Status versus Reputation as Motivation in Online Communities

Morena Rivato
Aarhus University
mor@mgmt.au.dk

Michael A. Zaggl
Aarhus University
zaggl@mgmt.au.dk

Abstract

The continued active participation of contributors is crucial for online knowledge exchange communities. In many communities, virtual credit scores measure contributions and play a pivotal role in motivating active participation over time. We use status theory to characterize virtual credit as a double-edged sword to participation dynamics. We hypothesize that virtual scores reflect status rather than reputation and produce a non-linear effect by motivating contributions when participants are of low status but demotivating participants once they achieve high status. We test our theorizing on a dataset of a large Q&A community. Consistent with our hypotheses, we find robust evidence that status-seeking is a positive source of motivation but self-depletes, meaning that cumulating status in the community reduces the motivational drive of status-seeking. This study contributes to the literature on the motivations to participate in voluntary online knowledge exchange communities by offering an explanation of the dynamics of continued active participation.

Keywords: Crowdsourced knowledge, Motivation, Status, Continued participation, Reputation.

1. Introduction

Crowdsourced knowledge production and exchange are critical sources for innovation and knowledge growth (e.g., Majchrzak & Malhotra, 2013; Majchrzak, Malhotra, & Zaggl, 2021). The motivation to voluntarily spend time and effort to help strangers in online knowledge exchange communities has received much attention from scholars (e.g., Ye & Kankanhalli, 2017; Erden, Von Krogh, & Kim, 2012). This literature has provided deep insights into why participants contribute (e.g., Von Krogh, Haefliger, Spaeth, & Wallin, 2012; Roberts, Hann, & Slaughter, 2006; Ke & Zhang, 2010). However, this literature implicitly characterizes participants' motivations as static (Ke et al., 2010; Roberts et al., 2006) without accounting for the fluctuations in the degree of participation over time (Goes, Guo, & Lin, 2016).

Many crowdsourcing communities struggle with retaining their contributors and experience declines in participation over time (Simonite, 2013). For example, the number of Wikipedia contributors has declined since it peaked in Mach 2007 (Halfaker, Geiger, Morgan, & Riedl, 2013). Other platforms, such as Friendster and MySpace, disintegrated entirely. Thus, there is a theoretical need to account for the dynamics in motivations.

Much of the motivation to actively participate in online exchange builds on virtual scores, which reflect the quality and quantity of contributions (Lee, Park, & Zaggl, 2022; Xu, Nian, & Cabral, 2020). Participants can contribute by answering or asking questions. Voting mechanisms make the credit systems more sophisticated. The resulting accumulated scores are publicly visible. Most of the literature characterizes this accumulated score as reputation (Wasko & Faraj, 2005; Dellarocas, 2003, 2005; Bolton, Katok, & Ockenfels, 2004; Lee et al., 2022; Xu et al., 2020), a form of information that indicates an actor's future behavior from the present behavior (Raub & Weesie, 1990). This definition predicts the continuation of past behaviors and performance (Pollock, Lee, Jin, & Lashley, 2015; Kim & King, 2014): if a crowd participant contributes today, her active participation in the future is more likely. This continuity allows participants to benefit from their credit scores, for example, by signaling their skills to potential employers (Lee et al., 2022; Xu et al., 2020).

However, in contrast to reputation, the notion of status characterizes virtual credit scores differently. Status is the relative standing of an individual within a social hierarchy (Sauder, Lynn, & Podolny, 2012; Thye, 2000; Berger, Cohen, & Zelditch Jr, 1972); it reflects the degree to which an individual is admired and respected by others (Magee & Galinsky, 2008). Besides psychological and emotional reasons, people often seek higher status to gain economic and social advantages (Merton, 1988; Roberts et al., 2006). However, participants reduce effort as soon as they achieve status (Merton, 1988; Bothner, Kim, & Smith, 2012), the payoffs from further contributions decline dramatically, and participations may "resting on their laurels." Thus, the status theory describes the discontinuation of

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continued active participation once the contributor reaches a certain status, explaining a non-linear, dynamic contribution behavior over time. Meanwhile, the reputation theory describes the continuation of past performance and behaviors and thus predicts a linearly increasing contribution behavior (Pollock et al., 2015; Kim et el., 2014).

