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The Influence of Negative Emotions in an Online Brand Community on Customer Innovation Activities

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Abstract

With Web 2.0 increased user participation in diverse e-communities results in prevalence of information, including emotional information. We examined the influence of negative emotion in an online brand community, MyStarbuckIdea.com developed to collect diverse customer ideas for firm's innovation, with the purpose to investigate how such emotion affects customer innovation activities in the community. We first established several hypotheses on the relationships between discrete negative emotions and innovation activities. Then, having collected 84,918 customer ideas, we conducted POS tagging and term-based matching to calculate the inclusion and intensity of negative emotion, using negative emotion lexicon which we developed. As a result of testing hypotheses with regression models, we show that 1) negative emotion significantly affects innovation activities in the brand community and frustration is the most influential among the discrete negative emotions; 2) as the intensity level of negative emotions increases, so does their influence.

1. Introduction

The Internet has brought revolutionary changes in accessing information, especially in terms of quantity and diversity of information. Information on the Internet has mainly been factual information such as news or data about an object. As Web 2.0 technology spreads, however, emotional information such as opinions or reviews have begun to transfer more vibrantly into the cyber community, because online interactions among individuals and groups in diverse e-communities has become prevalent. Thus, prominence is given to the social aspect of the web.

In light of these changes, analysis on emotions in an e-community context has attracted a great deal of attention from both researchers and practitioners. Bollen et al. [4] derived a sense of public mood from an analysis of emotions contained in Twitter feeds, and showed that public mood in online community is highly correlated to the fluctuation of the stock index and can even be a predictor of economic indicators. In an online forum context, Chmiel et al. [10] examined a vast amount of postings with statistical approach, and posited that emotion can be a factor which promotes interactions among community members. In addition, emotional information obtained from a movie community [9] can be used as determinants of a movie's success. These studies demonstrate that emotion is a significant factor in explaining, predicting and influencing human behavior and social phenomena, and similar conclusion can be found in the existing emotion literature [6, 23].

In this study, we chose an online brand community as our research context with the aim of acquiring a deeper understanding of the influence of emotions. The online brand community has helped firms (e.g., Harley-Davidson) to become a global leading brand by supporting easy interactions between firm and customers, and among customers, thereby leveraging customer loyalty and marketing efficiency [16]. Recently, some online brand communities are evolving into a community of new functionality, such that it encourages customers to participate in innovation activities such as idea generation or discussion for idea development [28, 34]. These new brand communities support firms' innovation in an effective way and this is why various firms from diverse industries have launched their own brand communities.

As in other e-communities, diverse emotional information transfers and diffuses through interactions among customers in a brand community. And such emotions can possibly influence customer activities in a brand community. Specifically, we set our focal point on negative emotions, since negative emotions have been given more weight in business literature for their greater influence than positive ones. For example, negative emotions can trigger negative word of mouth which can result in negative consequences such as loss of brand image [8]. Thus, in this study, we question whether or not negative emotions are influential on customer innovation activities in a brand community, and further, whether they bring positive or negative consequence. Stemming from these questions, we derive detailed questions which have rarely been discussed in previous works:

- Does negative emotion in customer opinions affect customer innovation activity in a brand community?
- Do discrete negative emotions (e.g., *anger*, *frustration*, etc.) in customer opinions affect

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customer innovation activity differently in a brand community?

- Does the intensity of negative emotion as a whole and discrete negative emotions contained in customer opinions affect customer innovation activity differently in a brand community?

To address these questions, we first categorize negative emotions derived from prior research to analyze in more detail the influence of each category of negative emotion on innovation activities in a brand community. Sentiment analysis allowed us to examine customers' emotions in a large set of customer review texts.

2. Literature Review

2.1 Brand Community

Brand community can be defined as a specialized community based on a structured set of social relationships among the users of a brand [34]. As web 2.0 environment spreads, customers can now participate in various e-communities much more freely [29], and these changes have begun to attract attention in the brand community research area. That is, as customers' knowledge sharing and diffusion of relevant information has taken place very easily and quickly in online brand communities [2, 28], diverse drivers of brand community, their impacts on brand community, and marketing program or strategy through online brand community have drawn attention of many researchers [1, 29].

