Value Co-Destruction: a Text-Mining-Based Mixed Method Study on Social Media Interactions

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ABSTRACT

To better understand how big data interconnects firms and customers, we analyse the role of customers' emotions in the process of value co-destruction in a social media context. We perform a text mining based algorithm capable of identifying anger, expectation, disgust, fear, and sadness in peaks of problematic social interactions. The developed algorithm associated with an in-depth qualitative analysis shows how to employ unstructured big data to understand the role of negative emotions in the process of value co-destruction.

Key Words: value co-creation, value co-destruction, bid data, mixed methods, social media.

1. INTRODUCTION

Service-dominant (S-D) logic suggests that value is co-created by firms and customers (Vargo & Lusch, 2004, 2008). Recent literature has started to acknowledge that the relationships among actors sometimes lead to value co-destruction (VCD) rather than value co-creation (VCC). VCD is defined as "an interactional process between service systems that results in a decline in at least one of the system's well-being" (Plé & Cáceres, 2010, p. 431).

VCD has been addressed by only a limited number of studies, just a few of them have considered how the interactions among actors lead to VCD (Prior & Marcos-Cuevas, 2016), and nobody has studied which feelings, emotions, and moods are involved in these problematic social interactions. Moreover, despite the voluntary sharing of personal information and the uploading of contents on various online social media present some unique opportunities for companies to interact with their customers, the current research on VCD has mainly focused on offline settings also neglecting the use of big data (Xie, Wu, Xiao, & Hu, 2016). By handling big data through appropriate statistical methods, it is possible to portray customer emotions and reflect their value co-destructing actions. Despite the rapid growth in social media sites and in data mining for emotion (sentiment analysis), little research has tied the two together (Thelwall, Wilkinson, & Uppal, 2010) and fewer has understood VCD in the online context.

In this theoretical context, central questions like "Which emotions are involved in the process of VCD?" and "How emotions affect the interactional process between firm and customers?" remain unanswered. As a consequence, the purpose of this paper is to develop a useful algorithm capable of analyzing data from a firm's Facebook page and automatically discern users' positive and negative opinions which in turn may trigger VCC or VCD and to qualitative analyze peaks of negative comments to understand which topic triggered the VCD. To do so, we will employ an explanatory sequential mixed design (Creswell, Plano Clark, et al., 2003) which will involve collecting quantitative data first and then explaining the quantitative results with in-depth qualitative analysis. We will collect data from Huawei Mobile UK Facebook page to assess whether emotion such as anger, expectation, disgust, fear, and sadness are related to VCD.

2. LITERATURE REVIEW

The interactional process is a course in which two or more actors have reciprocal actions and influences over time (Plé & Cáceres, 2010). The interaction between actors is necessary to initiate value *co*-creation and/or *co*-destruction (Echeverri & Skålén, 2011).

Researchers have pinpointed four different kinds of problematic social interactions connected to VCD. The first, *customer misbehaviour,* is defined as actions by customers who intentionally, overtly, or covertly disrupt functional interactions by violating the accepted norms of conduct (Echeverri, Salomonson, & Aberg, 2012; Kashif & Zarkada, 2015). The second, known as *contradictory interactions,* happened when the actors involved in a business relationship have divergent opinions that effective spoil their interactions. The third, defined as *conflictual interactions,* is the result of divergent opinions, but, in this case, lead to real conflicts between actors (Vafeas, et al., 2016). Finally, *negative interactions* refers to all interactions that are undesirable for one or more actors (Smith, 2013). In the above-mentioned debate, some scholars consider problematic social interactions as a determinant for VCD (Echeverri & Skålén, 2011; Worthington & Durkin, 2012) or value diminution (Vafeas et al., 2016). For example, a recent empirical study examining how employees deal with client misbehaviour, including the resources expended while doing so, indicated that both client misbehaviour and resource non-integration led to VCD (Echeverri et al., 2012; Frau, Cabiddu & Muscas, 2018). This view is complemented by other scholars who maintain that misbehavior, contradictory, conflictual, and negative interactions trigger and encourage misuse of resources (Kashif & Zarkada, 2015; Smith, 2013), which is an input for VCD. On the other hand, some scholars disagree by claiming that contradictions and conflicts might be a source of VCC (Fyrberg Yngfalk, 2013; Laamanen & Skålén, 2014). For instance, Fyrberg Yngfalk (2013) suggests that "contradictory resource integration and interactions are fundamental for value to be co-created" because they start a process of "new interpretations and meaning creation" for innovative solutions. Resonating with the previous studies, Laamanen and Skålén (2014) suggested that conflicts promote innovation and creativity because conflicts are an inherent characteristic of human interactions and conflictual interactions are, "neither positive nor negative". In the Information System (IS) literature, early signs of both value creation and destruction are depicted showing that an IS artifact may be internally contradictory in the way that users of IS co-create and co-destruct value at the same time (Vartiainen & Tuunanen, 2016).

