Leveraging Linguistic Signaling to Prompt Feedback in Open Innovation Communities

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Abstract: Organizations are increasingly using open innovation communities (OICs) to gain external ideas. The success of OICs in promoting innovation, however, depends not just on posting activity by participants, but, crucially, on whether or not responses are subsequently received. Drawing on signaling theory, our study tries to explore how to leverage linguistic signals expressed in idea descriptions to influence feedback from two key parties: the moderator and peers. Linguistic features are divided into affective signaling (i.e., linguistic style matching, negative emotion, and impoliteness) and informative signaling (i.e., post length and quality). The research model is empirically tested on a large dataset collected from the Huawei community. Results show that both affective and informative signaling are e□ective in invoking feedback from the moderator. We also find that only negative emotion is positively associated with feedback from peers, while the effects of other signals show different trends. This research provides practical insights into how to maintain the viability of OICs.

Keywords: feedback, signaling theory, ideas, open innovation communities

1. INTRODUCTION

With the paradigm of Open Innovation (OI) [1], organizations often have reached outside of their boundaries to elicit ideas from large and diverse crowds. Among various approaches to obtaining external ideas, Open Innovation Communities (OICs) have gained great popularity. Indeed, examples of OICs can be found in di□erent industries such as Lego, Saleforce, and Huawei. Not only the posted ideas are important for innovation, but feedback is also of vital importance [2]. Previous studies mainly concentrated on factors such as peer recognition, reciprocity, and community incentives on members' response behavior in OICs context. How the content itself impacts the willingness of participants to expend time and e□ort to respond is rarely examined. In light of these gaps and concerns, we focus on the antecedents of feedback and examine how these sociolinguistic factors exert influences on feedback behavior from different parties. Our first research question asks: ***What kinds of linguistic characteristics embedded in idea posts can affect feedback from the moderators?*** Apart from the moderator's feedback, innovation-related conversations among members also play an important role in facilitating the viability of the community. Consequently, the second research question is: ***What kinds of linguistic characteristics embedded in idea posts can affect the amount of interactions from peers?***

2. THEORETICAL FOUNDATION AND HYPOTHESES

Signaling theory originates from the research of labor market [3]. In the context of OICs, ideators who submit innovation suggestions are signalers. Private information refers to the deliberate strategies that ideators use. Receivers are the moderator or those participants who have access to the information and thereafter potentially o□er responses to them. Signals are how these idea providers linguistically communicate, which is carried out via online messages. In the presence of information asymmetries, ideators could choose deliberate linguistic signals to potentially under-informed others in an efficient and e□ective fashion to obtain a sufficient amount of desired interaction in return. A□ective and informative signals are two major types of properties embedded in social media

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context content [4]. We evaluate the effects of three affective signals, namely *linguistic style matching*, *negative emotion*, and *impoliteness*. Similarly, two important informative signals in ideas are *post length* and *quality*.

3. RESEARCH METHODOLOGY

We obtained data from the OIC of Huawei (https://club.huawei.com/), which is one of the most important windows for Huawei company to listen to "the voice of the customer" (VOC). The crawler tool Web Scraper inserted in Google Chrome is used for data acquisition. We tracked all information available between March 2018 and March 2020. Our data features 95,668 ideas posted by 70,821 community members, 548,367 responses by peers and 29,544 responses by moderators. We employ two regression models: a logistic model for feedback from the moderator and a NB regression for feedback from peers. We use MLE method to estimate these coefficients and adopt robust standard errors clustered within each member to avoid heteroskedasticity.

4. RESULTS

In the affective signaling dimension, the coefficients of linguistic style matching, negative emotion and impoliteness are 0.348, 0.207 and -7.026, respectively, with statistically significant effects of all these explanatory variables ($p < 0.01$). Thus, hypotheses H1a, H2a and H3a are supported. In the informative signaling dimension, both post length ($\beta = 1.164$, $p < 0.01$) and quality ($\beta = 0.964$, $p < 0.01$) has a significant positive relationship with feedback from the moderator. Moreover, the coefficient value of squared post length is significant and negative ($\beta = -0.196$, $p < 0.01$). Thus, hypotheses H4a and H5a are supported. Negative emotion ($\beta = 0.047$, $p < 0.01$) are positively related to feedback from peers, while linguistic style matching ($\beta = 0.019$, $p > 0.1$) and impoliteness ($\beta = -0.557$, $p > 0.1$) are insignificant, therefore providing support for H2b and H3b, but not for H1b. Both post length ($\beta = -0.089$, $p < 0.01$) and quality ($\beta = -0.284$, $p < 0.01$) has a significant negative relationship with feedback from peers. However, the coefficient of squared post length is significant and positive ($\beta = 0.017$, $p < 0.01$). This result indicates a minor U-shaped relationship between post length and feedback from peers. Therefore, H4b and H5b are not confirmed.

5. CONCLUSION AND DISCUSSIONS

All of these findings are of great significance both in theory and in practice. Theoretically, we investigate a broad array of linguistic signals observed within ideas to better understand what motivates feedback in OIC environment. Moreover, we assess the distinct impacts of these signals on receiving feedback from two parties: the moderator and peers. From a managerial perspective, this study offers insights that can be utilized to better exploit of OICs. Our findings suggest that attention needs to be paid to the linguistic formulation of ideas. Moreover, if receiving feedback from the moderator is the goal of the participant composing a post, the sentiment of the idea, the style of the idea, the level of politeness in the idea, the length of the idea, and the quality of the idea all need to be carefully considered by the ideator. Future research could incorporate different dimensions such as informational or emotional feedback to better explore the mechanism of linguistic features on feedback. Besides, the generalizability of our study might be limited because we examined only a single community. Extending our research to other similar communities could validate and elaborate our findings.

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