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Habit Formation in Online Communities

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Abstract

A long standing dilemma of online communities is that a small group of community members account for a disproportionate amount of contributions. Prior studies built on intent-based explanations cannot fully explain the phenomenon. This paper introduces the concept of habit formation as a key driver of individual contributions and investigates how habit is formed and how it influences individuals' participation behavior in online communities. We propose that a threshold of behavioral repetitions exists for individuals to develop a habit. Once the threshold is surpassed, the habit of participation grows stronger and becomes self-reinforcing. We also propose that habit formation weakens the influence of reciprocity, social capital and competition on user participation in virtual communities. Using a panel data of 130,882 postings across 115 discussion boards, we find support for all the hypotheses. Our analysis contributes to the emerging literature on routinized information technology use.

Keywords: virtual community, habit formation, human behavior, longitudinal study

HABIT FORMATION IN ONLINE COMMUNITIES

"There is no more miserable human being than one in whom nothing is habitual but indecision, and for whom the lighting of every cigar, the drinking of every cup, the time of rising and going to bed every day, and the beginning of every bit of work, are subjects of express volitional deliberation."

-William James, cited in Limayem et al (2007)

Introduction

"An online community is defined as a large collectivity of voluntary members whose primary goal is member and collective welfare, whose members share a common interest, experience, or conviction and positive regard for other members, and who interact with one another and contribute to the collectivity primarily over the net" (Sproull and Arriaga 2007). Online community members can communicate, interact, develop relationships, and collectively and individually seek to obtain information they need in such an information technology (IT)-enabled virtual space (Lee et al. 2002).

Online communities make it possible for community members to generate questions and obtain answers for issues of common interest. For example, members can discuss innovative product usage in online product communities (Jeppensen and Frederiksen, 2006), share stock tips in virtual investment-related communities (Gu et al., 2007), or address technical support issues via firm-hosted online customer service forums (Moon and Sproull, 2001; Armstrong and Hagel, 1996; Jeppessen and Frederiksen, 2006; Kraut et al. 1996). Online communities not only help community members but also benefit businesses. Press reports and academic studies have shown that online communities can significantly reduce companies' research and development costs, and customer service costs (Jeppesen and Frederiksen, 2006).

A long standing question in the study of online communities is what motivates community members to share knowledge with other members for free (Olivera et al 2008; Ma and Agarwal, 2007; Jeppesen and Frederiksen, 2006; Wasko and Faraj, 2000; Rafaeli and LaRose, 1993). Many insightful findings have been obtained in this area (Wasko and Faraj, 2000; Ma and Agarwal, 2007; Bock et al. 2005; Asvanund et al. 2004; Butler, 2001; Kuk 2006; Butler et al 2007). From economic and social psychological perspectives, researchers have identified a number of intrinsic and extrinsic motivators that influence community members' willingness to participate. The central argument is that community members contribute to an online community when the benefits they receive (or perceive that they receive) outweigh their costs of contributing information. Online communities that can provide positive net benefits are assumed to be better able to attract and retain members, and hence to survive over the long term (Butler 2001). Benefits such as economic rewards, reputation effects, status, peer approval, and establishment of perceived identity verification have all been identified as factors influencing participation.

However, despite the insights on individual motivations, the prior studies cannot fully explain the behavior of an important group of community members – hard core members. Surveys of participants in online communities and other online social networks reveal that "the majority of participants leave the community once their needs are met" (Shah 2006). However, "a small set of [members] … remains involved … and they are critical to the long term viability [of the community]" (Shah 2006). We call this small set of members *hard core* members.

An important characteristic of the behavior of hard core members is that they make frequent and repeated contributions and their contributions do not seem to be mainly motivated by economic or social concerns (Shah 2006). Rather, their contributions appear to be routinized, i.e. the result of a habit. The goal of this study is to understand how habit of participation is formed among virtual community members and model the influence of habit on individual contribution behavior.