All in all, the *interactional process* is acknowledged as inherent in the collaborative formation of value, while it is somehow unclear how it can be characterized as a source of VCC or VCD. In this debate, our work sheds light on the process of interaction among firms and customers in a social media setting by analyzing the emotions felt by the users during the interaction process. In doing so, this study adopts quantitative techniques to distinguish positive and negative user's comments, to divide them into homogenous groups and to pinpoint peaks of negative comments in which the main user's emotions are identified during the interactions whit the firm and other users in the consequent VCD process. Nevertheless, a need exists in the literature to not only obtain quantitative results but to explain such results in more detail, especially in terms of problematic social interactions and emotions because little is known about the mechanisms behind VCD.

3. METHODS

To analyze the role of customers' emotions in the process of VCD in a social media context, we employ the explanatory sequential mixed method research design (Creswell et al., 2003). This research design includes collecting, analyzing, and integrating quantitative and qualitative methods in one study. In our work, the priority is given to the quantitative part and the qualitative one is used to help to explain the quantitative results. Our work needs a mixed methods approach since quantitative methods discerned positive and negative comments, identified peaks of problematic social interactions and find the relationships between topics and emotions during the peaks, but they did not provide any detail about the topics discussed during the peaks and with king of interaction characterize the topic. The qualitative analysis added depth to the study by exploring the abovementioned topics and links with emotions and the kind of interactions. Therefore, our research purpose and related questions are congruent with employing mixed methods.

We focused our attention on Huawei Facebook page because of its fast market development and the big number of online interactions that take place and with enabled us to answer our research questions. We selected the UK Huawei Facebook page for the greatest number of likes and followers compared with the other English-speaking pages of the company. Huawei Technologies Co. Ltd. is a Chinese company of ICT and telecommunications that develops systems, network solutions, and technological products all over the world. It is one of the most important brands in the mobile and telecommunications industry.

3.1. Data Collection and Data Cleaning

Quantitative stage. The dataset consists of 29,945 records and it is made up of both postings and comments posted on the Huawei UK Facebook page from September 2011 to January 2017. It was created employing NCapture, a browser application of NVivo software and then converted to an excel file. A first data cleaning process concerned the removal of 3,125 records relative to comments from external pages and their comments, inasmuch we considered just the dyadic interactions between Huawei Mobile and its customers in the firm UK Facebook page. From the remaining 26,820 only the 22,955 comments posted by users within the Huawei Mobile UK Facebook page were considered for the analysis. Successively, the "stop words" (i.e. articles, conjunctions, and prepositions) were removed after being listed by using an existing lexicons stored in the "tm" R package (Meyer et al., 2008).

Qualitative stage. The quantitative data analysis identified the peaks of negative comments. For each of them, we made a qualitative dataset selecting negative comments which were published during the period of the negative peak. Every comment was associated with a label (1, 2 or 3) as a result of the quantitative Topic Analysis, so we could create for each peak three homogenous subgroups according to the topic of the interactions. Finally, the datasets were uploaded into NVivo 10 for the thematic qualitative data analysis. A summary of the datasets is shown in Table 1.

Table 1: Number of comments grouped for topic and actor per each peak of problematic social interactions.

