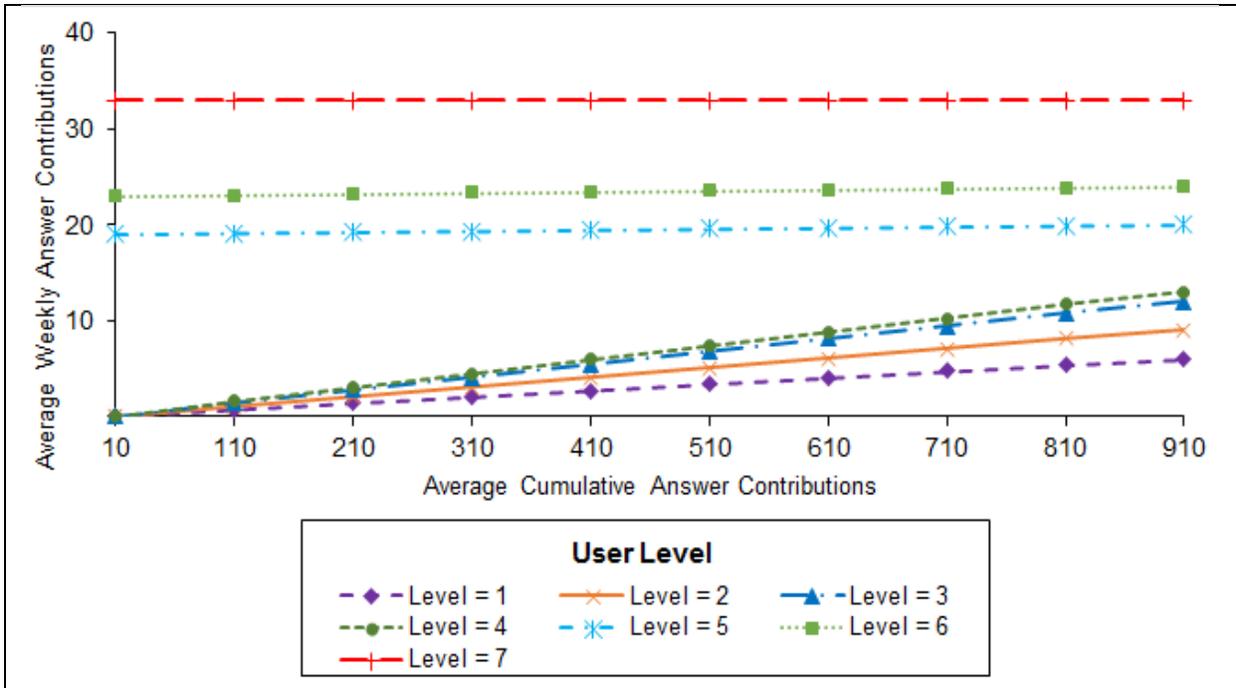


Figure 5. Cumulative Past and Subsequent Answer Contributions by User Level

Table 1. Literature Review Summary and Gaps Filled by this Paper

| Research Stream | Literature | Theoretical Focus of Previous Research | Theoretical Focus of This Paper |
|---|--|--|--|
| Organizational KM systems | Ahuja et al. [2]; Beck et al. [9]; Bock et al. [14]; He and Wei [37]; Kankanhalli et al. [47, 48]; Reagans and McEvily [80]; Xu et al. [106]; Yu et al. [108] | Motives for knowledge contribution and seeking by organizational employees | Effects of social reputation as represented by membership levels |
| | | Incentives are economic or job-related only | Purely noneconomic incentive mechanisms |
| | | Habit moderates the importance of intention to contribute and seek knowledge | Main effects of habit and other boundary conditions that may strengthen or weaken the effect of habit |
| Online professional communities | Chiu et al. [20]; Faraj et al. [26]; Ma and Agarwal [62]; Phang et al. [73]; Wasko and Faraj [99]; Zhang [111] | Motives for knowledge exchange | Role of IT-enabled incentives, membership levels, and habit |
| Wikipedia- and OSS- types of online communities | Benkler and Nissenbaum [11]; Cho et al. [21]; Hars and Ou [36]; Peng and Dey [72]; Ransbotham and Kane [78]; von Krogh et al. [97]; Wen et al. [101]; Zhang and Wang [112]; Zhang et al. [110] | Project success and failure | (Not our focus) |
| | | Motives for project contribution | Effects of purely noneconomic incentive mechanisms and membership levels |
| Customer-based, firm-hosted online communities | Bretschneider et al. [15]; Gu and Jarvenpaa [33]; Janzik and Raasch [43]; Jabr et al. [42]; Jeppesen and Frederiksen [45]; Wiertz and de Ruyter [103] | Self-marketing, firm recognition, altruism, and social interaction as important motives to contribution behavior | Effect of social recognition in the form of points awarded to peer-voted best answers; effect of membership levels |
| Online Q&A communities | Adamic et al. [1]; Fichman [27]; Gazan [31]; Harper et al. [35]; Kim and Oh [50]; Li et al. [58]; Lou et al. [61]; Raban [76]; Rosenbaum and Shachaf [82]; Savolainen [84]; Shachaf [85]; Shah and Kitzie [86]; Vasilescu et al. [95]; Wu and Korfiatis [105], Yang et al. [107] | Importance of incentive and reputation systems | How incentive systems influence members' actual knowledge-sharing behavior |
| | | Various psychological motives for knowledge contribution, including social capital incentives | Role of IT-enabled incentives, membership levels, and habit |