Habits are learned sequences of acts that are automatic responses to specific cues, and habits are functional in obtaining certain goals or end-states (Hull, 1943; Triandis 1977, 1980). These studies indicate that habit formation has two distinctive characteristics. First, habit formation is a self-reinforcing process (Moon and Sproull, 2001). Previous experience helps individuals to improve their skills and their ability to enjoy the activity which in turn enhances the current experience. For example, listening to music leads to accumulation of skills of music appreciation. Such skills enable people to enjoy music better and motivate them to listen to more music. In online communities, interacting with others allows an individual to learn about the environment and other members of the

community. The more an individual participates in discussions, the more he accumulates knowledge and social capital in the community which leads to more future interactions. The self-reinforcing process suggests that an individual's participation in online communities is not time independent. Rather, it is influenced by his or her experience with past participations. Studies on habit formation also indicate that a threshold of repeated actions exists to initiate the self-reinforcing process. Second, habitual behaviors are routinized responses. When a habit is activated, the habitual behavior becomes largely automatic. In such cases, individuals simply duplicate their past actions without much consideration for economic or social concerns.

In the information systems literature, many have noted the importance of going beyond models of intention and expectation to understand technology use behavior (e.g., Kim and Malhotra 2005; Limayem et al 2007; Wu and Kuo 2008; Venkatesh et al 2008; Limayem and Cheung, 2008). However, little attention has been paid to understand the process of habit formation and how it affects participation in online communities. This study addresses the gap by proposing a model of the habit formation process. We then test the model using panel data comprising 130,882 postings by 22,457 members in 115 discussion boards over a 6-month time period in a firm-hosted online community. The analysis shows that a threshold does exist for the formation of a participation habit. Once the threshold is passed, repeated actions become self-reinforcing, leading to the formation of habit. We also find that habit significantly reduces the influence of social and economic factors on individual participation in virtual communities. Moreover, we find that effects of habit are stronger among high-ranking community members than among low-ranking community members.

The rest of this study is organized as follows. Section 2 provides a literature review on the concept of habit. Section 3 develops hypotheses on habit formation process. Section 4 describes the data and summarizes the empirical results. Discussions are presented in Section 5.

Literature Review

Online communities are commonly referred to as Internet forums, online discussion boards, web forums, and bulletin boards. In online communities, members share their knowledge with other members to help others solve problems or answer other members' questions on issues of common interest (Sproull and Arriaga 2007). In this paper, two key features of an online community are important. First, a community is generally self-organizing. It is made up of members who voluntarily choose to participate. Members are free to post their questions or to answer other members' questions as they so desire. Second, participation is open to anyone interested in the topics and information. The discussions and postings are open to all members even those who do not make any contributions. These two features raise the long-standing issue of what motivates community members to share knowledge (Wasko and Faraj, 2000; Wasko and Faraj, 2005; Olivera et al 2008). Using different theoretical foundations, researchers have identified several factors influencing members' motivation to participate.

Intrinsic and extrinsic motivators

Observing that members who make the most contributions in an online music innovation community are a small set of hobbyists rather than professionals, Jeppesen and Frederiksen (2006) argue that it is intrinsic motivation that really motivates members to make contributions to online communities. Intrinsic motivation comes from positive self-evaluation that is based on competence and perceived social acceptance. To pursue positive self-evaluation, people may engage in activities just for the sake of the activity itself, rather than for extrinsic rewards (Bandura, 1986). Members may contribute information in an online community because they perceive that doing so is self-fulfilling (Kollock, 1999). Similarly, answering questions posted by others may engender a "feeling of competence" and "sense of autonomy" (Amabile, 1993; Ryan and Deci, 2000).