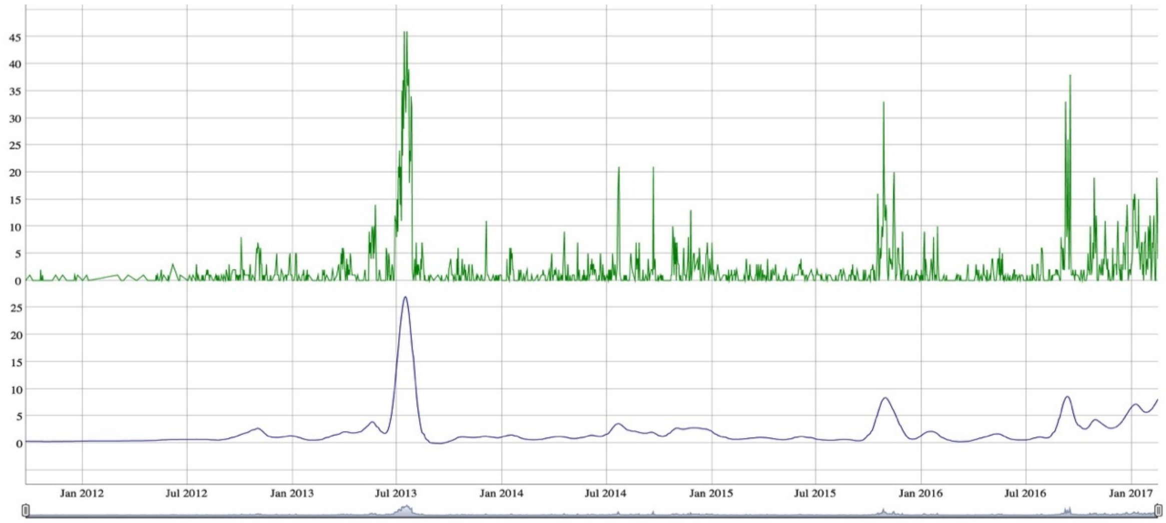
	First peak	Second peak	Third peak
Topic 1	400	90	76
Topic 2	170	77	57
Topic 3	169	50	69
Total Customers' comments	739	217	202
Firm's comments	61	22	58

3.2. Data analysis

Quantitative stage: The algorithm. The Sentiment Analysis was carried out using the text2vec R package (Selivanov, 2016). Firstly, we constructed a document-term matrix (DTM), i.e. to vectorize text by creating a map from words to a vector space. Then a logistic regression model was fitted to that DTM, using the database "sentiment140" (Go et. al, 2009), which consists of 1,578,627 records already classified as either positive or negative. Finally, we applied the model to our data, obtaining for each comment the probability of their positivity, ranges from 0 (totally negative comment) to 1 (totally positive comment). In order to define the probability threshold to divide the comments into positives and negatives, ROC analysis was performed, obtaining the threshold that maximizes the correct classification of the comments. Adopting ROC analysis, it was assumed the comments can only be positive or negative since users post in a firm's social media page to express her/his opinion which is hardly neutral. The obtained threshold is 0.52. Once negative comments have been identified and selected, that is comments with a probability of their positivity lower than 0.52 (20.12% of the overall comments), it was possible to represent graphically their distribution (Figure 1). In the upper panel is represented the real distribution, while in the bottom panel the smoothed one.

Throughout the entire time span analyzed, there were sub-periods in which the distribution of the negative comments reached significant peaks. The identification of such periods was necessary to focus on the Content Analysis of the relative comments. We identified three periods: 1) from June 23 to August 11, 2013; 2) from October 23 to November 17, 2015; and 3) from December 26, 2016, to January 30, 2017.

Figure 1: Negative Comments Distribution. The solid black line is the cubic smoothing spline.



In order to identify groups of the negative comments that differed according to the words used, Topic Analysis was performed. We used the Latent Dirichlet Allocation (LDA), implemented in the R package "topicmodels" (Hornik & Grün, 2011). Since the dataset consists exclusively of predictably negative comments, its classification was done with the aim of identifying the negative words that featured the same groups of comments and not the topics discussed. The search for such groups had the purpose of cataloguing negative comments based on users' words that are linked to certain feelings, emotions, and moods. The topics identified have been characterized by words that have frequently appeared in comments about each topic.
Finally, Topic Sentiment Analysis was performed searching for feelings and moods experienced by users who have expressed their negative opinions over a given period. Usually emotion lexicons are limited and small because of the high cost needed for their creation. Nevertheless, Saif and Turney (2013), through a crowdsourcing project, created a large word-emotion and word-polarity association lexicon, called "nrc" lexicon. That is one the most word-emotion and word-polarity association lexicon available. In fact, lexicon "nrc" consists of 13,901 words that are accompanied by a wide variety of feelings and/or emotions (positive or negative) such as anger, expectation, disgust, fear, happiness, sadness, surprise and trust. For these reasons, "nrc" lexicon was employed to perform the topic sentiment analysis.

Qualitative stage: The thematic analysis: For every identified peak, we performed a two-phase coding process. All comments were inductively coded following the instructions of Miles and Huberman (1994). In the first coding phase, we looked for descriptive and interpretative codes. At the end of the first phase, we obtained a former collection of structured codes, which was the base for the second coding phase. As a second coding phase, we sought thematic codes (Miles and Huberman, 1994). Here, we could identify and explain the topics discussed during the peaks of negative comments. Once the within-peak analysis ended, we had a list of topic for each peak. We used that list to perform a cross-thematic analysis by which we realized whether the topic is simply idiosyncratic to a single peak or consistently replicated by several peaks (Eisenhardt and Graebner 2007). The overall qualitative analysis served for deepening the quantitative ones.

