Managing the uncontrollable: Empirical studies of user-generated content online

Lee, H.H.

Publication date
2014

CHAPTER 5

CREATIVE PARTICIPATION: COLLECTIVE EMOTIONS IN ONLINE CO-CREATION PLATFORMS[1]

ABSTRACT

Can collective emotions influence collective community outputs, and if so, how can these emotions be managed online? This research investigates the influence of collective user emotions on collective performance, namely, collective creativity (i.e., number of creative ideas) and participation (i.e., number of comments) in an online co-creation platform. It finds that negative collective emotions reduce subsequent creativity, but encourage future participation. Companies can manage collective emotions via influencing individual user emotions by specifying employees' communication style; positive user emotions can be enhanced by employees' positive emotions, and reduced by employees' negative emotions. Moreover, employees' task-oriented communication style can evoke both positive and negative user emotions, whereas a proactive style reduces them. Overall, this study suggests that retaining active users by managing the desired collective emotions seems to be an efficient approach in creating a productive online co-creation community.

[1] This chapter is based on a paper that is under first-round review at an international journal (with W. van Dolen as second author).

5.1 INTRODUCTION

Emotional expression is the epitome of online communication. The role of emotions in online information creation and transmission is well established at the individual level (e.g., Berger and Milkman, 2012; Kim and Gupta, 2012). The influence of emotions at the collective level has not yet been studied, however, even though the success of many online activities such as co-creation has been said to rely on users' collective efforts. Decades of research in organizational behavior suggest that collective emotions do not only influence individual behaviors, but also organizational performance and group outcomes (Barsade and Gibson, 1998; George and Brief, 1992). Recent work in information science has demonstrated the causal impact of collective emotions on online community developments (e.g., Chmiel et al., 2011). Although it is clear that collective emotions do exist and are influential, little is known about how these collective emotions are formed online and how they affect online activities.

Of all consumer online activities, co-creation platforms have attracted considerable attention among scholars. Users' participation and their creative ideas are proven to create value for companies (Healy and McDonagh, 2013; Hoyer et al., 2010; Kozinets, Hemetsberger and Schau, 2008). Many companies have established such platforms to obtain and leverage the benefits of collective consumer creativity. Co-creation processes often involve emotional engagement with the brand (Payne et al., 2009), but previous studies of online co-creation revolved around technical perspectives of site accessibility and usability (Novak, Hoffman and Yung, 2000). Despite the recognized significance of emotions in managing co-creation experiences (Kohler et al., 2011), no prior research has investigated the influence of collective emotions on online co-creation community performance. Can collective emotions influence collective community outputs, and if so, how can these emotions be managed online?

We approach these research questions in two stages. In order for an innovation community to sustain itself, companies not only rely on users to contribute their creative ideas, they also require users to comment on other users' ideas. Thus, we first distinguish two user activities on co-creation platforms as outcome variables: user creativity (i.e., the number of creative ideas) and user participation (i.e., the number of comments). We identify whether collective emotions influence these activities and how. Since a collective emotion is the aggregation of individual emotions, in the second stage of our study we focus on how individual users' positive and negative emotions are shaped by employees' communication styles, i.e., how the employees of the company can manage the platform. The theory of emotional contagion asserts that emotions can directly spread from one person to another (Hatfield, Cacioppo and Rapson, 1993). In line with this, we examine whether employees can have a direct influence on user emotions through emotional expression during communications. In addition to their emotional influences, community moderators are often instructed to communicate with users in certain ways. Thus we also study how these communication styles, such as reactive/proactive (Kohler et al., 2011) and task- and social-oriented approaches (van Dolen, Dabholkar and de Ruyter, 2007) may influence user emotions.

This study makes several contributions to the literature. Prior research on co-creation and online community has focused on antecedents of user contributions (e.g., Füller, Jawecki and Mühlbacher, 2007; Füller, Matzler and Hoppe, 2008; Tsai, Huang and Chiu, 2012) and on platform designs that enhance user experiences (e.g., Kohler et al., 2011; Nambisan and Nambisan, 2008). However, getting users to join well-designed platforms does not guarantee the success of co-creation communities. Productive innovation platforms require both quantity and quality of user contributions. Whereas prior research has tended to focus on attracting more users, the present study directly measures the quality of outcomes, i.e., creativity of the contributed ideas.

Moreover, little attention has been paid to how an affective environment can help sustain and secure continuous creativity and ongoing user participation. Most prior literature focuses on cognitive and rational aspects of community management. By introducing the concept of collective emotions into our analysis, we demonstrate how the affective characteristics of a community can drive its user activities, and we enrich the understanding of the nature of online co-creation community development.

Finally, community moderators, who often represent particular brands, may have a critical influence on motivating and sustaining member participation (e.g., Leimeister et al., 2009; Wise, Hamman and Thorson, 2006). The aggregated individual user emotions can result in collective user emotions, which in turn influence the community outputs, as will be illustrated in the first part of our study. Our findings shed light on how companies can manage collective emotions via individual user emotions through employees' direct participation in communities.

The chapter is organized as follows. First, we discuss collective emotions and their influence on community output. Next, we discuss how employees' communication style can influence collective emotions via user individual emotions. In Section 3, we briefly describe the methodology used in our study, followed by our findings. We conclude our discussion with comments about managerial implications and future research.

5.2 COLLECTIVE EMOTIONS AND USER INNOVATION PLATFORMS

5.2.1 Collective Emotions

Collective emotions have been defined generally as emotions that are shared by a large number of individuals (Brief and Weiss, 2002). Emotions serve as informational cues for others to evaluate the social environment (Keltner and Haidt, 1999), thereby shaping individuals' behavior (Schwarz, 1990). In general, positive emotive cues are believed to result in positive responses, whereas negative emotions elicit negative reactions. When personal emotions are spread from one person to another and shared by a group of individuals, they transform into group emotions (Rhee, 2006), which can be viewed as the aggregated sum of individual emotions, that is, the "affective composition of the group" (Barsade and Gibson, 2012: 119). These collective emotional states are critical to maintain the viability of a group in achieving its common goals (Frijda and Mesquita, 1994; Haidt, 2003).

In the organizational literature, it has been demonstrated that collective emotions can activate or deactivate group actions (e.g., Sy, Cote and Saavedra, 2005) and have a direct influence on group performance (e.g., Piderit, 2000). Prior research in online communities has found evidence that internet communication can facilitate the creation and moderation of collective emotions, which are critical to sustain the communities (Chmiel et al., 2011; Chmiel et al., 2011). Group emotions can be positive or negative. Positive emotions such as excitement and joy (e.g., Barsade, 2002) and negative emotions such as fear and anger (e.g., Hatfield, Cacioppo and Rapson, 1993) have been empirically found to be shared within a collective of interacting individuals. Negative collective emotions curtail prosocial behavior (George, 1990), while positive collective emotions are positively related to group performance (Barsade and Gibson, 1998).