In order to shed more light on motivations in online crowds and account for the observed dynamics, we pose the research question: Does the notion of status better than the notion of reputation account for continued active participation in online knowledge exchange communities? Based on status theory, we expect a dynamic contribution behavior of participants. Specifically, we hypothesize that crowd participants are positively motivated when receiving virtual credit for their contributions. However, cumulating virtual credit reduces the probability of future active participation.

We test our hypotheses on a longitudinal dataset of 8678 participants in a crowd-based knowledge exchange community over more than seven years. We focus on the participants' answers posted as responses to questions in the User Experience community in Stack Exchange. Consistent with our hypotheses, virtual credit encourages continued active participation while negative credits have a detrimental effect. Moreover, cumulative virtual credit scores reduce the motivational source of status-seeking.

Our paper contributes to the literature on motivation in crowds and online communities by offering an explanation accounting for the dynamics of continued active participation. We also add conceptual clarity by differentiating between reputation and status (Smirnova, Reitzig, & Sorenson, 2022; Lampel & Bhalla, 2007; Wasko et al., 2005).

2. Theoretical Background and Hypotheses Formulation

2.1. The Notion of Reputation

Reputation is a widespread concept relevant in many social interactions. It can be defined as a form of information to reduce incomplete information about an actor. Indeed, reputation indicates the future behavior of an actor by inferring from her past behavior. An actor develops a reputation, for example, for being honest (Greif, 1989), aggressive (Kreps & Wilson, 1982), or erratic (Kim et al., 2014). Individuals acquire reputation through desired behavior. In behaving consistently in the desired way, for example, being honest, paying back debt in time, etc., the actor builds a positive reputation that allows others to extrapolate this desired behavior into the future (Greif, 1989). The opposite behavior builds a negative reputation. Thus, the concept of reputation anchors on the continuation of past performance and behavior (Pollock et al., 2015; Kim et al., 2014) because consistent behavior at every interaction is a requirement to sustain reputation (Pollock et al., 2015). Since its origins, the reputation mechanism establishes trust and reciprocal benefits in the context of asymmetric information distinguishing reliable individuals within a community based on past conduct (Greif, 1989).

The notion of reputation is rooted in economics, in particular, in the context of markets with asymmetric information, for example, in medieval trade guilds (Greif, 1989) and online trade, such as eBay (Bolton et al., 2004; Dellarocas, 2003, 2005) or on labor markets and higher education (Arrow, 1973). Products can also have a reputation; the concept of reputation, however, is usually associated with the actor (e.g., Rao, 1994).

Holders of a desirable reputation, such as honesty and reliability, have advantages in initiating partnerships and enabling business transactions (Greif, 1989). A satisfied customer will spread positive word of mouth or leave a positive rating in a digital context (Bolton et al., 2004; Dellarocas, 2003, 2005), promoting the seller's positive reputation, which reduces the information asymmetry of future potential buyers, increasing the likelihood that they become actual buyers. From the perspective of the potential customers, reputation—whether good or bad (honest or dishonest)—makes the behavior more predictable. This predictability will expose the reputation holder to opportunities unavailable for those actors without a positive reputation. In few words, reputation helps the reputation holder to be selected by others. The same applies to overcoming information asymmetries about actors' qualities.

Similarly, in hiring decisions, certificates and diplomas represent signals indicating the underlying qualities of the actor (Arrow, 1973). The owners of these certificates benefit from being selected by recruiters. Thus, reputation helps overcome moral hazards and adverse selection problems by making reputation holders selectable by others and increasing the opportunities to engage in desirable interactions.

Besides markets with asymmetric information, the notion of reputation is also critical in public goods and game theory (Milinski, Semmann, & Krambeck, 2002). Here, reputation is less about overcoming information asymmetries, but it essentially has the role of projecting past behavior into future behavior. An actor's reputation reflects mainly on whether she cooperated or defected in past interactions as an indication of future cooperation. Thus, reputation sustains cooperation in public goods, where resources are free and object to overutilization and free ride (Milinski et al., 2002).

Individuals with a positive reputation for contributing to the common good receive exclusive incentives, such as recognition, from their peers. In turn, the peers acquire a reputation for themselves if they contribute, risking losing it if they free ride (Ostrom, 2000). This indirect reciprocity (Alexander, 2017) enables cooperation between strangers and promotes consistent support for the future benefits of all participants (Bolton et al., 2004; Dellarocas, 2003).