4. RESULTS

The percentage of each sentiment and for each topic was calculated based on the frequency of negative words, which are similar to those sentiments in each group's comments for each peak of problematic social interactions analysed. Table 2 shows the results obtained for the first period. This period is definitely the most numerous, grouping 739 negative comments, as well as the most unbalanced with the number of the comments of the topic 2 are more than double of those of the other two. It is easy to note that the comments of topic 2 are characterized by Disgust and Anger, reaching the values approximately close to 29%, whereas all the three reminder sentiments lower than 20%. The comments on topic 1 are mainly represented by Fear, Expectation, and Sadness, with 27.5%, 25.9%, and 23.7%, respectively. Finally, in topic 3 the most represented sentiment is still Disgust (24.5%), while Sadness and Anger are a step lower.

Table 2: Number of comments (%) and sentiments percentage distribution of the three topics identified in the first period (23/06/2013-11/08/2013).

No.	Topic	Anger	Expectation	Disgust	Fear	Sadness
169 (23)	1) The company copies the competitors	11.4	25.9	11.4	27.5	23.7
400 (54)	2) Business partners selection disapproval	27.8	19.3	29.5	10.5	12.9
170 (23)	3) Poor devices quality	21.2	14.8	24.5	17.0	22.6

Concerning the second period, Table 3 illustrates the sentiment distribution of the 217 comments that make it up. Topic 1 is well represented by Disgust (27.1%) and Fear (21.4%) since Anger, Expectation, and Sadness acquired less importance all reaching 17.1%. While, the comments on topic 2 are clearly characterized by Expectation, much more than those of the other topic 1 and 3, achieving a 30.2%. Here, also Anger and Disgust assume importance both reaching 20.8%. Finally, the comments on topic 3 are represented principally by three sentiments, in order of importance, they are Expectation, Disgust, and Fear, with 27.5%, 23.5%, and 22.1% respectively. Just a step under there is Sadness (15.5%) and the least is Anger (11.4%).

Table 3: Number of comments (%) and sentiments percentage distribution of the three topics identified in the second period (23/10/2015-17/11/2015).

No.	Topic	Anger	Expectation	Disgust	Fear	Sadness
77 (35)	1) The new product does not like	17.1	17.1	27.1	21.4	17.1
50 (23)	2) Shipment / distribution problems	20.8	30.2	20.8	13.2	15.1
90 (42)	3) Ugly device	11.4	27.5	23.5	22.1	15.5

The last period concerns 202 negative comments (Table 4). The topic 1, Sadness is the most characterizing sentiment (28.3%), followed by Expectation and Fear, 26.4% and 22.6% respectively. Noteworthy it is to highlight the extremely low value obtained by Disgust (5.7%). Topic 2 is characterized by Expectation (25.9%) and Disgust (22.4%), inasmuch as the other sentiments reach certainly lower values: Anger 19.0%, Sadness 17.2% and Fear 15.5%. Lastly, in topic 3, Expectation is the sentiment with the highest value (33.3%). Among the other four sentiments, solely Anger exceeds the threshold of 20%, obtaining a value equal to 21.8%.

Table 4: Number of comments (%) and sentiments percentage distribution of the three topics identified in the third period (26/12/2016-30/01/2017).

No.	Topic	Anger	Expectation	Disgust	Fear	Sadness
69 (34)	1) Limited compatibility with network companies	17.0	26.4	5.7	22.6	28.3
76 (38)	2) Technical issues	19.0	25.9	22.4	15.5	17.2
57 (28)	3) Disliked device feature	21.8	33.3	12.8	17.9	14.1