Business practitioners also have begun to take an interest in brand community, and many firms have started to establish an online brand community along with these environmental changes of web 2.0. An online brand community provides many advantages to customers, including expansion of communication, a tool for marketing strategy, and acquisition and interchange of ideas and requirements. First, online brand communities are an interesting melding of face-to-face meeting and virtual community, operating with a variety of electronic devices and networks [1, 2]. Rapid communication is allowed in an online brand community among customers, as well as between customers and a firm [2, 34]. Second, an online brand community is an important facet of marketing because it brings a simple contact method with tremendous cost reduction [1, 2]. An online brand community as a binding marketing tool can enhance the loyalty of customers and brand recognition very easily [34]. Third, an online brand community helps firms directly gain customers' opinions and ideas [28, 29].

Recently, the third advantage mentioned above is attracting close attention especially of the firms which utilize their brand community as a strategic asset to innovate themselves. This trend can be understood in the same context as the "open innovation" approach, which advocates acquisition of external knowledge to complement a firm's internal resources [7]. This is why such a brand community is sometimes called as "innovation community", and in these communities, customers are usually encouraged to contribute to innovation by taking part in activities such as suggestion, evaluation and collaborative development of ideas for innovation.

In this study, we measure the influence of negative emotions in customers' ideas in an online brand community on customers' innovation activities: 1) drawing support among customers; 2) promoting discussion among customers for the development of the idea; and 3) contributing to the firm's innovation.

2.2 Negative Emotions and Sentiment Analysis

Sentiment analysis is considered a useful method, because sentiment analysis makes it possible to analyze and extract emotions and sentiments in a formal or informal text in an automatic way [25, 43]. So far, sentiment analysis has allowed us to: 1) extract the entities and attributes that are represented in an opinion; 2) summarize the opinions expressed in a text; 3) determine whether a given text is subjective or objective; 4) classify whether the opinion in a given text is positive or negative [24, 27, 36]. In previous studies, product reviews or movie reviews have been the main context to which researchers generally applied sentiment analysis method, thereby classifying positive and negative opinions [25, 36]. More recently, researchers extend or subdivide emotions into more specific levels instead of dichotomizing them as positive or negative [4, 43]. In such studies, categories of discrete emotions are used to classify emotions and it is shown that there are differences among discrete emotions in the relationship with a target variable in the e-communities domain [4, 43].

One of discrete emotions that we felt are necessary to focus on is negative emotion, providing that negative emotions have attracted more attention in business literature [26, 30, 41], and researchers have tried to examine discrete negative emotions [6, 21, 24]. However, service research has utilized only a limited number of negative emotions [42]. In the paper, we develop this study based on the categories of negative emotions proposed by Diener et al [11]. Their categories of negative emotion are: 1) *fear*, 2) *anger*, 3) *shame*, 4) *sadness* [11]. Tronvoll [44] extended this category with the fifth category, frustration [44]. We use these five categories to analyze our target dataset to extract negative emotions from each customer opinion. Specific emotions that belong to each category of negative emotions are as follows [44]: 1) *fear* (including the emotions of *worry, anxiety and nervousness*); 2) *anger* (including the emotions of *irritation, disgust* *and rage*); 3) *shame* (including the emotions of *guilt, regret and embarrassment*); 4) *sadness* (including the emotions of *loneliness, unhappiness and depression*); 5) *frustration* (including the emotions of *resignation, powerlessness and despair*).

In our research, we employ sentiment analysis methodology with five categories of discrete negative emotions in order to extract the sentiment in customers' opinions and measure its intensity.

3. Hypotheses

3.1 The Influence of Negative Emotions

Fundamentally, information about negative traits which can cause a negativity bias to incur, has a stronger impact in the human brain than do positive traits [17, 32]. Similarly, a negative opinion about a product or service in the market place has a disproportionally greater weight than a positive one [32]. This negative bias has been explained in various ways. Ito et al. [17] argues that people tend to give more weight on the messages which contain negative things. In addition, because positive words are much more frequently used than negative words, negative words contained in a message commonly shows distinctiveness and novelty, providing another reason for the bias [5]. These characteristics of novelty and distinctiveness of a message with negative words may increase its possibility of being remembered and attended to. Therefore, the message is likely to be more weighed in decision-making that requires differentiation among other messages [15]. Moreover, a negative message has a tendency to be considered more credible than a positive one, because there are common normative pressures which push people to say things in a positive way. Accordingly, when hearing something negative, people might consider it sincere, because it is less likely to have been affected by the normative pressures [19].