2.2. Reputation in Online Knowledge Exchange

In online knowledge exchange communities, reputation represents a fundamental element of the motivation to contribute. Online knowledge exchange communities resemble public goods, and as in the game-theoretic reasoning mentioned, reputation takes a central role in this context. The online context makes it even easier for the reputation to fulfill its role as an information source about prior contribution behaviors. In online communities, it is possible to use virtual credit scores, which can be obtained from peers' assessments and voting on the contributions. The online context has the advantage of making reputation explicit, while in most offline settings, reputation is implicit. In offline contexts, actors who inform their behavior on the reputations of others need to keep track of the behavior of these others (Zaggl, 2017).

Thus, it is not surprising that reputation is fundamental in motivating knowledge contributions in online communities. Signaling in job-market situations utilizes actors' reputations to enable them to find (better) jobs, and participants contribute knowledge to signal their skills to potential recruiters (Lee et al., 2022; Xu et al., 2020). Other sources of motivation also depend on reputation, such as reciprocity (Zeitlyn, 2003) or recognition and acknowledgment inside the community (Lampel et al., 2007; Wasko et al., 2005).

In our empirical context, different forms of sources of virtual credit are possible. The platform allows the poster of a question to select the answer that best replies to the question. It is also possible for all other crowd participants to vote on answers; they can cast positive and negative votes. Figure 1 provides an overview of our research model.

Consistent with the concept of reputation, we predict that positive score allocations motivate participants and increase their continued active participation in the community. In specific, we pose the following hypotheses:

Hypothesis 1a (H1a): Positive virtual scores from the knowledge seeker are positively related to the knowledge contributor's answer recurrence.

Hypothesis 1b (H1b): Positive virtual scores from the community peers are positively related to the knowledge contributor's answer recurrence.

Hypothesis 1c (H1c): Negative virtual scores from the community are negatively related to the knowledge contributor's answer recurrence.

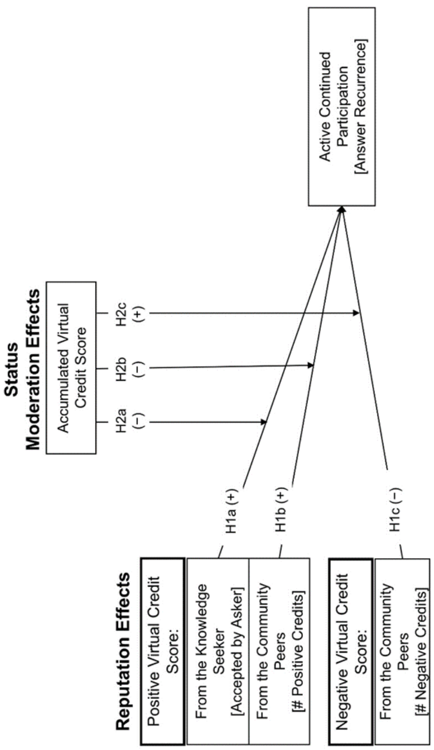

Figure 1. Research model.

2.3. The Notion of Status

Status describes the social position or standing of actors (Podolny, 1993; Magee et al., 2008; Sauder et al., 2012). It reflects the degree to which an actor is admired and respected by others (Magee et al., 2008). Individuals can achieve status in different ways, for example, by group membership (e.g., occupation) (Berger, Rosenholtz, & Zelditch Jr, 1980) or social ties (e.g., connections with high-status actors) (Sauder et al., 2012), or ownership of status symbols (Thye, 2000). Moreover, voluntary donations to charity and unchangeable demographic traits such as sex, race, age, and beauty can spur status (Webster Jr & Hysom, 1998).

The status grants distinct benefits to the status owner. High-status suppliers can charge higher prices (Roberts, Khaire, & Rider, 2011) and more easily attract business partners (Podolny, 1993). High-status researchers attract over-proportional attention (Merton, 1988) and referees judge high-status athletes more leniently (Kim et al., 2014). To mobilize such benefits, actors strive to increase status (Anderson, Hildreth, & Howland, 2015).