5.2.2 Collective Emotions and Community Output

It is only recently that marketing scholars have tried to understand the role of emotions in innovative behaviors (Wood and Moreau, 2006). Positive emotions are often linked with creativity. Creativity can be broadly defined as the "production of novel and useful ideas in any domain" (Amabile et al., 1996: 1155). In the context of company-hosted co-creation communities, as in our study, we thus measure the level of creativity by counting the number of ideas that are implemented by the company. Extant studies suggest that positive emotions indicate a welcoming environment for people to explore and be more creative (Fredrickson, 2001). People who experience positive emotions tend to think more creatively (e.g., Sy, Cote and Saavedra, 2005), and they are cognitively flexible to engage in tasks such as product design. Participants on user-innovation platforms also claim that experiencing positive emotions such as excitement, fun, and joy motivates them to contribute more ideas (Füller, Jawecki and Mühlbacher, 2007).

Conversely, negative emotions can hinder cognitive processing (Isen, Daubman and Nowicki, 1987), which consequently inhibits creative thinking. The collective negative emotions of a group have been associated with counterproductive behaviors and lower group performance (Duffy and Shaw, 2000). Negative group emotions such as anger, anxiety, and envy are found to reduce the group's efficiency, particularly its creativity (Rhee, 2006). Consequently, we argue that positive collective emotions in online user-innovation communities have a direct impact on the collective creativity of the group. In other words, positive collective emotions can increase the number of creative ideas contributed to the community, whereas negative collective emotions would reduce the number. We thus hypothesize as follows:

H1a: Positive collective emotions have a positive impact on collective user creativity.
H1b: Negative collective emotions have a negative impact on collective user creativity.

Concurrently, users may participate in user-innovation platforms by making comments on others' ideas. The level of user participation can be measured by the total number of comments made on the platform. Although positive emotions typically lead to positive comments and negative emotions lead to negative ones, past studies have observed a "negativity bias." Not only may negative comments lead to higher impact on readers' evaluations, people tend to generate more negative comments than positive ones (e.g., Anderson, 1998). Negative emotions such as anger and frustration seem to carry more weight (Baumeister et al., 2001) and cause people to take action. Accordingly, we suggest that when users experience positive emotions on the innovation platform, they are less inclined to make comments, compared to when negative emotions are experienced. Consequently, positive collective emotions would result in a lower number of user comments. On the other hand, a negative environment has been empirically shown to trigger more thread comments (Chmiel et al., 2011). We thus predict that collective negative emotions will lead to more total comments. Therefore, we hypothesize as follows:

H2a: Positive collective emotions have a negative impact on collective user participation.
H2b: Negative collective emotions have a positive impact on collective user participation.

5.2.3 Employee Communication and User Emotions

One way in which companies can facilitate collective emotions is to manage individual participants' emotions through expressing certain emotions via employees who have direct contact with users. The communication style of the frontline service personnel often determines the relationship between a company and its customers (Morgan-Thomas and Veloutsou, 2013). Similar to the offline context, employees operating on the internet (whether considered to be managers or moderators of the forum) are the ones having such direct contact with online users. The emotional expression of employees can elicit similar affective reactions from the receivers. This direct spread of emotions is referred to as the emotional contagion process (Hatfield, Cacioppo and Rapson, 1993). Emotional contagion is rooted in crowd psychology, where an individual's behavior and emotions are influenced by what occurs at the collective group level. When an employee influences a user through direct communications, observations, or subconscious social influence, the effect can spread through the group of users. The collective emotions, in turn, would sustain these emotions among the group via continuous emotional contagion. This effect is the fundamental underlying mechanism of modern network marketing (Iyengar, van den Bulte and Valente, 2011) and online information diffusion (Angst et al., 2010).

The effect of emotional contagion between employees and customers has been widely studied in the past. In the service environment, employees are found to be able to influence customer emotions via emotional contagion (e.g., Hennig-Thurau, et al., 2006). While positive emotions of employees lead to positive emotions of customers, negative emotions of employees result in negative reactions from customers. Furthermore, Du, Fan and Feng (2011) show that positive emotional displays by employees not only increased the number of positive emotional displays from customers, but also reduced their negative emotional displays. Similarly, such emotional contagion has been demonstrated in organization studies among employees and between employers and employees (e.g., Barsade, 2002). It was found that an individual's affective displays, which are triggered by the leader's affective displays, can influence emotions at the group level through the process of emotional contagion (Dasborough et al., 2009). We thus propose that employees in user-innovation platforms can act as emotion agents that influence users' emotions via the route of emotional contagion. Positive user emotions may be enhanced by employees' positive emotions and reduced by employees' negative emotions. Similarly, employees' positive and negative emotions can decrease or increase the users' negative emotions. Accordingly, we formulate Hypothesis 3 as follows:

H3a: Employees' positive emotions increase individual users' positive emotions and decrease individual users' negative emotions.
H3b: Employees' negative emotions decrease individual users' positive emotions and increase individual users' negative emotions.

Other than emotional displays, moderators on forums are often instructed to communicate with users in a certain style. The communication style shapes the quality of employees' communication and signifies the quality of the relationship between a company and its users (Kozinets, 2002). Prior studies have discussed various communication styles of online community moderators that could influence the desired outcomes (e.g., Dabholkar, van Dolen and de Ruyter, 2009; van Dolen, Dabholkar and de Ruyter, 2007). For instance, the focus of the communication has been found to influence communication efficiency. In general, these styles can be separated into task-oriented communication, which is directly related to the assigned tasks, and social-oriented communication, which focuses on building relationships. It is suggested that task-oriented communication indicates a good quality of communication (Adjei, Noble and Noble, 2010). However, prior studies have shown that task-oriented communication leads to a tendency for cognitive-based processing and only indirectly influences the affective-based thinking process (Dabholkar, van Dolen and de Ruyter, 2009). In other words, when users encounter task-oriented communication, they are more likely to focus on the tasks rather than having emotional responses. Prior empirical online research supports the theory that there is less emotional communication in a task-oriented environment compared to a social-emotional one (Derks, Bos and Grumbkow, 2007). We suggest that when users are encouraged to think critically through employees' task-oriented communication, they are less likely to express their comments emotionally. Therefore, we posit Hypothesis 4 as follows:

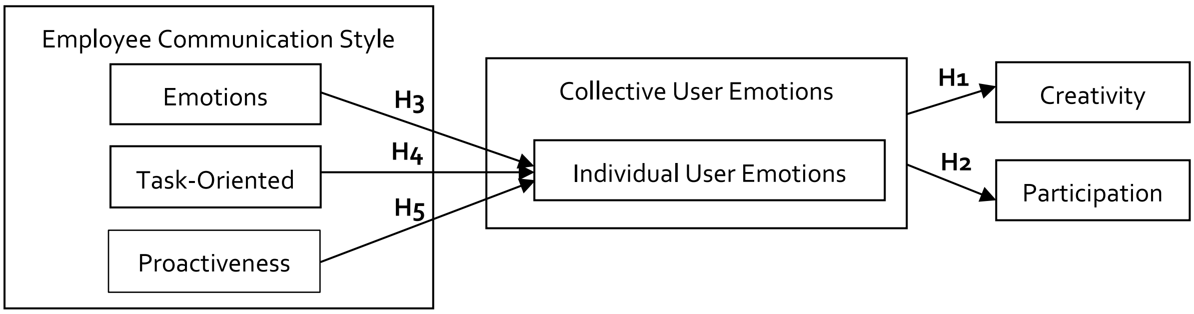
H4: Employees' task-oriented communication decreases users' positive and negative emotions.