This bias in information processing is empirically tested in some e-communities. Negative messages are adopted and diffused by audiences more easily compared with positive ones in Twitter context [35]. In a web forum, user opinions which contain negative words show higher tendency to be attentive to users and promote user engagement [10].

In this study, we expect that there will be also negative bias among customers in an online brand community context, as is discussed in the above. If so, customer ideas containing negative words will be adoptable and attentive by both customers and company. Therefore we hypothesize:

Hypothesis 1a: A customer idea containing negative emotions is likely to draw support from other customers.

Hypothesis 1b: A customer idea containing negative emotions is likely to promote discussion among customers.

Hypothesis 1c: A customer idea containing negative emotions is likely to lead to a contribution to the innovation of firms.

3.2 Distinction among Discrete Negative Emotions

In psychology literature, researchers have tried to find modes of categorizing basic emotions, and accordingly, emotions have been categorized in many ways. The *wheel of emotions*, proposed by Plutchik [37], classifies emotions into *anticipation, joy, anger, surprise, fear, sadness, disgust,* and *acceptance*. As well, Izard [18] distinguishes ten primary emotions, and Diener [11] considers discrete emotions as consisting of two positive emotions and four negative emotions. These studies have offered structured views on emotion by which other related disciplines may extend their literature.

In the business domain, emotion has long been a research issue [6]. And negative emotions especially have drawn more attention, because such negative emotions may trigger negative consequences on the business and they need to be attentive to that reality [39]. Romani [40] showed that specific negative emotion could incur specific customer behavior related to brand in different ways. For example, worry may lead to brand switching and anger can trigger complaining. Westbrook et al. [45] explains the emotional responses to product or consumption experiences, according to the basic emotion classification.

Recently, sentiment analysis is applied to investigate the influence of each discrete emotion on human behavior or social phenomena in e-community context. Bollen et al. [4] proposed 6 dimensions of emotions, i.e. c*alm, alert, sure, vital, kind,* and *happy*, and analyzed public mood from Twitter feeds for each dimension. Their results showed that the change of a specific public mood, *calm* is highly associated with stock index fluctuation. Kamvar et al. [20] presented an emotional search engine based on Plutchick's [38] emotion category. They visualized that certain demographic information (e.g. age or gender) and social events (e.g. Obama's Election Day) are associated with different discrete emotions. Kim et al [22] concerned what emotion a user tends to express after receiving a message containing a certain emotion. Their findings showed that there exist emotional patterns, and *greeting, sympathy, worry,* and *complaining* play significant roles of influencing other emotions in e-community context.

As above, specific links are expected to exist between a certain emotion and a certain human behavior or social phenomena. In our context, we think that there are differences among discrete emotions in terms of their influence on customer innovation activities in an online brand community. That is, there might be a certain discrete negative emotion which affects customers more than other discrete emotions. Hence, we hypothesize as follows:

Hypothesis 2a: Each discrete negative emotion in customer opinions will be likely to be different in drawing support among customers.

Hypothesis 2b: Each discrete negative emotion in customer opinions will be likely to have a difference in promoting discussion from customers.

Hypothesis 2c: Each discrete negative emotion in customer opinions will be likely to have a difference in leading to contribution to the innovation of firms.

3.3 Distinction in Intensity Level of Negative Emotions

Intensity refers to how strong is an emotional strength of a message [46]. Humans can differentiate between moderate and strong emotions in a text. For example, *outraged* may be considered as a stronger negative emotion than *annoyed*. In accordance with our context, we intuitively and naturally perceive that "*the new card management site makes me furious*" represents more intense emotional state than "*the new card management site makes me irritated*".

Although many previous researchers have paid attention to detecting text subjectivity or sentiment polarity, some research has been conducted with the intensity level of emotions. Some researchers tried to measure the sentiment intensity [36, 46], and others analyzed the distinctions in the influence of emotions, depending on the different intensity level of the emotional state [33, 43]. Thelwall et al. [43] classified Twitter messages into five scales from no sentiment level to very strong sentiment level. They show that popular social events such as "The Oscars" are normally correlated with increases in sentiment strength in Twitter messages. Mohammad et al. [33] classified intensity level of words into four levels: no, weak, moderate and strong; this was done to examine how words evoke specific emotions depending on its intensity level. And their results show that words with the highest intensity level of emotions are most effective in arousing emotions.