Besides members' individual intrinsic motivations, extrinsic factors are also identified as influencing individuals' willingness to share knowledge (Bock et al. 2005). Extrinsic motivators usually refer to anticipated extrinsic rewards. These rewards could include monetary incentives, promotional points, or reputation and social identity. It has been shown that explicit rewards are effective in motivating people to share knowledge (Smelser and Swedberg, 1994). In explaining programmers' innovative efforts in open source software communities, Lerner and Tirole (2002) recognize the importance of "peer recognition." They argue that the reputation capital gained is a means of enhancing an information provider's position in the community. Similarly, Constant et al. (1996), Donath (1999) and Jones et al (1997) have shown that building reputation is a strong motivator for active participation. Using a social capital theory perspective, Wasko and Faraj (2005) argue that members engage in social interaction based on an expectation that it will lead to social rewards such as approval, status, and respect. Members perceive that they

gain status by answering frequently and intelligently in the online community (Lakhani and von Hippel, 2003). Taking a social psychological perspective, Ma and Agarwal (2007) further point out that perceived identity verification can promote members' contribution in online communities. This is because establishment of one's online identity can enhance one's reputation and self-esteem. Established identity can also amplify the possibility of future reciprocation (Ma and Agarwal, 2007). In addition, collective social effects, i.e. the positive effects of being together in a community, can also have influence on members' behavior. The connections between individuals, or the structural links created through the social interactions between members in a virtual community, are important predictors of collective action (Wasko and Faraj, 2005; Burt, 1992).

Habits

It is found that the more members are in regular contact with each other, or actively participate in community discussions, the more likely they are to develop a "habit of participation" and act cooperatively with other members (Marwell and Oliver, 1988). Habit formation also plays an important role in explaining continued IS use after initial adoption (Kim and Malhorta 2005). However, little is known how such habit is formed and what strategies a business can take to encourage habit formation. Previous research findings in the field of social psychology have provided us insights to understand what habit is and what factors affect the formation of habit. In addition, in the economics literature, significant amount of efforts have been devoted into the understanding of how habit affects individuals' choices and how to precisely measure its effects by using a large amount of secondary data. This study incorporates these two streams of literatures into our analysis on the formation of habit and its effect on online community participation. Consistent with the economics and psychology studies, habit is conceptualized as "the extent to which people tend to perform behaviors (use IS) automatically because of learning" (Limayem et al. 2007).

Studies of the habit effect on people's behavior in the economics literature can be traced to the 1960's (Gorman, 1967; Nerlove, 1958; Stone, 1966). Incorporation of the habit component into utility functions significantly improved utility maximization theories because it makes it possible to generate dynamic demand and supply functions (Becker and Murphy, 1988). In economic theory, once a habit is formed for the consumption of a particular product, consumers become less sensitive to economic concerns such as product price (Becker, Grossman, and Murphy, 1994; Heien and Durham, 1991; Dynan, 2000).

In general, economic theories argue that the reason a habit is formed is that past behavior increases the marginal utility of current and future repetitions of the same behavior (Pollak, 1970; Becker and Murphy, 1988). Thus, past behavior can stimulate behavior in the current time period. For example, consumption of cigarettes is a type of habit forming behavior. Although cigarettes are harmful, if the marginal utility of current consumption is increased (by past consumption) to a greater degree than the marginal harm from consumption, greater past consumption of cigarettes will stimulate current consumption (Heien and Durham, 1991). We leverage this insight in identifying the habit formation process in this study.

Hypothesis Development

Habit formation has two unique features (Verplanken and Orbell, 2003). The first feature of habit formation is that habit is formed through a history of repetition and is self-reinforcing. The more frequently people repeat a behavior, the more likely that behavior becomes habitual (Ajzen, 2001; Ronis, Yates, and Kirscht, 1989; Verplanken and Aarts, 1999). This self-reinforcing process of habit formation is driven by the underlying learning processes in both benefit recognition and cost reduction. In the context of online communities, members learn from their past contributions and become more familiar with the community and its members. As a result, he is better able to identify common values and synergies between him and other members of the communities. This allows him to obtain higher benefits from his participation in the community in the form of higher status, reputation or social identity. Past participation in the online communities also help the member to find more efficient ways to obtain information from and interact with other community members, thus reducing the participation costs. These learning processes enable a positive association between past behavior and future behavior in the habit formation process.