| Table 2. Variable Details | | |
|------------------------------------|--|--|
| Variables | | Variable Descriptions |
| Dependent variables | $A_{This_{i,t}}$ | This week's answers |
| | $Q_{This_{i,t}}$ | This week's questions |
| Independent variables | <u>Main effects</u> | |
| | $NumWeeks_{i,t-1}$ | Number of weeks as member, as of last week |
| | $PctPromo_{i,t-1}$ | Proportion of points till promotion, as of last week |
| | $Level_{i,t-1}$ | Level during last week |
| | $A_{This_{i,t-1}}$ | Number of answers during last week |
| | $Q_{This_{i,t-1}}$ | Number of questions during last week |
| | $A_{Till_{i,t-1}}$ | Cumulative number of answers, as of last week |
| | $Q_{Till_{i,t-1}}$ | Cumulative number of questions, as of last week |
| | $PctStarsTill_{i,t-1}$ | Cumulative percent stars received, as of last week |
| | $PctBestTill_{i,t-1}$ | Cumulative percent best answers, as of last week |
| | <u>Interaction effects</u> | |
| | $NumWeeks_{i,t-1} * A_{This_{i,t-1}}$ | Interaction between users' tenure, as of last week and their answers last week |
| | $NumWeeks_{i,t-1} * A_{Till_{i,t-1}}$ | Interaction between users' tenure and their total answers, as of last week |
| | $Level_{i,t-1} * A_{This_{i,t-1}}$ | Interaction between users' levels, as of last week and their answers last week |
| | $Level_{i,t-1} * A_{Till_{i,t-1}}$ | Interaction between users' levels and their total answers, as of last week |
| | $NumWeeks_{i,t-1} * Q_{This_{i,t-1}}$ | Interaction between users' tenure, as of last week and their questions last week |
| | $NumWeeks_{i,t-1} * Q_{Till_{i,t-1}}$ | Interaction between users' tenure and their total questions, as of last week |
| | $Level_{i,t-1} * Q_{This_{i,t-1}}$ | Interaction between users' levels, as of last week and their questions last week |
| $Level_{i,t-1} * Q_{Till_{i,t-1}}$ | Interaction between users' levels and their total questions, as of last week | |

| Table 3. Descriptive Statistics and Pearson Correlations | | | | | | | | | | | | |
|--|--------------------|--------|--------|--------|--------|--------|--------|--------|--------|-------|--------|-------|
| Variable | Mean (Std dev) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 |
| 1 $A_{This_{i,t}}$ | 1.781 (11.431) | 1.000 | | | | | | | | | | |
| 2 $A_{This_{i,t-1}}$ | 2.387 (60.034) | 0.123 | 1.000 | | | | | | | | | |
| 3 $A_{Till_{i,t-1}}$ | 240.010 (1152.508) | 0.333 | 0.055 | 1.000 | | | | | | | | |
| 4 $Q_{This_{i,t}}$ | 0.484 (1.964) | 0.364 | 0.045 | 0.129 | 1.000 | | | | | | | |
| 5 $Q_{This_{i,t-1}}$ | 0.598 (3.974) | 0.134 | 0.095 | 0.108 | 0.287 | 1.000 | | | | | | |
| 6 $Q_{Till_{i,t-1}}$ | 52.940 (119.205) | 0.170 | 0.028 | 0.347 | 0.338 | 0.209 | 1.000 | | | | | |
| 7 $NumWeeks_{i,t-1}$ | 93.174 (63.958) | 0.019 | -0.005 | 0.140 | -0.030 | -0.013 | 0.185 | 1.000 | | | | |
| 8 $PctPromo_{i,t-1}$ | 0.578 (0.276) | -0.048 | -0.011 | -0.115 | 0.027 | 0.006 | 0.029 | 0.032 | 1.000 | | | |
| 9 $Level_{i,t-1}$ | 1.773 (1.033) | 0.353 | 0.057 | 0.569 | 0.160 | 0.115 | 0.377 | 0.232 | 0.192 | 1.000 | | |
| 10 $PctStarsTill_{i,t-1}$ | 0.120 (0.228) | 0.162 | 0.032 | 0.294 | 0.128 | 0.098 | 0.301 | 0.076 | -0.039 | 0.315 | 1.000 | |
| 11 $PctBestTill_{i,t-1}$ | 0.155 (0.130) | 0.010 | 0.006 | 0.031 | -0.009 | -0.006 | -0.005 | -0.010 | -0.016 | 0.170 | -0.027 | 1.000 |