In light of this research, we may consider that the intensity level of emotions can be a significant factor that affects customer behaviors in an online brand community. Thus, we expect that customer ideas with a higher intensity level of emotions tend to evoke relevant emotions and promote engagement of other customers, and thus appeals to firms to pay more attention to such ideas. Thus, we hypothesize as follows:

Hypothesis 3a: A customer idea containing a higher intensity level of negative emotions is more likely to draw support from other customers.

Hypothesis 3b: A customer idea containing a higher intensity level of negative emotions is more likely to promote discussion from other customers.

Hypothesis 3c: A customer idea containing a higher intensity level of negative emotions is more likely to lead to contribution to the innovation of firms.

4. Research Methodology

Aiming at analyzing the correlation between the negative emotions in customer opinions and their influence on brand community, we conduct our research following the flow as shown in Figure 1. First of all, we collect customer opinions from a brand community, MSI (http://MyStarbucksIdea.com), and store them into a database. Using NLProcessor (2000), we attached POS (Part-of-Speech) tags on each of word in all customer opinion text. Then we used *Negative emotion lexicon* which we developed for our research, to extract the information about inclusion and intensity of negative emotion on each customer opinion. Ordinary least square (OLS) and logistic regression analysis were conducted to see whether the influence of negative emotions in customer opinions were significant. We will explain the process in more detail.

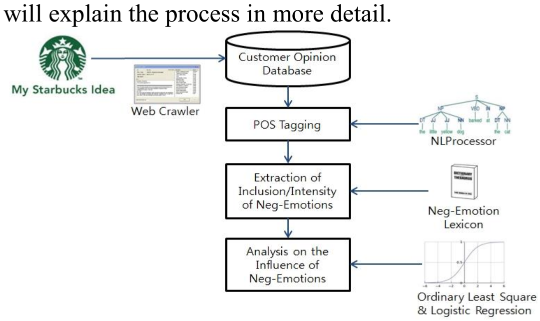

Figure 1. Research flow

4.1 Research Context

Among the most popular online brand communities is MSI, which was launched in March 2008, and more than 100,000 customer ideas were posted. To participate in MSI, customers have to register an account to submit their ideas. Any member can share any idea. Thus, various ideas are shared like complaints about past experiences, expectations to be fulfilled, or suggestions for the improvement of the product. Customers can vote for these ideas to promote favorable ideas, or demote unfavorable ideas. Each idea has its own point and the point can be increased or decreased by customers' promotion or demotion. This voting can be viewed as customer-led quantified idea evaluation, and the point represents how many customers agree to it. Customers can also comment on ideas to discuss with other members including the ideator and also the MSI staffs. As initial idea is rough in many cases, this discussion plays an important role in refinement or further development of ideas. If an idea is reviewed to be promising enough to be implemented by Starbucks management, the idea gets into the under review process, in which final decision is made by Starbucks whether to implement it or not.

4.2 Data Collection and Operationalization

We developed a web crawler for data gathering from MSI. We could collect totally 84,918 ideas for over two weeks from July 2, 2012 through July 15, 2012. Gathered data includes status, point, posted date and comments of each idea. Ideas with missing values, duplicated ones, or those written in non-English characters were discarded. Ideas consisting of less than five words were also excluded. Finally, 69,983 ideas were used for our experiment.

The dependent variables are *Support*, *Discussion* and *Contribution* which we operationalized from collected data. *Support* represents the degree to which an idea draws other members' support, and is measured by customers' voting. Considering the normality, we use its log value in our experiment. *Discussion* means the extent to which an idea promotes customer engagement for discussion over ideas. This is measured by the number of comments attached to each idea. *Contribution* is a binary variable which indicates whether or not the idea is determined as an idea promising enough to be implemented for the innovation of Starbucks. The independent variables are negative emotions and five discrete negative emotions in customer ideas. They are measured in two aspects of inclusion and intensity of each emotion word using Negative emotion lexicon which we developed for this study. We will look at this lexicon in more detail later. To normalize each idea in terms of its length, *word count* is used as a control variable. Considering the variance of the *word count*, we also took its log value. Definitions and acronyms for all variables are described in Table 1.

4.3 POS Tagging

POS tagging refers to "the process of assigning appropriate lexical category to individual word in a sentence of a natural language" and it has been playing important roles in Natural Language Processing area [12]. Words can have different meanings depending on the lexical category, e.g. "*good*" as an adjective has a positive meaning but as a noun has a neutral meaning. To identify such difference, we applied POS tagging on our dataset using NLProcessor, which outputs linguistic information by marking text with XML tags directly.