An important implication of the habit formation process is that the relationship between past repeated actions and future actions is not linear. Habit effect is stronger for frequently-practiced behaviors than for less-practiced behaviors (Quellette and Wood 1998). This is because frequently-practiced behaviors make the processes that control for such behaviors automatic, while less-practiced behaviors require conscious decisions. The self-reinforcing nature of habit formation indicates a curve-linear relationship between past behavior and current behavior. An individual's past behavior becomes more predict of his or her future behavior as he gradually develops

habit. The role of previous behavior in predicting future behavior has been considered in a variety of contexts (Verplanken and Orbell 2003). For example, Becker et al. (1994) studies habit formation among smokers and show that, once people are addicted to smoking, their past level of cigarette consumption significantly predict their future cigarette consumption. That is, individuals with higher number of repeated behaviors in the past are much more likely to continue the pattern than those with lower number of repeated behaviors.

We therefore propose:

Hypothesis 1*: There is a significant curve-linear relationship between past and current posting behavior in virtual communities. The more a community member posted in the past, the more likely his past postings will predict his number of postings in the current time.*

The second feature of habit formation is that individual behavior becomes less influenced by social and economic concerns as they form habit. In the context of virtual communities, prior studies have suggested that community resource, reciprocity and competition are the mainly factors that influence individual participations.

Community resource can have a significant impact on community members' decisions to participate. Members are a primary form of resources in online communities (Butler 2001). A participant is more likely to locate information, obtain recognition, status and other benefits in large communities. As such, individuals are more interested in participation in large communities (e.g. Gu et al. 2007). However, habit formation could have a negative moderating effect on the influence of community resource. As participations become automatic, individuals make fewer conscious participation decisions and are thus less influenced by the availability or the lack of community resource.

We therefore propose:

Hypothesis 2: *Habit formation weakens the influence of community size on individual contribution in virtual communities.*

Another main motivating factor for individual participation in virtual communities is the desire to reciprocate. Blau (1964) suggests that the norm of reciprocity commonly occur in social interactions. Individuals who receive benefits or gifts from others feel obligated to repay the benefits. This obligation could be directed towards to original giver in the case of direct exchange or to the society in general in the case of generalized exchange. In virtual communities, individuals obtain benefits from others by asking questions and receiving answers. As such, social exchange theory suggests that individuals who have asked more questions will be more motivated to contribute to the communities in later periods. Habit formation, however, could negatively moderate the relationship between benefits received in the past and contribution in the current period. This is again because participation decisions are more likely to be automatic as an individual forms habit and such decisions are less influenced by social and economic concerns.

We therefore propose:

Hypothesis 3: *Habit formation weakens the influence of number of questions asked by an individual in the past and his future contribution in virtual communities.*

Individual participation in virtual communities is also influenced by economic concerns (Krishnan et al. 2003). Public good theory suggests that individuals are more likely to free ride in a community with a high contribution level than in a community with a low contribution level. This is because the marginal benefits of contribution are lower in a community with many community members compete for recognition and attention. Therefore, the level of community participation is negatively associated with an individual's contribution level. However, as we explained earlier, habit formation makes participation decisions automatic and, as a result, reduces the influence of the community participation level.

We therefore propose:

Hypothesis 4: *Habit formation weakens the influence of community contribution level on individual contributions in virtual communities.*

To encourage individual contributions, an increasing number of virtual communities bestow titles on members based on their contribution level. However, how such titles influence individual participation is not well-understood. In particular, these titles are often permanent, i.e. an individual never loses a title once he obtains it. What motivates individuals to continue contributing to the community after obtaining the title? The theory on habit formation offers

an explanation. Titles could be used to encourage repeated contributions and entice habit formation among users. After individuals receive the titles, they continue to make contributions because of habit. Therefore, the habit effect is likely to be stronger among high ranking members.