Furthermore, recent theorizing and research in online communication has established the importance of companies adopting a reactive or a proactive approach. A proactive communication style, which signifies that online users are welcome and willing to actively engage in online activities, is suggested to lead to more favorable user behaviors (Kohler et al., 2011). Likewise, proactive communication on the part of companies is considered to be more effective on company-initiated platforms than on consumer-generated platforms (van Noort and Willemsen, 2012). This is because the purpose of company-initiated platforms, such as brand-sponsored co-creation communities, is to allow companies to proactively engage in conversations with online users (Kelleher, 2009). Similarly, during service encounters a proactive employee is found to enhance a company's relationship with customers and to encourage customers to repeat the visit in the future (de Jong and de Ruyter, 2004). However, proactive communication does not always result in favorable responses. In organizational studies, proactive behaviors were shown to be perceived negatively by supervisors due to their

suspicion of individual motives (Lam, Huang and Snape, 2007). In fact, in an online environment, proactive communication is found to result in less affective reactions in establishing interactive conversations, when compared to reactive communications (Liu and Shrum, 2009). Thus, we suggest that in user-innovation platforms, proactive communications from employees may result in a lower level of affective reactions. We hypothesize the following:
H5: Employees' proactive communication decreases users' positive and negative emotions.

The resultant conceptual framework of the above hypotheses is depicted in Figure 5.1.

Figure 5.1 Conceptual Framework and Hypotheses



5.3 METHODOLOGY

5.3.1 Sample and Data Collection

To test the hypotheses, we analyzed a well-developed company-hosted user-innovation community, Dell's IdeaStorm. Since its official launch in February 2007, this community where users can freely register to contribute ideas and make comments has been complimented as one of the best crowd-sourcing practices (Sullivan, 2010). Unlike many other user-innovation practices, Dell encourages employees to actively participate in the community; and some of the initial employee activities have been previously investigated (Di Gangi and Wasko, 2009; Di Gangi, Wasko and Hooker, 2010), which makes the community suitable for our study. Prior research addressed the creativity of this particular forum, but focused on individual users' characteristics (Bayus, 2013). Our study builds on the research methods established in the study of Bayus (2013), while aiming to determine the influence of collective emotions on collective community output.

We extracted all discussion threads from the community using a web crawler written with Java, including all the ideas, comments, authors, and their time stamps when available. We gathered data from the first posts that appeared at launch to those posted on April 30, 2011. Community users and employees were identified and categorized based on their profiles. During the four-year period, 14,404 ideas were documented, among which 427 (2.96%) had been implemented or partially implemented by Dell; 84,784 comments were extracted, among which 81,054 (95.60%) were posted by 9,436 unique users, and 3,730 (4.40%) were posted by 91 employees. To examine how collective emotions influence creativity and participation, the longitudinal observations of all comments were aggregated into daily data for further analysis. To study the impact of employees on user emotions, the data were aggregated into a longitudinal panel structure across users.

5.3.2 Measures

In the following sections, we specify the definitions and coding processes of all measures. A summary and example of how each variable was coded can be found in Table 5.1.

First, we investigated the influence of collective emotions on community performance. Following the literature, we investigated two dimensions of community performance, namely, creativity and participation. CREATIVITY_t is defined as the number of ideas published on day *t* that were fully or partially implemented by the company during the course of observation; PARTICIPATION_t is defined as the number of comments posted on day *t*. To better interpret the data, we used the 10-base logarithm of PARTICIPATION_t as a dependent variable. The time stamps of these activities were based on the initial date that the posts appeared on the platform.

Collective emotions were computer-coded the same way as individual emotions. Following prior research (Duan, Gu and Whinston, 2008), we measured the possible short-term and long-term effects of collective emotions with two distinct variables: daily collective emotions and cumulative collective emotions. The positive collective emotions on day *t* of the community (POSITIVE_t) were calculated as the average percentage of positive words from all comments on that day. Similarly, the negative collective emotions on day *t* (NEGATIVE_t) were calculated as the average percentage of negative words from all comments on that day. Cumulative positive collective emotions on the community forum from day 1 until day *t* (CUMPOSITIVE_t) were calculated as the average percentage of all positive words from day 1 until the observing day. Likewise, cumulative negative collective emotions (CUMNEGATIVE_t) were calculated as the average percentage of all negative words on the community forum from day 1 until the day of observation.

In the second stage, to inspect the influence of employees' communication style on users' emotions, we coded the employees' and users' comments separately. Since 91 employees responded to only a limited number of discussion threads and did not have direct interactions with all users, we focused on those users who appeared in the same threads with the employees and traced their comments after the encounters. Individual emotions were computer-coded using Linguistic Inquiry and Word Count (LIWC; Pennebaker, Booth and Francis, 2007), based on the percentage of words that demonstrate either positive or negative emotions. The approach has proven useful in previous online communication studies (e.g., Berger and Milkman, 2012; Ludwig et al., 2013). We calculated the average percentage of positive words among all comments posted by user *i* on day *t* to represent the user average positive emotions ($POSITIVE_{it}$) and likewise for average negative emotions from user *i* on day *t* ($NEGATIVE_{it}$). Similarly, the emotions of employees were computer-coded like those of the users. We coded the employees' average percentage of positive words during all encounters with user *i* between the day that the user had previously made a comment and day *t*, on which a new comment from user *i* was made, as $ePOSITIVE_{it-1}$, and likewise for negative emotions $eNEGATIVE_{it-1}$.