4.4 Extraction of Negative Emotions and Discrete Negative Emotions

We first develop a negative emotion lexicon to extract negative emotion word from each customer idea. The negative emotion lexicon was developed, following the processes shown in Figure 2.

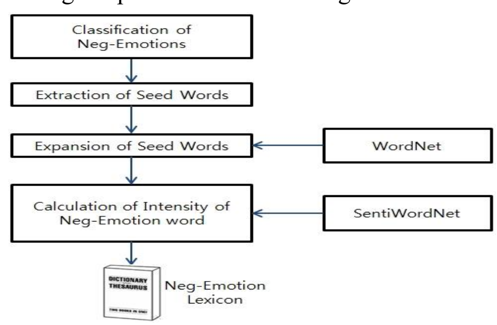

Figure 2. Construction Process of Lexicon for Negative Emotions

Table 1. Operationalization of Variables

Variable			Measurement	Acronym
DV	Support		Log value of the total point which an idea attained through voting	Support
	Discussion		The number of idea's comments	Discussion
	Contribution		Whether or not an idea is accepted to be reviewed by the firm for innovation	Contribution
CV	Word Count		The number of words an idea contains	Word_Count
IV	Inclusion of Negative Emotions		Whether or not an idea includes one or more negative emotion words	Neg_Inc
	Intensity of Negative Emotions		Sum of the sentiment score for all negative emotion words in an idea	Neg_Int
	Inclusion	Fear	Whether or not an idea includes one or more negative emotion words for each emotion respectively	Fear_Inc
		Anger		Anger_Inc
		Shame		Shame_Inc
		Sadness		Sadness_Inc
		Frustration		Frustration_Inc
	Intensity	Fear	Sum of the sentiment score for all negative emotion words in an idea for each emotion respectively	Fear_Int
		Anger		Anger_Int
		Shame		Shame_Int
		Sadness		Sadness_Int
		Frustration		Frustration_Int

Table 2. Five Negative Emotions & Set of Expanded Seed Words

Category	Subcategory / Seed word	Expanded Word
Fear	Fear, Worry, Anxiety, Nervousness	dread, dreadful, dreaded, panic, fright, affright, alarm, aversion, fearfulness, fearful, fearsome, etc.
Anger	Anger, Irritation, Disgust, Rage	anger, fury, resentment, wrath, indignation, angry, angered, fretful, annoyance, irritating, etc.
Shame	Shame, Guilt, Regret, Embarrassment	humiliation, humiliated, ashamed, mortified, dishonorable, shameful, regretful, etc.
Sadness	Sadness, Loneliness, Unhappiness, Depression	sad, grief, sorrowful, mournful, lonely, lonesome, lone, unhappy, depressed, blue, slump, etc.
Frustration	Frustration, Resignation, Powerlessness, Despair	frustrated, frustrating, discouraged, disappointment, dejected, powerless, helpless, etc.

4.4.1 Classification of Negative Emotions & Extraction and Expansion of Seed Words

We categorized negative emotions into five discrete negative emotions such as *fear, anger, shame, sadness*, and *frustration* as discussed already.

Each discrete emotion is categorized by four subcategories based on the empirical test result of Diener et al. [11] and Tronvoll [44]. We used these subcategories as seed words to construct negative emotion word sets for each discrete negative emotion. Using WordNet [31], we could expand the seed words as shown in Table 2.

4.4.2 Calculation of Intensity of Words in the Expanded Negative Emotion Word Set

We then, calculated the intensity of each word in the expanded negative emotion word set, to complete the negative emotion lexicon construction. The calculation is conducted using a WordNet-based lexical resource, SentiWordNet [14], which offers a set of sentimental words and other information related to each sentimental word. In SentiWordNet, a word can contain more than one POS, and can also have one or more meanings within a certain POS. For each meaning of a word, there are two scores which indicate positive and negative polarity of the meaning, respectively. The difference between these two scores (i.e., negative polarity minus positive polarity score) is the negativity score of the meaning (i.e., we call it, NSM.), and it implies how much negative sentiment the meaning possesses (see Table 3 for an example). In addition, each meaning has an index, which indicates the order of frequency, showing how frequently the word is used with the meaning. The negative sentiment score of each word (i.e., NSW) is calculated using weighted average of NSMs of all meanings within a certain POS, where we used the inverse of the index of each meaning as a weight for each meaning's NSM. The pseudo-code for intensity calculation of negative emotion words for negative emotion lexicon construction is described in Figure 3. For example, intensity of an expanded negative word, "*frustrated*", is calculated from {(0.75)*1 + (0.375)*(1/2) + (1)*(1/3)}/{(1 + (1/2) + (1/3)}. An example of the negative emotion lexicon is shown in Table 4.