Status and reputation are similar and often used interchangeably, although inherently different (Sorenson, 2014). The lack of a clear distinction is rooted in the fact that the two notions have emerged and developed independently in diverse research traditions but often describe similar or overlapping phenomena. The term status is predominantly used in sociology, while reputation is a concept originating in economics. As reputation, status is a socially constructed concept that allows discrimination between actors (Sauder et al., 2012; Gould, 2002). Status owners, like reputation owners, benefit from it in their social interactions, such as in market transactions. Also, status and reputation are interrelated, and reputation can fertilize status.

However, the main difference between status and reputation is that status reflects a position in a social hierarchy, while reputation reflects past behavior used to indicate future behavior (Sorenson, 2014; Kim et al., 2014). Another distinction between status and reputation is in the "stickiness" of status ordering; once achieved a certain standing in the hierarchy, in the event of changes in the level of performance or behavior, there is a slower change in status compared with the individual's reputation. Because status is conferred socially by the community members, there can be a distorted relationship between individual performance and objective quality (Gould, 2002; Meservy, Fadel, Kirwan, & Meservy, 2019). High-status contributors get more attention and credit than their low-status counterparts, independently of the quality of their contributions (Kim et al., 2014; Meservy, Jensen, & Fadel, 2014). Furthermore, high status can erode performance due to complacency and the self-satisfaction it yields (Bothner et al., 2012).

Empirical evidence from prior studies in online communities shows that achieved status impacts continued participation differently over time. In a public goods setting, where contributions are voluntary and object to free-ride from other community members, tools promoting participant recognition and social standing are necessary to create exclusive incentives for those participating actively in the community. However, the effectiveness of these virtual credit scores changes as the involvement with the community progress. New members may value first-time recognition since it raises their confidence and self-esteem (Lampel et al., 2007), while repeated same-status accreditation can trigger saturation and a decline in participation (Bhattacharyya, Banerjee, Bose, & Kankanhalli, 2020). The ever-increasing effort required to reach the higher ranks can decrease participation, especially for contributors driven by social standing rather than hedonistic motives (Goes et al., 2016). And high-status members may feel justified in resting on their laurels since they have already proven their value and efforts (Bothner et al., 2012).

Building on status theory, we pose the following moderating hypotheses:

Hypothesis 2a (H2a): A contributor's accumulated virtual score moderates the relationship of positive virtual scores from the knowledge seeker on the contributor's answer recurrence in the way that a higher accumulated virtual score reduces the positive effect of positive credits.

Hypothesis 2b (H2b): A contributor's accumulated score moderates the relationship of positive credits from the community peers on the contributor's continued answer recurrence in the way that a higher accumulated virtual score reduces the positive effect of positive credits.

Hypothesis 2c (H2c): A contributor's accumulated score moderates the relationship of negative credits from the community on the contributor's answer recurrence in the way that a higher accumulated virtual score reduces the negative effect of negative credits.

These hypotheses claim that higher accumulated scores, which imply a better standing of the contributor within the community, reduce the motivation for continued active participation. By contrast, the notion of reputation would predict a positive, self-reinforcing, or at last neutral effect by the accumulated virtual score.

3. Dataset and Method

3.1. Research Context

Our research context is the User Experience[1] community in Stack Exchange[2]. Stack Exchange is a crowd-based question-and-answer website hosting different communities with a large variety of topics, such as programming languages and photography. Each member can voluntarily ask or answer questions without financial compensation in return. In the User Experience community, participants are interested in software development that yields seamless and enjoyable experiences for the user. The members can ask questions to solve their technical issues within the field or answer questions to share their knowledge to help others.

Stack Exchange is a suitable empirical setting for our investigation since it has a sophisticated virtual credits system to motivate and regulate the behavior of the members of the community. In particular, knowledge contributions can get positive credits from peers if the

[1] https://ux.stackexchange.com/

[2] https://stackexchange.com/

answer is valuable or negative credits otherwise. In addition, the originator of a question (asker) can accredit an answer as the best answer given. These credits allocate score points, and the accumulated score signals the expertise and the trust gained from the peers.

For our investigation, we collected the complete dataset from the launch of the User Experience community on January 3, 2012, to December 31, 2018. We consider all registered participants (an account is needed to participate) that posted at least one answer and revisited the community later. For each knowledge contributor, we disregard all the answers beyond the fourth due to the dramatic decrease in the number of participants that contributed more than four answers. The final dataset contains 17,305 answers posted by 8,678 participants.