The other two employee communication factors, namely task-oriented communication style and proactive approach, were manually coded. Task-oriented communication was coded following the same method as in Adjei, Noble and Noble (2010). Adapting from Adjei, Nobel and Noble (2010), task-oriented comments ($eTASK_{it-1}$) were defined as "employee comments that were related to the initial idea posts." We calculated the average percentage of comments that were classified as task-oriented during the previous encounter(s) with user *i* until day *t*, i.e., (task-oriented comments/total number of comments)*100. Lastly, based on definitions by Kohler et al. (2011) and van Noort and Willemsen (2012), proactiveness ($ePROACTIVE_{it-1}$) was coded as the employee comments that were initiated by employees without any solicitation on the part of users. We calculated the percentage of comments that were classified as proactive during the prior encounters with user *i* until day *t*, i.e., (proactive comments/total number of comments)*100.

Two coders, the author of this thesis and a second coder who had not participated in the development of the coding scheme (and also not the co-author of this chapter), independently analyzed each employee comment; along with the employee comments, the coders also read the title and content of each idea, and the user comments that were written prior to the employees' comments. The coders practiced the coding scheme on 50 comments, and necessary changes were made to ensure that the instructions were clear. The two coders then coded all employee comments separately. The intercoder reliability suggested a sufficient result. The Cohen's Kappa for task-oriented communication and proactiveness was .89 and .87, respectively, with percentages of agreement at 97.0% and 94.3%. After the independent coding process, the two coders resolved any differences through discussion.

Table 5.1 Coding Descriptions and Examples

Variable	Coding Definition	Coding Methods
User Emotions		
$POSITIVE_{it}$	Percentage of positive words of all the comments from user *i* on day *t*	Coded through textual analysis (LIWC)
$NEGATIVE_{it}$	Percentage of negative words of all the comments from user *i* on day *t*	
$POSITIVE_t$	Percentage of positive words of all the comments on day *t*	
$NEGATIVE_t$	Percentage of negative words of all the comments on day *t*	
$CUMPOSITIVE_t$	Average percentage of positive words of all the comments from day 1 until day *t*	
$CUMNEGATIVE_t$	Average percentage of positive words of all the comments from day 1 until day *t*	
Community Output		
$CREATIVITY_t$	Number of ideas published on day *t* which have been implemented or partially implemented by May 10, 2011	Obtained with WebCrawler
$PARTICIPATION_t$	Number of comments published on day *t* across all idea threads	
Employee Communication		
$ePOSITIVE_{it}$	Average percentage of positive words of all the employee comments in all the encounters with user *i* from the day the user previously commented until day *t* on which user *i* made a new comment	Coded through textual analysis (LIWC)
$eNEGATIVE_{it}$	Average percentage of negative words of all the employee comments in all the encounters with user *i* from the day the user previously commented until day *t* on which user *i* made a new comment	
$eTASK_{it}$	Percentage of task-oriented employee comments in all the encounters with user *i* from the day the user previously commented until day *t* on which user *i* made a new comment	Manually coded
$ePROACTIVE_{it}$	Percentage of proactive employee comments in all the encounters with user *i* from the day the user previously commented until day *t* on which user *i* made a new comment	
Control Variables		
$CUMCREATIVITY_t$	Cumulative number of implemented or partially implemented ideas from Day 1 until day *t*	Obtained with WebCrawler
$CUMPARTICIPATION_t$	Cumulative number of comments from Day 1 until day *t*	
$IDEAS_t$	Total number of ideas posted on day *t*	
$WEEKEND_t$	A dummy variable measures whether an idea was posted during weekends	
$YEAR_t$	Series of dummy variables measure which year the ideas and comments first appeared on the forum	

<table>
<tr><td>$eTIMELINESS_{it}$</td><td>Average of the response latency of all the employee comments in all the encounters with user i from the day the user previously commented until day t on which user i made a new comment</td><td rowspan="3"></td></tr>
<tr><td>$eDURATION_{it}$</td><td>Average of the length of all the employee comments in all the encounters with user i from the day the user previously commented until day t on which user i made a new comment</td></tr>
<tr><td>$eFREQUENCY_{it}$</td><td>Total number of all the employee comments in all the encounters with user i from the day the user previously commented until day t on which user i made a new comment</td></tr>
<tr><td>$EMOTIONALITY_{it-1}$</td><td>Average of the sum of percentage of positive and negative words in all comments made by user i until day t on which the user made a new comment</td><td rowspan="2">Coded through textual analysis (LIWC)</td></tr>
<tr><td>$POSITIVITY_{it-1}$</td><td>Average of the difference between the percentage of positive and negative words in all comments made by user i until day t on which the user made a new comment</td></tr>
<tr><td colspan="3">Examples of Employee Communication</td></tr>
<tr><td colspan="3">Original Idea:
Please make it available: Dell Dock for Windows XP user (posted by user_1543 on July 4, 2008)

Comments:

Have you looked recently? It's up on the support site now (for Windows Vista)... (posted by user_8432 on July 5, 2008)

@jeopardy Yes I have look at support site and it not work on Windows XP From Chris (posted by user_1543 on July 5, 2008)

What happens if you download the one that's there (presumably Vista only then) and try installing that? (posted by user_8432 on 7^{th} July, 2008)

@jeopardy error said this: Dell Dock Setup Error This product requires at least Windows Vista. Setup cannot continue. (posted by user_1543 on 7^{th} July, 2008)

All- Indeed we do not have the Dock for XP users at this point. I am asking to understand if this is a plan for the future, More info to come! (posted by employee_21 on July 7, 2008)</td></tr>
<tr><td colspan="3">Coding:</td></tr>
<tr><td colspan="3">Emotions: 0% of positive or negative emotional words.</td></tr>
<tr><td colspan="3">Task-oriented: The comment was coded as task-oriented because the employee acknowledged the idea and explained the action that he would take.</td></tr>
<tr><td colspan="3">Proactiveness: The comment was coded as proactive because no one was asking for employees prior to this comment.</td></tr>
<tr><td colspan="3">Timeliness: We coded July 4 to 7 as 4 days. When the employee responded on the same day, we coded it as 1.</td></tr>
<tr><td colspan="3">Duration: Total count of 31 words.</td></tr>
<tr><td colspan="3">Frequency: There is only one employee response in this thread.</td></tr>
</table>

5.3.3 Control Variables

In estimating the influence of collective emotions on community performance, we took into account the short-term and long-term effects of previous community outputs and made them control variables. According to previous literature, internet users are drawn by popular items (Duan, Gu and Whinston, 2009). The more popular a discussion thread, the more likely that people will continue adding comments to it. We therefore controlled for the participation and number of creative ideas presented in the community until day *t*, as past activity level may serve as informational cues that influence users' decisions to participate in a community. We coded the number of creative ideas that were posted the day before ($CREATIVITY_{t-1}$), representing the short-term effect, and coded the cumulative sum of the creative ideas until the day before ($CUMCREATIVITY_{t-1}$) as the potential long-term effect. Likewise, we controlled for the number of comments posted the day before ($PARTICIPATION_{t-1}$) and the cumulative sum of the participation until the day before ($CUMPARTICIPATION_{t}$). When predicting the quantity of participation, we also controlled for the creativity of the day ($CREATIVITY_{t}$), since increasingly creative ideas could potentially attract more discussion. In addition, as the total number of ideas posted on that day could have directly influenced the number of creative ideas contributed, we controlled for the number of total ideas posted on day *t* ($IDEAS_{t}$).