We therefore propose:

Hypothesis 5: *Habit effects are stronger among highly-ranked members than among low-ranked members.*

Data and Empirical Model

Our empirical context is an online technical support community hosted by Dell Inc. The community enables Dell product users to exchange information about their experiences using Dell products and solve technical problems among themselves. Dell technical support community consists of 115 discussion boards. Each discussion board focuses on a specific product category, so that members can easily find topics they are interested in. Discussion boards vary significantly in size, ranging from 2 members to 4,177 members. Figure 1 shows the distribution of membership size across all discussion boards. By analyzing user participations in these discussion boards, we are able to identify the habit formation process and how habit moderates the influence of social and economic concerns on individual contributions to virtual communities.

Figure 1 Membership Distribution across Discussion Boards
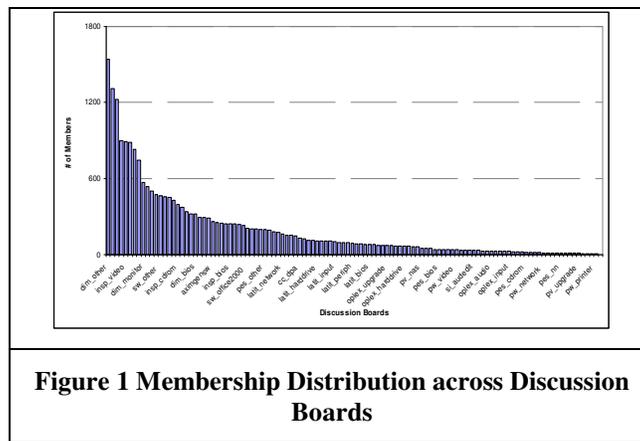
In order to determine if habit effect exists in members' participation behavior and how strong that effect is, it is necessary to follow community members' posting behavior for a sufficient long time period. The time window we selected is from Jan 1, 2005 to June 29, 2005. During this period, we recorded every posting of 236,958 distinct members. The panel data allow us to not only identify differences across community members but also changes in each individual member's behavior over time. Besides posting records, information in this daily panel data includes message ID, board ID, members' identification numbers, members' ranks, the order of each posting, total number of postings for a given message thread, posted date and time of each posting, and registration date of each member and the cumulative number of postings by each member. Table 1 shows the summary statistics of the key variables used in this study.

Dependent Variable

We use the total number of answers provided by each member in a given week as the dependent variable. We use weekly contribution data instead of daily because individual behavior varies within a week due to factors unobserved by researchers. Some individuals are more active during weekdays while others are more active during weekends. Aggregating individual contributions to a weekly basis controls for the variation.

Independent Variables

Habit Stock: To identify the level of habit formation of each individual, we develop a measure of habit stock using weighted-average of the individual's contribution levels in the past. The weight is higher for more recent contributions and lower for older contributions. We use a recursive weighted average approach to measure habit stock:

$$HabitStock_{it} = \alpha \times HabitStock_{it-1} + (1 - \alpha) \times Contribution_{it-1}$$

α in the above equation controls for the speed of the updating process in calculating habit stock. Higher α indicates that habit stock is heavily influenced by recent contributions while lower α indicates that old contributions could have a long lasting influence on habit formation. In this study, we choose α to be 0.5. Unreported analysis indicates that our result is not sensitive to the choice of α level.

Number of questions: The number of questions is counted for each member each week. One caveat is that we do not read each posting to determine whether it is a question or an answer due to the large data set. Instead, we leverage the thread structure in virtual communities and count the initial posting in each discussion thread as questions. This is because community members mostly initiate a new thread to ask for help. If a member initiates a large number of questions, it indicates that he or she relies heavily on the community to find help. Social exchange theory suggests that individuals are more likely to contribute in such a situation.