3.2. Variables

Table 1 gives an overview of the variables used. Our dependent variable is answer recurrence, the chance that the participant posts another answer. This operationalization matches our definition of a participant's active continued participation in the community.

The independent variables reflect the following activities: (1) The number of positive credits is the count of positive points that other community participants assigned to an answer within three months after posting the answer. Since this variable is highly skewed, we applied a logarithm transformation. (2) The number of negative credits is the count of negative points that other community participants assigned to an answer within three months after posting the answer. This variable is also log-transformed because of skewness. (3) The answer accepted by the asker is a dummy variable. As an originator of a question, it is possible to accredit one answer at a time with a green checkmark indicating that this is the best answer received within three months after posting the answer.

Table 1. Variable description.

Variable type	Variable name	Description
Dependent Variable	Answer Recurrence	Answer posting by a participant to a question in the community.
Independent Variables	# Positive Credits	The number of positive credits the focal answer received within three months from posting from the community peers.
Independent Variables	# Negative Credits	The number of negative credits the focal answer received within three months from posting from the community peers.
Independent Variables	Accepted by Asker	Dummy variable for whether the asker accredit the focal answer as the best answer within three months from posting.
Moderator Variable	Accumulated Score	The participant accumulated score at the time of the focal answer.
Control Variables	Accumulated Score	The participant accumulated score at the time of the focal answer.
Control Variables	Tenure UX	The number of months between the participant registration to the User Experience community and the focal answer.
Control Variables	Tenure SE	The number of months between the participant registration in one of the Stack Exchange communities and the focal answer.
Control Variables	Word Count	The number of words in the answer posted.
Control Variables	Year	The year of the answer.
Control Variables	Weekday	Dummy variable for the focal answer if on a weekday or a weekend.

The moderator variable is the accumulated credit score that accounts for the status of a participant within the context of User Experience at the time of the focal answer. To account for skewness, we applied the logarithm.

We use multiple control variables for the confounding effects that may influence the propensity of the contributor to answer. Most importantly, we control for participants' individual experiences within the online knowledge exchange community, and we consider three variables: *Accumulated Score, Tenure UX,* and *Tenure SE.* The *Accumulated Score* accounts for the community-recognized expertise of the participant by the User Experience members at the time of the focal answer. *Tenure UX* represents the experience within the User Experience community as the number of months since the participant joined the User Experience community and the focal answer. *Tenure SE* considers the transferable knowledge over how Stack Exchange works considering the number of months since the participant joined any Stack Exchange communities, including the User Experience community, and the focal answer. We also accounted for the number of words written in the answer since they represent individual style and behavior. We apply a logarithm transformation to *Word Count* to manage skewness. Next, we account for changes over time in the amount of activity in the community using the year and distinguishing between weekdays and weekends of the answer's posting since participants have different contribution behaviors over time (Xu et al., 2020). Furthermore, the year dummy variable allows us to control for time-fixed effects in our model.

Finally, we add robust standard errors clustered at the participant level. Tables 2 and 3 show the descriptive statistics and the correlation between the variables after the dataset truncation beyond the participant's fourth answer.

Table 2. Descriptive statistics.

Variables	N.	Mean	Median	S.D.	Min	Max
Answer Recurrence	17305	1.889	1	1.055	1	4
# Positive Credits	17305	2.559	1	9.057	0	264
# Negative Credits	17305	0.098	0	0.459	0	12
Accepted by Asker	17305	-	-	-	0	1
Accumulated Score	17305	65.08	11	129.479	1	2358
Tenure UX	17305	6.552	1	12.2555	0	88
Tenure SE	17305	22.21	16	22.645	0	122
Word Count	17250	119.7	93	102.1171	0	1800
Year	17305	-	-	-	2012	2018
Weekday	17305	-	-	-	0	1

Table 3. Pairwise correlations.