When exploring how employees can influence user emotions with their communication style, we controlled for individual user differences and other elements that have been previously identified to influence employee communication quality. Prior research suggests that some people are, in general, happier than others due to individual differences in cognitive and motivational process (Lyubomirsky, 2001). We therefore established the baseline of users' emotional profile according to their overall average emotionality and positivity. Based on the definitions put forward by Berger and Milkman (Berger and Milkman, 2012), user $EMOTIONALITY_{it-1}$ was quantified as the cumulative average of the total percentage of words that were classified as containing either positive or negative emotions of user *i* until the day before day *t*. The $POSITIVITY_{it-1}$ was quantified as the average of the difference between the percentage of positive words and negative words in each comment from user *i* until the day before day *t*. Also, as it is known that negative and positive emotions can occur simultaneously (Folkman and Moskowitz, 2000), we controlled for the opposite emotions when predicting user emotions.

Other employee communication quality measures including timeliness, frequency, and duration of encounters were coded according to Adjei, Noble and Noble (2010). Timeliness was operationalized as the response latency between an employee's comments and the prior user comments. When the employees made several comments in a thread, from the second comment onward, timeliness was calculated from the day that the first user commented after the employees' prior comments to the day that an employee made a new comment. The average of timeliness that user *i* has experienced until day *t*, on which the user made a new comment, was labeled $eTIMELINESS_{it-1.}$ Duration of encounters ($eDURATION_{it-1}$) was measured as the average number of words of employees' comments during all the encounters with user *i* until day *t* that the user made a new comment. Frequency ($eFREQUENCY_{it-1}$) was coded as the average number of total comments from employees during prior encounters with user *i* until day *t*. All the variables mentioned above were computer-coded. Finally, we also controlled whether the comment was posted on the weekend ($WEEKEND_t$) and in which year ($YEAR_t$). The descriptive statistics and the correlations of the main measures are provided in Table 5.2.

5.3.4 Analysis Methods

In our study, creativity was calculated based on how many creative ideas were posted per day. This approach included the underlying assumption that the idea went through a two-stage process. First, there needed to be at least one idea posted, and only from there could an inflow of creative ideas proceed. In addition, the idea-implemented rate has been low on the platform; merely 3% of the ideas were ultimately implemented. These two factors have resulted in many zeros in our data; out of 1,448 days of valid observations, 1,165 days (80.45%) had zero creative ideas. The distribution of $CREATIVITY_t$ was positively skewed (6.64) and zero-inflated. To model the influence of collective emotions on creativity, we thus adopted the Hurdle Negative Binomial Regression model (HNB). Following the arguments of Hinz et al. (2011), HNB is used to correct the data structure that is highly skewed, overdispersed, and contains a large share of zeros. Theoretically, the HNB is preferred over competing models, such as the Zero-Inflated Negative Binominal (ZINB) (Vuong, 1989). However, we still calculated ZINB for a robustness check.

The influence of collective emotions on participation was estimated by ordinary least squares (OLS) regression. However, as $CREATIVITY_t$ and $PARTICIPATION_t$ shared most of the independent variables, $CREATIVITY_t$ could be an instrumented variable and may account for the endogeneity (Duan, Gu and Whinston, 2008). We thus compared the model with the other competing calculation, generalized method of moments (GMM), as if there was a potential endogeneity bias. We applied the Durbin-Wu-Hausman test to investigate whether instrumental variable is preferred over OLS. The result suggested no evidence of endogeneity (χ^2=1.46, *p*=.23) and revealed that there is no need for structural modelling (Davidson and MacKinnon, 1993). The result of the C-test suggested the same pattern (.921, *p*=.34). Moreover, because the cumulative positive collective emotions and cumulative negative collective emotions included in our models are highly correlated, multicollinearity was a potential problem. Similarly, the control variables $CREATIVITY_t$, $CUMCREATIVITY_{t-1}$, $PARTICIPATION_{t-1}$, and $CUMPARTICIPATION_{t-2}$ are also fairly highly correlated. We thus orthogonalized the highly correlated variables so that all variance-inflation factors are less than 5, as suggested in previous studies (Pollock and Rindova, 2003; Rhee and Haunschild, 2006). Furthermore, the models were robust to heteroskedasticity and auto-correlations within panels.

We employed Feasible Generalized Least Squares (FGLS) to analyze the impact of employee communications on user emotions. This method was chosen to account for the potential inter-correlation between multiple observations per individual user that were due to unobserved individual characteristics (George, 2005). This fixed-effect approach is often chosen when there are potential omitted variables (Wooldridge, 2001), as in our case, to avoid potential heteroskedasticity and to produce robust results. We used STATA 12.1 to run all the statistical calculations mentioned above.

Table 5.2 Descriptive Statistics and Correlation Matrix of Key Variables

(a) Correlations						
Variables	1	2	3	4	5	6
1.POSITIVE$_{it}$	1					
2.NEGATIVE$_{it}$	-.07***	1				
3.ePOSITIVE$_{it-1}$	-.00	.02**	1			
4.eNEGATIVE$_{it-1}$	-.03***	.04***	.10***	1		
5.eTASK$_{it-1}$	.01	-.02*	-.30***	-.31***	1	
6.ePROACTIVE$_{it-1}$	-.01	.02	-.06***	-.04***	.16***	1
Descriptive Statistics						
Mean	4.6	1.22	3.61	.54	.83	.69
SD	6.53	2.30	3.63	1.29	.27	.29
Min	0	0	0	0	0	0
Max	100	50	50	14.29	1	1

(b) Correlations									
Variables	1	2	3	4	5	6	7	8	9
1.POSITIVE$_t$	1								
2.NEGATIVE$_t$	-.07**	1							
3.CUMPOSITIVE$_t$	-.00	.01	1						
4.CUMNEGATIVE$_t$	-.04	-.01	.84***	1					
5.PARTICIPATION$_t$	.01	.02	.09***	-.25***	1				
6.CUMPARTICIPATION$_t$	-.03	-.03	.18*	.46***	-.71***	1			
7.CREATIVITY$_t$	.03	-.01	-.31***	-.45***	.44***	-.38***	1		
8.CUMCREATIVITY$_t$	.03	.02	-.16***	-.62***	.66***	-.93***	.41***	1	
9.IDEAS$_t$	.02	.00	-.19***	-.39***	.74***	-.45***	.52***	.50***	1
Descriptive Statistics									
Mean	4.48	1.19	4.42	1.15	58.03	64124.45	.29	.6	8.13
SD	3.21	.83	.21	.09	75.33	23837.45	.81	.33	20.91
Min	0	0	2.26	.34	0	11	0	.28	0
Max	53.57	10	4.69	1.2	679	84784	13	2.42	290

Table (a) includes key variables used in models estimating user emotions with employee communication style; Table (b) includes key variables used in models estimating community outputs with collective emotions. *, ** and *** indicate significance at the p<.05, p<.01 and p<.001 level, respectively.