Table 3. An Example of NSMs of the Word

Word	POS	Index	Pos.	Neg.	NSM
frustrated	Adjective	1	0	0.75	0.75
frustrated	Adjective	2	0.125	0. 5	0.375
frustrated	Adjective	3	0	1	1

```
Input: words in the expanded negative emotion word set
Initialize Sum_of_Weighted_NSM = Sum_of_Weight = 0
For each word in an expanded negative emotion word set
    For each meaning of the word
        SumofWeightedNSM+= NSM/Index
        SumofWeight += 1/Index
    End
    NSW = SumofWeightedNSM/SumofWeight
End
Output: Intensity value for each word in the expanded negative emotion word set
```

Figure 3. Pseudo-code for Intensity Calculation of Negative Emotion Words based on SentiWordNet

Table 4. Example of Negative Emotion Lexicon

Category	Word	POS	Intensity
Sadness	*Sadness*	Noun	0.75
	Sad	Adjective	0.667
	Unhappy	Adjective	0.719
...	...	...	...

4.4.3 Calculation of Inclusion and Intensity of Negative Emotions in Each Idea

Utilizing the negative emotion lexicon which has been explained, we calculated the inclusion and intensity of negative emotion and those of discrete negative emotions in each customer idea. Calculating the inclusion of negative emotion is simple. If there exists one or more negative emotion word in a customer idea, the value of inclusion of the idea becomes 1, and otherwise 0. In this calculation, POS information is used to filter some negative words which are in fact positive or neutral considering their POS tags in ideas. Calculating the intensity of negative emotion is similar. Instead of 1 or 0, we assign the sum of intensity scores of all negative emotion words in each idea as the intensity value of the idea. POS information is also used in this case. Inclusion and intensity for each discrete negative emotion can be obtained in the same way.

4.5 Analysis of the Influence of Negative Emotions

We employed two types of regression models: ordinary least-squares (OLS) regression for the dependent variable *Support* and *Discussion*, and binomial logistic model for dependent variable *Contribution*. Table 5 shows the descriptive statistics of variables. In testing hypothesis 1, we employed 3 regression models as follows. In testing hypothesis 1, we employed 3 regression models as below.

$$\textbf{\textit{Support}} = \alpha + \beta_1 Word\_Count + \beta_2 Neg\_Inc \;\ldots\ldots\; (1)$$

$$\textbf{\textit{Discussion}} = \alpha + \beta_1 Word\_Count + \beta_2 Neg\_Inc \ldots\; (2)$$

$$\textbf{\textit{Pr(Contribution =1)}} = \Phi(\alpha + \gamma_1\ Word\_Count + \gamma_2\ Neg\_Inc) \;\ldots\ldots (3)$$

In testing hypothesis 2, we employed 3 regression models as below.

$$\textbf{\textit{Support}} = \alpha + \beta_1 Word\_Count + \beta_2 Fear\_Inc + \beta_3 Anger\_Inc + \beta_4 Shame\_Inc + \beta_5 Sadness\_Inc + \beta_6 Frustration\_Inc \ldots\ldots\; (4)$$

$$\textbf{\textit{Discussion}} = \alpha + \beta_1 Word\_Count + \beta_2 Fear\_Inc + \beta_3 Anger\_Inc + \beta_4 Shame\_Inc + \beta_5 Sadness\_Inc + \beta_6 Frustration\_Inc \ldots\ldots\; (5)$$

$$\textbf{\textit{Pr(Contribution =1)}} = \Phi(\alpha + \gamma_1 Word\_Count + \gamma_2 Fear\_Inc + \gamma_3 Anger\_Inc + \gamma_4 Shame\_Inc + \gamma_5 Sadness\_Inc + \gamma_6 Frustration\_Inc) \;\ldots\ldots\; (6)$$

In testing hypothesis 3, we employed 6 regression models in the same way as above. Then, we used SPSS 12.0 for the analyses.

5. Results

All hypotheses we developed are supported. The results of regression for testing hypothesis 1 are included in Tables 6, 7 and 8. The variable, inclusion of negative emotion is all significant across the three models.