Variables	1	2	3	4	5	6	7
1. # Positive Credits							
2. # Negative Credits	0.20 ***						
3. Accepted by Asker	0.11 ***	-0.04 ***					
4. Accumulated Score	0.09 ***	0.00	0.03 ***				
5. Tenure UX	0.07 ***	-0.01	0.00	0.33 ***			
6. Tenure SE	0.09 ***	0.02 *	0.01	0.26 ***	0.58 ***		
7. Word Count	0.05 ***	-0.06 ***	0.08 ***	0.06 ***	0.03 ***	0.04 ***	
8. Year	0.01	0.02 **	-0.01	0.01	0.27 ***	0.30 ***	-0.03 ***
9. Weekday	0.02 **	0.00	-0.01	0.00	0.00	-0.01 +	-0.04 ***

3.3. Estimation Model

We build on an extension of Cox's proportional hazard model (Cox, 1972) with adjusted variance to account for intra-subject correlation that arises from recurrent events in survival analysis. Specifically, in our context, every participant can post more than one answer, so we use the Prentice-Williams-Peterson conditional risk sets method to estimate the coefficients. We order the recurrence of each answer posting from each subject based on their start and end times (Prentice, Williams, & Peterson, 1981; Thenmozhi, Jeyaseelan, Jeyaseelan, Isaac, & Vedantam, 2019).

$$\lambda_{ik} = \lambda_0(t - t_{k-1})\exp\left(\sum_{z=1}^{3}\beta_{z,k}V_{z,i}(t) + \sum_{z=1}^{6}\theta_{z,k}W_{z,i}(t)\right) \quad (1)$$

Model (1) estimates the conditional risk set of continued active participation with the assumption of process renewal at each recurrence of an answer. Thus, the chance of the following answer posting is estimated only based on the information about the participant's immediately preceding answer posting. In addition, participant *i* is in the risk set for the *k*th answer only if they experience the *k*th-1 recurrence. When the influence of the measured effects may vary from event to event or when the interest lies in predicting the next event, we use this event-specific estimation method (Amorim & Cai, 2015). In detail, $\lambda_{ik}(t)$ denotes the chance of answer recurrence for the *i*th participant on her *k*th answer. $\lambda_0(t - t_{k-1})$ is the baseline chance of answer recurrence at the *kt*h answer posted calculated based on the pool of participants with *k*th answers posted who have the chance to write the successive one. $V_{z,i}$ represents one of the three independent variables *(# Positive Credits*, *# Negative Credits*, and *Accepted by Asker*), and $W_{z,i}(t)$ represents the control variables (*Accumulated Score*, *Tenure UX*, *Tenure SE*, *Word Count*, *Year*, and *Weekday*) specific for each answer posted. The coefficients $\beta_{1,k}$ through $\beta_{3,k}$ are the effects of interest since they address H1a, H1b, and H1c.

To address the moderator effects of status on the relationship between virtual credits and answer recurrence, we calculate the extended event-specific Cox model as follows (2). $M_i(t)$ represents the moderator (*Accumulated Score*). $\delta_{1,k}$ through $\delta_{3,k}$ are the coefficients of interest since they are relevant to answer H2a, H2b, and H2c.

$$\lambda_{ik} = \lambda_0(t - t_{k-1})\exp\begin{pmatrix}\sum_{z=1}^{3}\beta_{z,k}V_{z,i}(t) + \\ \sum_{z=1}^{3}\delta_{z,k}\left(V_{z,i} \times M_i(t)\right) + \\ \sum_{x=1}^{6}\theta_{x,k}W_{x,i}(t)\end{pmatrix} \quad (2)$$

4. Results

4.1. Hypothesis Testing

Table 4 reports the hazard ratio estimates from the extended Cox model. Hazard ratio estimates with a coefficient greater than 1 indicate a higher probability of continued active participation, while a coefficient smaller than 1 indicates a reduced chance of continued active participation. The results support H1a, H1b, and H1c.

Model 1 shows the relationship between the participants' continued participation and the (log) quantity of credits received within three months since the answer posting. *Accepted by Asker* has a significant positive impact on answer recurrence. Thus, if the immediately preceding answer, from a participant in the *k*th answer given, is accepted by the originator, we have an increase in continued participation by 21% (HR=1.209) compared to another contributor at the same *k*th answer recurrence without the preceding answer accepted, all the rest equal. Furthermore, the chance of answering again rises by 6% (HR=1.059) at every increase of one log unit in *# Positive Credits*.

Instead, the *# Negative Credits* have a detrimental effect on continued participation. It reduces by 22% (HR=0.776) the chance of answering again in the future, keeping all the other variables constant.