Table 4. Model Estimation for Questions and Answers this Week

| Variable | GMM (Questions) | | GMM (Answers) | |
|--|---------------------|----------------------|---------------------|---------------------|
| | One-step | Two-step | One-step | Two-step |
| QThis _{i,t-1} | 0.105** (0.003) | 0.034** (0.005) | 0.017 (0.014) | -0.020 (0.010) |
| AThis _{i,t-1} | 0.001** (0.000) | 0.0001 (0.000) | 0.018** (0.001) | 0.017** (0.000) |
| NumWeeks _{i,t-1} | -0.002** (0.000) | -0.002** (0.000) | -0.016** (0.001) | -0.013** (0.001) |
| PctPromo _{i,t-1} | 0.237** (0.032) | 0.201** (0.040) | -4.249** (0.180) | -2.909** (0.204) |
| Level _{i,t-1} | 0.118** (0.013) | 0.075** (0.019) | 3.738** (0.073) | 2.345** (0.100) |
| QTill _{i,t-1} | 0.005** (0.000) | 0.006** (0.000) | -0.00013 (0.001) | 0.004** (0.000) |
| ATill _{i,t-1} | 0.00001 (0.000) | -0.00006* (0.000) | 0.001** (0.000) | 0.002** (0.000) |
| PctStarsTill _{i,t-1} | -0.049 (0.048) | -0.006 (0.075) | -0.506 (0.249) | -0.263 (0.228) |
| PctBestTill _{i,t-1} | 0.049 (0.073) | 0.246* (0.080) | -5.043** (0.406) | -3.036** (0.343) |
| (Questions model only) NumWeeks _{i,t-1} * QThis _{i,t-1} (Answers model only) NumWeeks _{i,t-1} * AThis _{i,t-1} | -0.363** (0.013) | -0.208** (0.019) | -2.989** (0.089) | -3.524** (0.105) |
| (Questions model only) NumWeeks _{i,t-1} * QTill _{i,t-1} (Answers model only) NumWeeks _{i,t-1} * ATill _{i,t-1} | -0.194** (0.010) | -0.431** (0.026) | -0.220** (0.057) | -0.494** (0.112) |
| (Questions model only) Level _{i,t-1} * QThis _{i,t-1} (Answers model only) Level _{i,t-1} * AThis _{i,t-1} | -0.011 (0.013) | 0.069** (0.017) | 6.957** (0.086) | 7.216** (0.089) |
| (Questions model only) Level _{i,t-1} * QTill _{i,t-1} (Answers model only) Level _{i,t-1} * ATill _{i,t-1} | -0.025 (0.010) | 0.051* (0.020) | -0.249** (0.066) | 0.024 (0.091) |
| Model fit (Adjusted R ²) | 29.93% | 31.50% | 42.87% | 52% |
| Model F-test (p-value) | 0.000 | 0.000 | 0.000 | 0.000 |
| Sargan test (p-value) | 12.22 (0.002) | 17.82 (0.058) | 19.03 (0.008) | 52.62 (0.126) |
| Arellano-Bond test | | | | |
| AR(1): p-value | 0.137 | 0.241 | 0.069 | 0.594 |
| AR(2): p-value | 0.500 | 0.116 | 0.344 | 0.399 |
| Users | 2920 | 2920 | 2920 | 2920 |
| Observations | 23,172 | 23,172 | 23,172 | 23,172 |

Notes. Standard errors are shown in parentheses. * $p < 0.01$; ** $p < 0.001$

^a The Wooldridge tests check for serial autocorrelation

^b The Modified Wald test checks for groupwise heteroskedasticity

^c The Arellano-Bond test checks serial correlation in first-differenced errors