5.4 RESULTS

We first examined the influence of collective emotions on community performance. Table 5.3 depicts the estimated results for creativity. HNB and ZINB yielded similar coefficients of predicting variables, though AIC, BIC, and log-likelihood suggested that the ZINB model may have a better fit. However, checking the differences between the predicted and observed results, we found that ZINB underestimated the chance of having non-creative ideas and overestimated the chance of having one creative idea. This poor estimation is reflected in its result for the control variable $IDEAS_t$, which was calculated to have a negative impact on the probability of change in odds always being zero. Since the chance of having a creative idea is always higher when there is one idea than when none is posted, the direction of the coefficient for $IDEAS_t$ in ZINB did not make sense. Thus, we reported only the coefficient results from HNB. The results from HNB suggested that positive collective emotions had no impact on creativity ($POSITIVE_t$: β=.880, *p*=.239; $CUMPOSITIVE_{t-1}$: β=3.071, *p*=.071). H1a was rejected. On the other hand, $CUMNEGATIVE_{t-1}$ was found to negatively influence creativity (β=-11.05, *p*=.022). This means that when the cumulative negative collective emotions increase by 1% in the comments, the number of creative ideas decreases by 11.05. H1b was thus confirmed. However, it is noteworthy that the daily negative collective emotions, $NEGATIVE_t$, did not yield any impact (β=-.106, *p*=.692).

Table 5.4 displays the results of the influence of collective emotions on user participation. The OLS model was the preferred model based on the previously mentioned endogeneity test results. It also yielded better model fit and was therefore chosen. The results indicated that positive collective emotions have no long-term impact on participation ($CUMPOSITIVE_{t-1}$: β=.0324, *p*=.19), but they do have a short-term effect; this factor had a marginal negative impact on the same-day participation ($POSITIVE_t$: β=-.00701, *p*=.046). H2a was supported. Conversely, negative collective emotions appeared to have a long-term positive effect ($CUMNEGATIVE_{t-1}$: β=.106, *p*=.013), while having no short-term effect ($NEGATIVE_t$: β=.0256, *p*=.18). H2b was confirmed.

Table 5.3 Determinants of Number of Creative Ideas

	Model1 (HNB)		Model2 (ZINB)	
$Pr(CREATIVITY)_t$	Negative-Binomial	Logit	Negative-Binomial	Inflate
$POSITIVE_t$	.0880	.0270	.142**	.245*
	(.0747)	(.0297)	(.0451)	(.112)
$NEGATIVE_t$	-.106	-.0395	.195	.757*
	(.267)	(.127)	(.149)	(.367)
$CUMPOSITIVE_{t-1}$	3.071	.689	1.561	-3.430
	(1.701)	(1.293)	(1.006)	(6.073)
$CUMNEGATIVE_{t-1}$	-11.05*	-2.116	-6.794*	2.948
	(4.816)	(3.615)	(2.856)	(15.74)
$CREATIVITY_{t-1}$	-.0231	.168	-.00777	.252
	(.0536)	(.0960)	(.0378)	(.340)
$CUMCREATIVITY_{t-2}$	-1.168**	.248	-.822***	-1.196
	(.364)	(.561)	(.242)	(1.661)
$IDEA_t$	.00796***	.0237***	.00559***	-.261**
	(.00201)	(.00577)	(.00140)	(.0868)
$YEAR2008_t$	.0327	.0230	-.347	-3.153
	(.452)	(.300)	(.248)	(1.776)
$YEAR2009_t$	.126	-1.224**	-.513	-1.221
	(.555)	(.396)	(.466)	(1.507)
$YEAR2010_t$	-13.936	-2.317***	-.972	-.514
	(12.877)	(.536)	(.811)	(1.559)
$YEAR2011_t$	-12.585	-1.624**	-2.636***	-5.403
	(11.966)	(.578)	(.563)	(3.410)
$WEEKEND_t$	.0233	-.139	-.0260	-.0621
	(.252)	(.173)	(.158)	(.468)
Intercept	-1.388	-1.987	.0599	11.09
	(2.233)	(2.370)	(1.330)	(9.675)
AIC	1.085		1.081	
AIC*N	1599.4		1565.4	
BIC	1741.9		1707.9	
Log likelihood	-772.7		-755.7	
N	1448			

Notes. The two models documented above examined the number of creative ideas in two different stages. First, listed as Logit or Inflate, the models estimated the chances of having at least one creative idea. In the second stage, each model predicted the number of ideas based on the input factors. The two models yielded similar results. Though ZINB appeared to have a better fit, NHB had more precise estimation. The cumulative average of negative emotions, along with the past creative performances, reduced creativity. Robust standard errors are listed in parentheses. Significant levels are indicated with asterisks: $^{*}p$<.05, $^{**}p$<.01, $^{***}p$<.001.

Table 5.4 Determinants of Level of Participation

$PARTICIPATION_t$	Model 1 OLS	Model 2 GMM
$POSITIVE_t$	-.00701*	-.00694
	(.00351)	(.00359)
$NEGATIVE_t$	.0256	.0260
	(.0191)	(.0192)
$CUMPOSITIVE_{t-1}$	.0325	.0205
	(.0249)	(.0296)
$CUMNEGATIVE_{t-1}$	.106*	.0970
	(.0423)	(.0520)
$CREATIVITY_t$	.0273*	-.0531
	(.0134)	(.105)
$CUMCREATIVITY_{t-1}$	.0306	.0970
	(.0188)	(.0353)
$PARTICIPATION_{t-1}$	.345***	.354***
	(.0260)	(.0307)
$CUMPARTICIPATION_{t-2}$	-.0502	-.0987
	(.0387)	(.0642)
$IDEA_t$	.00606***	.00720***
	(.000739)	(.00180)
$YEAR2008_t$	-.0643	-.0687
	(.0446)	(.0506)
$YEAR2009_t$	-.694***	-.721***
	(.0625)	(.0768)
$YEAR2010_t$	-1.145***	-1.192***
	(.0795)	(.104)
$YEAR2011_t$	-.964***	-1.009***
	(.0863)	(.107)
$WEEKEND_t$	-.245***	-.242***
	(.0250)	(.0258)
Intercept	.549***	.563***
	(.0579)	(.0661)
R^2	.838	.835
adj. R^2	.837	.833
AIC	1370.6	1402.8
BIC	1449.4	1481.6
Log likelihood	-670.3	-686.4
N	1412	1412

Notes. The two models above examined the influence of emotional climate on the number of comments. OLS had a better fit and the results from endogeneity test also suggested that OLS model is preferred. Negative emotions, creativity, and past participation seemed to enhance participation, while positive emotions had a negative effect. Robust standard errors are listed in parentheses. Significant levels are indicated with asterisks: $^{*}p<.05$, $^{**}p<.01$, $^{***}p<.001$.