In Model 2, we add the quadratic relation to *# Positive Credits* since positive credits from peers represent the fastest way to accumulate score points between the available virtual credits mechanisms[3]. We find an increase in the positive effect of the number of positive credits for each increment of one log unit, equal to 19% (HR=1.187). Previously, this effect was lower due to the negative impact of the high number of positive credits an answer can get, depicted by the coefficient of the number of positive credits squared (HR=0.958).

Table 4. Credits effect on knowledge contribution.

Variables	Model (1) HR (Robust SE)	Model (2) HR (Robust SE)	Model (3) HR (Robust SE)
Independent Variables			
# Positive Credits (log)	1.059*** (0.012)	1.187*** (0.028)	1.373*** (0.054)
# Positive Credits (log)^2		0.958*** (0.009)	0.906*** (0.020)
# Negative Credit (log)	0.776*** (0.050)	0.796*** (0.050)	0.700*** (0.088)
Accepted by Asker	1.209*** (0.031)	1.201*** (0.031)	1.406*** (0.058)
Moderator Effects			
# Positive Credits (log) × Accumulated Score (log)			0.955*** (0.014)
# Positive Credits (log)^2 × Accumulated Score (log)			1.017*** (0.005)
# Negative Credits (log) × Accumulated Score (log)			1.049* (0.024)
Accepted by Asker × Accumulated Score (log)			0.949** (0.016)
Controls Variables			
Accumulated Score (log)	0.954*** (0.008)	0.954*** (0.008)	0.975* (0.01)
Tenure UX (log)	0.902*** (0.012)	0.902*** (0.012)	0.899*** (0.013)
Tenure SE (log)	0.730*** (0.027)	0.731*** (0.027)	0.731*** (0.027)
Words Count (log)	1.075*** (0.013)	1.072*** (0.013)	1.070*** (0.013)
Year 2013	1.042 (0.037)	1.048 (0.037)	1.054 (0.037)
Year 2014	0.981 (0.035)	0.991 (0.035)	0.995 (0.035)
Year 2015	0.933 (0.038)+	0.943 (0.039)	0.949 (0.039)
Year 2016	0.987 (0.040)	1.000 (0.040)	1.007 (0.040)
Year 2017	0.854*** (0.047)	0.866** (0.048)	0.871*** (0.048)
Year 2018	0.937 (0.052)	0.948 (0.052)	0.953 (0.052)
Weekday	1.048 (0.032)	1.051 (0.032)	1.050 (0.032)
Wald test	929.9; p≤2e-6	942.7; p≤2e-6	982.5; p≤2e-6
Robust score test	793.8; p≤2e-6	805.6; p≤2e-6	821; p≤2e-6

HR: Hazard Ratio; SE: Standard Errors. (1): Prentice-Williams-Peterson event-specific method;
(2): Prentice-Williams-Peterson event-specific method with # Positive Credits quadratic relationship;
(3): Prentice-Williams-Peterson event-specific method with the Status moderator effect;
*** p < 0.001; ** p < 0.01; * p < 0.05; + p < 0.1

In Model 3, we investigate the moderation effects. The interaction effects of the moderator are significant for *Accepted by Asker* and *# Positive Credits* in support of H2a and H2b. A higher accumulated score decreases the positive impact of answer acceptance by 5% (HR=0.949) and by 4.5% (HR=0.955) the positive effect of positive credits from peers on knowledge contributors' continued participation. The reduced reliance on virtual credits mechanisms based on the status achieved also holds for the interaction effect with the *# Negative Credits* in support of H2c. Higher status levels reduce the negative impact of negative credits from peers by 5% (HR=1.049) at a 5% significance level.

Looking at the control variables, only *Weekday* is not statistically significant. In line with our theorizing, *Accumulated Score (log)* harms answer recurrence. At the same *k*th answer recurrence, a participant with a higher status has a lower chance of continuing posting answers. In addition, *Tenure SE* and *Tenure UX* show that older participants, in terms of months since they sign-up in the communities, have a lower chance of continued participation. This dropout trend shows the retention issue of participants in online communities. *Word Count* has a positive hazard ratio toward answer recurrence. Thus, the length of the answer shared positively impacts the continued participation of the knowledge contributors. Finally, the contributions made during the year 2017 signed a significant downward trend in the chance of the participant's continued participation.