The results of regression for testing hypothesis 2 are included in Table 9. There are differences among the discrete negative emotions. Significance for each variable is varying depending on models, and only frustration is proved to be significant consistently.

Table 6. Results of OLS (Influence of Inclusion of Negative Emotion on *Support*)

Var.	B	S.E.	t-value	Sig.
Neg_Inc	.017	.002	7.797	**.000*****
Word_Count	.000	.000	1.275	.202
(Constant)	6.517	.001	7389.711	.000

*** p<0.005, ** p<0.01, * p<0.05

Table 7. Results of OLS (Influence of Inclusion of Negative Emotion on *Discussion*)

Var.	B	S.E.	t-value	Sig.
Neg_Inc	.554	.100	5.519	**.000*****
Word_Count	.002	.000	5.124	.000
(Constant)	1.629	.042	39.143	.000

***** p<0.005, ** p<0.01, * p<0.05z**

Table 8. Results of Logistic Regression (Influence of Inclusion of Negative Emotion on *Contribution*)

Var.	B	S.E.	Sig.	Exp(B)
Neg_Inc	.310	.091	**.001*****	1.364
Word_Count	.000	.000	.923	1.000
(Constant)	-4.065	.042	.000	.017

*** p<0.005, ** p<0.01, * p<0.05

The results of 6 regression models for testing hypothesis 3 are summarized in Table 10, where we show significance and B (or Exp(B)) value of each variable. The results show that the higher the intensity level of negative emotion in each idea is, the more the significance of its influence on customer innovation activities and customers' contribution to innovation except for *fear* on support and contribution, *anger* on discussion and contribution, and sadness on discussion. Among discrete negative emotions, *frustration* is found to be the most influential.

Table 5. Descriptive Statistics of Variables

Variable			Observation	Mean	Std. Dev.	Min.	Max.
DV	Support		69983	6.519	0.159	0	11.173
	Discussion		69983	1.845	7.515	0	1026
	Contribution		69983	0.017	-	0	1
CV	Word Count		69983	92.191	88.139	5	2774.5
IV	Inclusion of Negative Emotion		69983	0.096	-	0	1
	Intensity of Negative Emotion		69983	0.091	0.334	0	5.846
	Inclusion	Fear	69983	0.045	-	0	1
		Anger	69983	0.006	-	0	1
		Shame	69983	0.017	-	0	1
		Sadness	69983	0.014	-	0	1
		Frustration	69983	0.022	-	0	1
	Intensity	Fear	69983	0.030	0.171	0	3.15
		Anger	69983	0.007	0.093	0	2.666
		Shame	69983	0.020	0.159	0	3.502
		Sadness	69983	0.014	0.135	0	3.5
		Frustration	69983	0.017	0.127	0	2.25

Table 9.Results of OLS and Logistic Regression (Influence of Inclusion of Negative Emotion and Discrete Emotions on *Support*, *Discussion* and *Contribution*)

Var.	Support	Discussion	Contribution
	Sig. (B)	Sig. (B)	Sig. (Exp(B))
Fear_Inc	**.032* (.006)**	**.000*** (.684)**	.173 (1.197)
Anger_Inc	**.018* (.017)**	.076 (.609)	.947 (.978)
Shame_Inc	**.004*** (.013)**	**.004*** (.624)**	.052 (1.430)
Sadness_Inc	**.000*** (.024)**	.450 (.178)	**.010** (1.627)**
Frustration_Int	**.000*** (.027)**	**.000*** (.694)**	**.020* (1.469)**

*** $p<0.005$, ** $p<0.01$, * $p<0.05$

Table 10.Results of OLS and Logistic Regression (Influence of Intensity of Negative Emotion and Discrete Emotions on *Support*, *Discussion* and *Contribution*)

Var.	Support	Discussion	Contribution
	Sig. (B)	Sig. (B)	Sig. (Exp(B))
Neg_Int	**.000*** (.015)**	**.000*** (.773)**	**.000*** (1.403)**
Fear_Int	.218 (.004)	**.000*** (1.426)**	.061 (1.312)
Anger_Int	**.020* (.015)**	.126 (.465)	.971 (.989)
Shame_Int	**.019* (.009)**	**.015* (.439)**	**.040* (1.355)**
Sadness_Int	**.000*** (.026)**	.089 (.359)	**.001*** (1.664)**
Frustration_Int	**.000*** (.032)**	**.000*** (.809)**	**.014* (1.565)**

*** $p<0.005$, ** $p<0.01$, * $p<0.05$

6. Discussion

Three insights emerge from the results of our study. The first is the significant influence of negative emotions in an online brand community context. In the online brand community which is to utilize customer ideation, we found that customer ideas containing negative emotion tend to draw support and promote discussion from customers, and lead an ideator to contribute to the firm's innovation. This is consistent with our expectation derived from the arguments of negative bias literature [15, 17, 32], and the results of recent empirical studies [10, 35].