In the second part, we examined how the employee communication style influences user emotions. Table 5.5 summarizes the estimated results of user emotions under the influence of the employees' communication style. Among all the registered users, only 797 unique users, having made comments and shared at least two encounters with employees, were included in the analysis. We found that the communication style $ePOSITIVE_{it-1}$ had a positive impact on positive user emotions (β=.0178, *p*<.001) but did not reduce negative user emotions (β=.000297, *p*=.506). H3a was partially confirmed. Similarly, $eNEGATIVE_{it-1}$ had a negative impact on positive user emotions (β=-.0701, *p*<.001) but did not increase negative user emotions (β=.00154, *p*=.503). H3b was also partially confirmed.

We then examined the effects of the two communication-style factors, task-oriented and proactive comments from employees, on user emotions. $eTASK_{it-1}$ was found to have a positive effect on both users' positive (β=.379, *p*<.001) and negative emotions (β=.0453, *p*<.001). This result suggested that task-oriented employee comments in general led to more emotional responses, which was opposite to what we expected. Thus, we rejected H4. Contrary to $eTASK_{it-1}$, $ePROACTIVE_{it-1}$ was found to have significant negative effects on both $POSITIVE_{it}$ (β=-.837, *p*<.001) and $NEGATIVE_{it}$ (β=-.0778, *p*<.001), suggesting that a proactive message in general resulted in a lower degree of emotions in user comments. Therefore, H5 was accepted.

Table 5.5 Estimating User Emotions with Employee Communication

	Model 1 $POSITIVE_{it}$	Model 2 $NEGATIVE_{it}$
$ePOSITIVE_{it-1}$	.0178***	.000297
	(.000158)	(.000447)
$eNEGATIVE_{it-1}$	-.0701***	.00154
	(.00119)	(.00230)
$eTASK_{it-1}$	.379***	.0453***
	(.00231)	(.00770)
$ePROACTIVE_{it-1}$	-.837***	-.0777***
	(.00309)	(.00402)
$POSITIVE_{it}$		-.0267***
		(.000271)
$NEGATIVE_{it}$	-.157***	
	(.000756)	
$POSITIVITY_{it-1}$	.238***	-.0698***
	(.000171)	(.000560)
$EMOTIONALITY_{it-1}$	.111***	.0862***
	(.000110)	(.000789)
$eDURATION_{it-1}$	-.000800***	.00172***
	(.0000161)	(.0000641)
$eFREQUENCY_{it-1}$	-.00235***	-.000992***
	(.0000212)	(.0000612)
$eTIMELINESS_{it-1}$	-.000694***	-.0000302
	(.0000124)	(.0000535)
$WEEKEND_t$	-.410***	.00920**
	(.00103)	(.00317)
$YEAR2008_t$	-.390***	.0354***
	(.00495)	(.00184)
$YEAR2009_t$	-.587***	.105***
	(.00665)	(.00991)
$YEAR2010_t$	-.744***	.106**
	(.0567)	(.0357)
$YEAR2011_t$	-.463**	-.467***
	(.171)	(.0146)
Intercept	3.912***	1.086***
	(.00120)	(.00550)
Number of Comments	9466	
Wald X^2	258439861.1	77351.4
Number of Users	797	

Notes. The two models above examined the influence of employee communications on user emotions. Positive emotions seem more likely to be influenced by employees than negative emotions. Robust standard errors are listed in parentheses. Significant levels are indicated with asterisks: $^{*}p<.05$, $^{**}p<.01$, $^{***}p<.001$.

5.5 DISCUSSION AND IMPLICATIONS

5.5.1 Findings and Theoretical Implications

The surge of online co-creation communities has increased the interest in understanding what contributes to the success of such practices. Based on prior research (e.g., Füller, Jawecki and Mühlbacher, 2007), it is clear that emotions play a key role in driving user contributions in these platforms, but less is known about how collective emotions of the community can affect the community performance. Furthermore, although online-community research has examined how a certain management style and platform design can enhance user experiences during the co-creation process, less attention has been given to how the affective environment of the community, e.g., collective emotions, might shape community outcomes, namely creativity and participation. The current research examines the role of collective emotions in two stages. By attempting to understand how companies can manage collective emotions in a way that subsequently influences community output, we shed light on potential drivers of successful co-creation practices.

Our findings contribute to the existing literature of online user-innovation communities. First, they highlight the importance and challenges of managing user emotions. While negative user emotions seem hard to change, positive user emotions increase when employees' positive emotions increase; and they decrease when employees express negative emotions. Furthermore, an employee with a proactive communication style appears to decrease user emotions, both positive and negative, whereas a task-oriented communication style generally increases user emotions. Second, our results illustrate that collective emotions can be used to predict the community's collective creativity and participation on user-innovation platforms: positive collective emotions have no impact on creativity and lower the level of participation, whereas negative collective emotions reduce creativity and increase user participation.

This research links the concept of collective emotions to studying online user-innovation communities. Previous studies have focused on functional aspects of co-creation platforms and suggestions for modifying the platform design to enhance user experiences (e.g., Kohler et al., 2011). However, hedonic motivations, such as pursuit of pleasure and enjoyment, which are often associated with emotions, are important for increasing co-creation participation (Antikainen, Mäkipää and Ahonen, 2010). The results of the present study support our hypothesized framework that collective emotions signify the affective environment of the community, which accounts for subsequent idea submissions and comment making. Moreover, part of the mechanism of forming collective emotions is through emotional contagion. We provide empirical evidence that, to a certain extent, employees can manage the collective emotions through their own emotional displays, along with other communication styles.

Confirming our hypotheses, the results suggest that collective emotions can influence community output. However, it is important to note that collective emotions have opposite effects on creativity and user participation. In particular, the opposite effect of negative collective emotions decreasing creativity and increasing user participation is evident in our study. This highlights the importance of making a distinction between contributing novel ideas (i.e., initiating a discussion) and making comments (i.e., participating in discussions) in future co-creation studies. The results confirmed that users may perceive a community with a highly negative emotional climate as a risky and problematic environment (Gasper, 2003), which discourages creative thinking but encourages contributions of comments to help solve this problem. These findings suggest that in developing user-innovation platforms, if the purpose is to generate as many useful ideas as possible, companies should focus on reducing negative emotions. Conversely, when the purpose is to increase overall participation by attracting a higher number of user comments, negative collective emotions are actually favorable. The paradoxical effect highlights the importance of managerial choices to design a small but highly creative community or a large but less creative one.