4.2. Robustness Checks

We replicate our results using the coarsened exact matching (CEM) method to examine the robustness of our model (Iacus, King, & Porro, 2012). The CEM algorithm allows us to address possible endogeneity. Matching answers with similar known characteristics may exploit the variations in the dataset to obtain more accurate estimates. For instance, unobservable peculiarities may inflate, or deflate, virtual scores' effect on continued active participation. We aim to control for such endogeneity matching answers based on the known experience of their authors using *Tenure SE*, *Tenure UX*, and *Accumulated Score*. In this way, we leverage unexpected patterns such as matching answers written by high-status members, which usually get positive credits, to check their posting behavior when they receive negative credits.

Furthermore, we sample the contributors three times to balance the observations for the three treatments in our investigation, namely *Accepted by Asker*, *# Positive*

[3] While only the asker can accept one of the answers as the best answer, all the members with at least 15 accumulated score points can provide positive credit.

Credits, and # *Negative Credits*. We enforce exact matching to each year the participants join any Stack Exchange communities (*Tenure SE*), and each year the participants register to the User Experience community (*Tenure UX*) while coarsening for *Accumulated Score* based on realized data characteristics. We also define relevant cutpoints for the # *Positive Credits* and the # *Negative Credits* independent variables, turning them into multicategory treatments before applying the CEM algorithm. We implement the method using the CEM package in the R software (Iacus, King, & Porro, 2009).

The CEM algorithm confirm the findings from the previous analysis supporting the hypotheses H1a, H1b, and H1c.

5. Discussion and Conclusion

5.1. Theoretical Implications

Our first contribution proposes to account for motivations in crowd-based online knowledge exchange from a dynamic perspective. The current understanding of the motives driving participants to contribute to online communities portrays motivations as an innate trait (Von Krogh et al., 2012; Ke et al., 2010; Lee et al., 2022). We challenge this notion and show that motivations can be dynamic, and established practices can affect the motivation to contribute over time. We investigate motivations by analyzing the impact of virtual credits in every instance of knowledge contribution across the lifespan of each participant. Our study allows us to refine the literature on motivations and add to the growing branch on contingencies, which investigates the conditions of motivations to unfold. Our observation that the accumulated score, or current status, is at the base of the effectiveness of virtual credit mechanisms shows a tie between the contingencies and the source of reputation. Our dynamic perspective on self-depletion of the status effect can explain the phenomenon that many online communities observe, such as stagnation and reduced participation (Simonite, 2013; Halfaker et al., 2013).

The second contribution aims to increase the conceptual clarity in the motivational literature by distinguishing reputation and status. Whereas most of the literature associates the accumulated score in online communities and crowds with the concept of reputation (Dellarocas, 2005; Zaggl, 2017), our empirical results show much more consistency with the notion of status. Indeed, reputation predicts the continuation of behavior based on past behavior and performance (Pollock et al., 2015; Milinski et al., 2002); yet, our results show that the accumulated online score predicts the opposite: a decrease in participation. An improvement of the individual standing within the community has an antonym effect on continued participation, reducing the reliance on virtual credits, the motivational source of status-seeking, due to the self-reinforcing aspects of status and the loose coupling between effort and performance. Status perceptions of an individual create expectations that fuel the status order like a virtuous circus where members' perceptions are self-fulfill and self-reinforced (Berger er al., 1972; Webster Jr & Entwisle, 1976). This status organizing process attracts attention to the status holder independently from objective assessments of an individual's ability (Sorenson, 2014; Washington & Zajac, 2005; Gould, 2002).

Status and reputation conceptually overlap, which poses an epistemological challenge. Research on online knowledge exchange communities should pick up the distinction between the two concepts.

5.3. Limitations and Future Research

This study is limited in several regards. First, our study measures status as the only source of motivation, yet previous research shows that different forms of motivation operate simultaneously, influencing their individual effects (Roberts et al., 2006; Ke et al., 2010; Zhao, Detlor, & Connelly, 2016). Future research should aim for a holistic investigation, including other forms of motivation, to shed light on critical contingencies and provide more details on the dynamic of continued participation in crowd-based online knowledge exchange. For instance, career-relevant motivations are forms of motivation to consider since status fosters career opportunities, and we expect that both sources of motivation interact to some extent.

Second, we need to investigate the mechanisms beneath how individuals perceive their status and whether they consciously use it to rest on their laurels.

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