Table 1. Descriptive Statistics				
Variables	Mean	Std. Dev.	Min	Max
Ln(HabitStock)	0.20	0.49	0.00	5.89
Ln(#Questions)	0.03	0.15	0.00	2.48
Ln(ParticipationRate)	4.34	1.32	-0.69	6.19
Ln(#CommunitySize)	3.49	0.97	0.69	5.10
Bronze	0.85	0.36	0.00	1.00
Silver	0.08	0.28	0.00	1.00
Gold	0.04	0.20	0.00	1.00
Platinum	0.01	0.09	0.00	1.00
Diamond	0.02	0.12	0.00	1.00

Participation rate: We calculate participation rate of a virtual community as the total number of responses in the virtual community divided by the total number of questions posted. The rate reflects the level of contribution in the community and whether members are willing to contribute. Public good theory suggests that individuals are more likely to free ride in community with higher participation rate.

Community size: We measure community resource using number of active members in each discussion board for each week. Member size is a measure of resource availability. Participation benefits a member more in larger online communities in the form of faster response time and higher level of reputation and recognition (Haveman, 1993; McPherson, 1983; Rafaeli and LaRose, 1993).

Rank: A community member's rank is assigned by the online community based on his or her cumulative number of postings. The rank of a member is shown clearly below the member's user name in every posting and indicates a member's status in the community. The Dell technical support community provides five levels of ranks: bronze, silver, gold, platinum and diamond.

Table 1 shows that members ranked "Bronze" (the lowest rank) dominate the entire pool of members. They account for about 85% of total members. "Silver" members account for about 8% of total members, while "Gold", "Platinum" and "Diamond" members account for 4%, 1% and 2% of total members respectively.

Individual Effect: Surveys show that a variety of motivations affect individuals' motivation to participate. Some individuals participate out of altruism, while others participate out of reputational gains. This suggests that there is significant heterogeneity across individuals. To control for such heterogeneity, we control for individual effect using both fixed effect and random effect. Fixed effect allows us to focus on changes in individual behaviors and identifies how habit formation influences the behavior changes, while random effect allows us to leverage cross-sectional differences among individuals. Our analysis shows that results are qualitatively the same in the two approaches.

Empirical Model

We start with a base model that assesses how an individual's past habit affects his current posting level.

$$ln(Postings_{it}) = \beta_0 + \beta_1 ln(HabitStock_{it}) + \beta_2 ln(HabitStock_{it}) \times ln(HabitStock_{it})$$
$$+\beta_3 ln(BoardSize_{it}) + \beta_4 ln(Questions_{it-1}) + \beta_5 ln(ParticipationRate_{it}) + \delta_i + \varepsilon_{it} \qquad (1)$$

In the above equation, the dependent variable is current period posting level and the independent variables are habit stock, the square term of habit stock, the size of the discussion board that the individual participates in, number of questions posted by the individual in the past week and the community participation rate. We also include individual fixed effect in the base model. The coefficients on habit formation and the square term of habit formation measures how previous experience of contribution influences an individual's current contribution level, i.e. the habit effect. The coefficient on the square term captures the non-linear relationship and assesses how the habit effect changes with a individual's habit level. Hypothesis 1 suggests that the coefficient is positive. The coefficient on board size measures how community resource influences individual contribution. Prior studies indicate the coefficient shall be positive. Similarly, the coefficients on the number of questions posted in previous period and community participation rate measures the influence of reciprocity and competition on individual contributions. Prior studies suggest that the two coefficients shall be positive and negative respectively.