Second, there exist differences among discrete negative emotions in terms of their influence on customer innovation activities, and we found that *frustration*, *sadness* and *shame* are more influential than *fear* and *anger* in our brand community. Among all discrete negative emotions, *frustration* is found to be the most consistently and significantly influential on *Support, Discussion* and *Contribution*. We may interpret this result using the "*frustration-aggressive hypothesis*" which holds that *frustration* is direct cause of aggressive behavior [13]. According to Dollard et al., [13] *frustration* usually provokes some forms of aggressive behavior. In their theory, aggressive behavior is defined as a consequence of *frustration* such as infliction of injury to definite object that cause this sentiment [3, 13] Also, Dollard et al., [13] mentioned different aggressive forms theoretically were interchangeable with any aggressive act which may decrease their *frustration*. (p.50). As emotion is contagious to predispose other person to take a particular action [39], in our context we can speculate that *frustration* in customer ideas will more likely to affect other customers to take such an aggressive reactions to other customers. Therefore, as shown in our result, active voting for the customer ideas containing *frustration* (i.e. Support) and vibrant discussion over them (i.e. Discussion) might be interpreted as interchangeable reaction of aggressive behavior in respect to customer ideas containing *frustration*. And such aggressive reactions may make a firm hard to ignore the ideas containing *frustration* and push the firm to adopt the ideas for its innovation (i.e. Contribution).

Lastly, customers are more likely to react to an idea which expresses stronger negative emotions in an online brand community. That is, the intensity level of emotions is found to be a significant factor in an online brand community. As for most of the discrete negative emotions which significantly affect customer activities when they are included in customer ideas, their influence on customer activities is proportional to its emotional intensity. However, intensity of specific discrete negative emotion like fear does not follow the pattern of other discrete negative emotions. Just inclusion of fear in customer ideas, although its expression is not strong enough, can be sufficiently influential in drawing support from customers. It is shown that inclusion of shame is strongly influential on drawing support and promoting discussion, but the influence is relatively less proportional as its intensity level increases. Such different patterns depending on emotion type may come from the characteristics of each emotion.

7. Contribution and Conclusion

We have presented that negative emotions can play positive roles in an online brand community in terms of increasing customer engagement, and ultimately, influencing on firms' innovation. This provides an interesting contrast to prior studies which usually have considered negative emotions as negative due to their possible harmful consequences. We expect our study can contribute both to theory and to practice.

Theoretically, we extend the emotion research stream by testing empirically the influence of negative emotions contained in customer opinions on customer behaviors in an online brand community context in which the influence of emotion has rarely been discussed in previous literature yet. As a result of our study, we showed that both negative emotion and specific discrete negative emotions affect both customer innovation activity and customers' contribution to innovation significantly. Also, it is shown that intensity level can be a significant factor that affects customer behaviors in online brand communities.

From a managerial perspective, the results of this study can be used to develop guidelines for managing brand community. For example, our results imply firms had better prepare different approaches for exploiting customer opinions depending on the emotions therein. Firms need to pay more attention to the ideas containing negative emotion, since they can possibly be more influential to other customers. Firms are required to be more attentive especially to the ideas containing *frustration* than to the ideas containing anger or fear for the same reason. Besides, this study shows that how to classify large amount of customer ideas depending on their emotional information automatically. Since the case of too much information to be processed can possibly happen in most online brand communities, our approach can be meaningful for firms to mitigate such information overload problem by making it possible to predict each of customer idea's influence in its initial submission stage.

This study has several limitations that can provide opportunities for future study. First, we tested our hypotheses with a dataset obtained from a single online brand community. If we extend our research to some other brand communities, we may be able to validate and elaborate our findings. Second, we examined emotion from the perspective of its influence on customer innovation activities. If an analysis from other perspectives such as the idea contents factors or contextual factors is conducted, we may deepen our understanding about customer behaviors in online brand communities.

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