Moreover, it is worth noting that previous studies on the influence of emotions have focused on personal, short-term, and immediate influence (e.g., Berger and Milkman, 2012; Nambisan, 2003). Our results suggest that it is mainly the cumulative collective emotions, instead of the immediate collective emotions that shape the user activities. It is perhaps less likely that users will judge the affective environment of a community based on what has happened on a particular day. In particular, it takes time for a community to establish its collective emotions with aggregate contributions from all users.

It is important to note that employees have limited means of directly influencing user emotions with their own emotions. In general, employees seem more likely to influence positive user emotions than negative user emotions. Employees can only increase or reduce positive user emotions with their own positive and negative emotional displays. While employee negative emotions are found to be more efficient, with a stronger effect, in influencing user emotions, as suggested by previous literature (van Kleef, 2009), negative user emotions are more difficult to suppress or to change (Schaefer, 2010). This may be because in an environment in which people strive for negative emotions, people may resist emotional changes (Darmody and Bonsu, 2008). The fact that people are more likely to comment when they have negative emotions rather than positive ones may contribute to this propensity. Even if employee positive emotions can positively influence users, the users tend not to change their negative displays.

Along with emotional displays, we found that employees' task-oriented comments and a proactive communication style are paramount in influencing user emotions. Proactiveness in particular reduces overall user emotional expressions, both positive and negative. This suggests that even in company-hosted user-innovation platforms where direct feedback is welcomed and needed (Di Gangi, Wasko and Hooker, 2010), proactive participation by an employee may not always lead to favorable outcomes. While proactiveness softens negative user emotions, it also reduces positive user emotions. This might help explain why proactive participation by an employee is not always appreciated by forum users (Fournier and Avery, 2011). Because user participation (commenting behaviors in particular) is driven mainly by negative emotions, as confirmed in this study, users may not be motivated to contribute to a less emotionally charged environment.

On the other hand, task-oriented communication from employees was found to elicit both positive and negative emotions, which is opposite to what was hypothesized. This may be because of the actual content of the employee communication. Drawing on affective events theory, feedback about task performance (failure of a task, in particular) is regarded as an affective event in the workplace, which can induce emotional responses (Dasborough, 2006; Gaddis, Connelly and Mumford, 2004). Similarly, in the context of co-creation communities, employees' task-oriented comments may be perceived as a direct feedback to the user ideas and preceding discussions, which leads to subsequent user emotional responses. This may be an interesting aspect for future research.

To conclude, our study suggests that user activities on user-innovation platforms are influenced by the collective emotions of all participants. Employees may manage the community output by effectively influencing user emotions through controlling their communication style. The results offer an alternative approach for maintaining and designing user co-creation communities. Different from the current focus on identifying user motivations (e.g., Tsai, Huang and Chiu, 2012) and platform design (e.g., Nambisan and Nambisan, 2008), our study suggests that community development is an ongoing process. Along with the change of collective emotions on platforms between positive and negative, communities also develop their creativity and user participation. Cumulative negative collective emotions in particular can increase future user participation, i.e., the number of comments, but reduce subsequent creativity, i.e., the number of creative ideas. The collective emotions—aggregate emotions of all participants—are important in shaping collective community outputs.

5.5.2 Managerial Implications

Our study sheds light on how companies can manage user-innovation platforms by closely monitoring and managing collective emotions of the communities. Since negative collective emotions have opposite effects on two community outputs—namely, creativity and user participation—companies should choose a managerial approach based on their purpose. The counter-effects set a paradoxical challenge for companies to determine the goal of a community prior to its full development and to adjust their communication style accordingly during the process. In particular, if the priority is to maximize the creative output of innovation platforms, companies should focus on reducing negative emotions. On the other hand, if the priority is to maximize the size of community and to encourage comments and conversations, negative emotions are less of an issue. Yet companies should be aware that the continuing negative emotions would eventually reduce the willingness of users to submit creative ideas. The approach of tolerating negative emotions might be more suitable for companies that allow consumers to give comments on company-initiated ideas rather than encouraging the users to comment on user-developed ones.

In addition, if companies decide to have employees participating in co-creation communities, it is more efficient to regulate user emotions through adapting the employee communication style, such as focusing on task-oriented or proactive communication, instead of controlling employees' emotional displays. This is perhaps less demanding for employees, as overwhelming emotional labor can cause work withdrawal (Scott and Barnes, 2011). When employees are experiencing emotional exhaustion in an unwanted emotionally charged interaction, they may end up suppressing emotional displays even if they are instructed not to. However, it is worth noting that companies can either evoke user overall emotional responses by posting task-related comments or reduce the emotions by proactively participating in online conversations. This indicates that it may be difficult to control for and demand particular user emotions. It is thus crucial to carefully monitor the development of collective emotions and to adapt the style in a timely manner when needed. For example, when dealing with unwanted negative emotions, employees may proactively engage in the conversations but be restricted to administrative content instead of task-oriented comments.

5.5.3 Limitations and Future Research

Even though our research offers valuable insights into how emotions influence community performance, it has some limitations that require further research. Since the research involved only one specific platform, the results need to be treated with caution. In particular, combining other functional design factors that are suggested to influence user experiences might provide a more profound story of how a community environment may influence collective outputs. Moreover, due to the exploratory nature of investigating how collective emotions work in the context of online co-creation, specific emotions have not been identified or specified. Barsade and Gibson (1998) have suggested that studying group emotions based on specific discrete emotions, such as anger and joy, would help us better understanding the mechanism of collective emotion. It would be interesting to further identify which specific emotions can best influence collective community outputs and how.

Regarding the employee communication style, it would also be interesting to further clarify which specific emotions are elicited by employee task-oriented communication. Considering that it generates both positive and negative emotions, it is critical to understand exactly how users respond to employee task-related comments. Related to this, future research might also examine how emotions interact with the cognitive information in a message. The task-oriented communication style is a starting point to further understand how the content of employee communications should be formulated. In addition, prior research on collective emotions demonstrates the importance of the group leader identifying the dynamics of the emotional composition of groups (Sanchez-Burks and Huy, 2009). The success of managing collective emotions partially depends on how well employees can detect the current aggregate emotions in the community. Further research might examine how the emotional intelligence of employees influences the development of user-innovation platforms. This research, though only partially identifying the effect of emotional contagion from employees to users, does suggest that the role of emotions in online communities is a promising line of future inquiry.