We then expand base model to include the moderating effects of habit stock.

$$ln(Postings_{it}) = \beta_0 + \beta_2 ln(HabitStock_{it}) \times ln(HabitStock_{it})$$
$$+\beta_3 ln(BoardSize_{it}) + \beta_4 ln(Questions_{it-1}) + \beta_5 ln(ParticipationRate_{it})$$
$$+\beta_6 ln(BoardSize_{it}) \times ln(HabitStock_{it}) + \beta_7 ln(Questions_{it-1}) \times ln(HabitStock_{it})$$
$$+\beta_8 ln(ParticipationRate_{it}) \times ln(HabitStock_{it}) + \beta_9 Silver \times ln(HabitStock_{it})$$
$$+\beta_{10} Gold \times ln(HabitStock_{it}) + \beta_{11} Platinum \times ln(HabitStock_{it})$$
$$+\beta_{12} Diamond \times ln(HabitStock_{it}) + \delta_i + \varepsilon_{it} \qquad (2)$$

Equation (2) presents the full model that not only considers habit formation as a self-reinforcing process but also allows it to moderate the influence of social and economic concerns on individual contributions. The coefficient on the interaction term between discussion board size and habit stock measures the moderating effect on community resource. As the direct effect of community resource is positive, Hypothesis 2 indicates that the coefficient on the interaction terms will be negative as the influence of community resource weakens with habit formation. The coefficient on the interaction term between number of questions and habit stock captures the moderating effect on reciprocity. Since the direct effect of reciprocity is positive, Hypothesis 3 suggests that the coefficient on the interaction terms will be negative because reciprocity has less influence on individuals with habitual contribution. The coefficient on the interaction term between community participation rate and habit stock identifies the moderating effect on competition. As we mentioned earlier, the direct effect of competition is negative. Hypothesis 4 suggests that habit formation will reduce the influence of competition, therefore we expect the coefficient on the interaction term to be positive. Finally, Hypothesis 5 suggests habit effect is stronger among individuals with higher rankings. We therefore expect that the coefficients on high ranks to be larger than those on low ranks.

Column 1 and 2 in Table 2 reports the estimation results of equation (1) and (2) using fixed effect to control for individual heterogeneity.

Column 1 presents the result of the base model. The result shows that that the habit effect is curve-linear, indicates that individual with higher level of past contributions are much more likely to develop a habit of contribution in the future. This result is consistent with the prediction of Hypothesis 1. The result also reveals that for individuals with low habit stock, the influence of past contribution on future contribution is negative. This result suggests the presence of a threshold such that habit formation becomes self-reinforcing once the threshold is passed. The threshold can be calculated using the analysis result. Note that the coefficient on habit stock can be written as (-0.11 + 0.22 HabitStock). It is straightforward to show that the coefficient becomes positive once HabitStock exceeds 0.5, which is equivalent to a weekly posting of 0.5. That is, once an individual contributes more than 1 posting every two weeks, his contribution behavior will become self-reinforcing and start the habit formation process. Column 1 also suggests that the coefficients on the control variables for social and economic concerns are all significant and have the right signs.

Table 2. Habit Effect in Online Communities			
Variables	**Model with Habit Effects**	**Model with Habit and Moderating Effects**	**Model with Random Effects**
Ln(HabitStock)	-0.11*** (0.00)		
Ln(HabitStock) * Bronze		-0.21*** (0.00)	-0.21*** (0.00)
Ln(HabitStock) * Silver		0.03*** (0.01)	0.07*** (0.01)
Ln(HabitStock) * Gold		0.08*** (0.00)	0.14*** (0.00)
Ln(HabitStock) * Platinum		0.12*** (0.00)	0.20*** (0.00)
Ln(HabitStock) * Diamond		0.15*** (0.00)	0.17*** (0.00)
Ln(HabitStock)^2	0.20*** (0.00)	0.13*** (0.00)	0.13*** (0.00)
Ln(#Questions)	0.09*** (0.00)	0.29*** (0.01)	0.27*** (0.01)
Ln(ParticipationRate)	-0.13*** (0.00)	-0.15*** (0.00)	-0.11*** (0.00)
Ln(CommunitySize)	0.19*** (0.00)	0.20*** (0.00)	0.15*** (0.00)
Ln(HabitStock) * Ln(#Questions)		-0.16*** (0.00)	-0.16*** (0.00)
Ln(HabitStock) * Ln(ResponseRate)		0.06*** (0.00)	0.04*** (0.00)
Ln(HabitStock) * Ln(BoardSize)		-0.05*** (0.00)	-0.04*** (0.00)
Model for Individual Effect	Fixed Effect	Fixed Effect	Random Effect
Number of Observations	300,534	300,534	300,534
R-square (McFadden's Pseudo R-square)	47.36%	49.18%	66.04%

Column 2 presents the result of the full model. The result again shows that the habit effect is self-reinforcing once passing a certain threshold. Moreover, the analysis reveals that habit formation has significant moderating effects on the influence of community resource, reciprocity and competition. Consistent with our hypotheses, the direction of the moderating effects indicates that habit formation weakens the influence of social and economic concerns on individual contribution in virtual communities. Finally, the results in Column 2 reveal that habit effect is much stronger among high rank members, particularly among Diamond, Platinum and Gold members.

Column 3 in Table 2 re-analyzes Equation (2) using random effects to model individual heterogeneity across community members. The benefit of using a random effect model is that we can leverage cross-sectional variations to enhance the analysis. The results in Column 3 are essentially the same as those from the fixed effect model in Column 2. This indicates that our results are robust across different empirical settings.

Discussion and Limitation

The primary objective of this paper is to examine habit formation in online community participation and how habit formation moderates the influence of social and economic concerns on individual participation. Others have recognized the important role of routinized or automated IT use that occurs with little conscious effort (e.g., Limaeym et al 2007; Limayem and Moez 2008; Wu and Kuo 2008). Habit has also been recognized to play an important role in online communities (e.g., Dholakia et al 2004, Shah 2006). Prior studies suggest that habitual participation helps sustain the viability of an online community. We build on this work and focus on how habit is formed in online communities. We show that the habit formation process has two distinct characteristics. First, it is a self-reinforcing process. In the beginning of habit formation process, past participation has little influence on an individual's future participation. But as the individual becomes more involved in the community, participation becomes increasingly automatic and habit effect strengthens. This self-reinforcing nature of habit formation indicates the presence of a threshold. Once a sufficient number of repetitions are reached, the participation habit can be formed. We show the threshold is surprising low, at about 0.50 contributions per week. The identification of the threshold could help businesses optimize the design of online communities. For example, online community operators may consider providing reputational or economic incentives to members for biweekly contribution to encourage habit formation. This study also shows that habit formation significantly weakens the influence of social and economic concerns as participation becomes more automatic. We also show that habit effect is stronger for high ranking members.

Our analysis provides insights to both business practitioners and academic researchers. For a practical perspective, our results allow online community operators to have a better understanding of habit formation process and develop business strategies to encourage habit formation among their members. These strategies could include providing reputation status to individual members to facilitate habit formation. From a research perspective, we highlight that many participation decisions in online communities may not be due to deliberate decisions. Rather, individuals form habit over time and once the habit is formed participation decisions become automatic. This is especially true for the core group members of online communities that frequently contribute to the community.

We conclude by highlighting some of the limitations of the study. This paper only considers the positive impact of habit on continued participation in the community. Others (e.g., Verplanken and Aarts 1999) have noted that habitual routines can promote rigidity and resistance to change as the stability of the context decreases. Online communities are inherently fluid as contributors come and go unpredictably. Future research should examine habit formation in fluid online communities. The current study is unable to report on the underlying motivations of community members. While we infer the learning and habit formation process from their posting behavior, we cannot identify and measure the social-psychological processes that allow members to convert motivation into habits. Future research should combine the longitudinal analysis of postings with a survey method. The detailed text content of each posting is not available in the data set. Only the number of postings and the order of those postings in a message string were recorded, not the content of those postings. We encourage future researchers to consider careful analysis of posting contents to provide more insights into the habit formation process. Finally, the empirical context of this research is an online community hosted and sponsored by an IT company. Generalization of findings to other type of online community needs to be addressed in future studies.

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