Qualitative results: The *first peak* of problematic social interactions was discerned by three topics by the algorithm that the qualitative analysis labelled as: The company copies the competitors; Business partners selection disapproval; Poor devices quality. When accusing the company of copying its competitors, the customer felt Fear, disregarded Expectations and Sadness. Users express their dissent firmly and normally without using offensive or rude language excretions (see Table 5). On the other hand, the company replays to the accuse of coping, its interactions are limited to comments such as *"Hi [user name]. It has come to our immediate attention that you have posted a false comment. We will not allow such proven false statements [...]"*. The interactions concerning this topic can be categorized as contradictory. Sentiments like fear, sadness, and disregarded expectations can start and amplify the erosion of the relationships between the company and its customers activating the VCD process. While in the following two topics, interactions seemed to be more divergent and so conflictual. In topic 2, customers used a more aggressive language dictated by the anger released by the Huawei new commercial alliance. Although, the disgust felt by the users is expressed in a calmer tone which balances the anger comments. Once again, the company weakly responded: *"Some retailers are placing it [the mobile] on Sim Free which is close to what the PAYG price would be anyway"*. Therefore, from the joint analysis of the feelings, it emerged that the interactions of this topic are of a conflictual nature and capable of a more dangerous VCD process. Also in topic 3, the users express their disappointment about the devices quality in a decisive and lively way, being present in the mix of feelings a high percentage of Anger (21.2%). Here the interactions can be classified as conflicting. Although the negative sentiments did not trigger users' misbehaviour, they facilitate VCD since conflicts can alienate the company from consumers or break their trust relationship.

Table 5: Summary of the first peak of problematic social interactions

Topic	Quote example (sentiment)	Kind of interactions
1) The company copies the competitors	"I'm sensing copyright infringement" (Fear)	Contradictory interaction
	"Awful give me an iPhone any day" (Expectation)	
	"It's quite sad... it's like those who buy knockoff Louis Vuitton or Burberry because it's similar." (Sadness)	
2) Business partners selection disapproval	"Does it matter what phone it is? If it's on Vodafone it won't work..." (Disgust)	Conflictual interactions
	"It's a P6 but fuck Vodafone...." (Anger)	

3) Poor devices quality	"I got one by my work and managed less than a month as the phone is the worst item of technology I've ever used!!!! Truly, truly substandard rubbish." (Disgust)	Conflictual interactions
	"Huawei, your brand values are awful ☹. What warranty do you provide with your products? I had a Blaze that was faulty and you provided zero manufacturer support." (Sadness)	
	"Bought one, hated it, sold it! the Huawei UI is horrid!" (Anger)	

The *second peak* of problematic social interactions has been triggered by three main topics of conversation: The new product does not like; Technical issues; Poor device quality. Each of them involved a different mix of negative emotions which spoiled at several degrees the customer-firm interaction and so triggering VCD. The launch of a new product not belonging to the company classic product line has triggered a reaction of Fear and Disgust in the users of the Facebook page. Users express their negative opinion about the product aesthetics and functionality through the comments on the social media. While the company avoided answering to the criticisms and reacted gazing its attention only to customer technical requests: *"Hi [customer name], yes the Huawei Watch runs Android Wear and is compatible for Android 4.3+ and even Apple iOS 8.2+!"*. Here, the interactions do not result either in misbehaviour, conflictual or contradictory interaction. For this reason, the interactions of this topic have been classified under the broad category of negative interactions. From the firm point of view, neglecting customers' sentiments like fear and disgust can trigger VCD since customers can feel unheeded and stop providing useful feedback to the company. The second topic was about technical problems which caused a disregard of customer expectations and reactions of anger and disgust. In the customer, comments are frequent the use of impolite expressions and the use of bad words is also recurrent. In spite of the customers' aggressive comments, the company replayed providing more pieces of information about the technical issues. Even if the interactions in this topic can be traced back to the conflictual category, the company marginalized VCD by handling anger and disgust reactions produced by the customer disregard expectations.

Table 6: Summary of the second peak of problematic social interactions

Topic	**Quote example (sentiment)**	**Kind of interactions**
1) The new product functions do not like	"If I was going to buy a smartwatch, I would not get the Huawei which is like a flat tire, annoying and ugly." (Disgust)	Negative interaction
	"It's a shame it's so limited with functions when using iPhone. I was just about to purchase until I realized I can't even get SMS texts on it. What a shame."(Fear)	
2) Shipment / distribution problems	"I was promised my 6P would ship late last week or early this week. Tomorrow will be considered the middle of this week. No one can tell why it hasn't shipped today or if it will ship today. What's wrong with your distribution system??? I will be filing a BBB complaint next if it doesn't ship very very soon!" (Expectation)	Contradictory interaction

	"I wonder how you could take my money and send me another order number! Now I wait for a refund because the system only took my hard earned money. I will buy LG version. I feel bad for your team dealing with my anger!" (Anger)	
	"I was told mine 6P would ship late this week or very early next. If there is no shipment by then I'll be very upset…" (Disgust)	
3) Ugly device	"Crappy off-brand junk" (Expectation)	Conflictual interaction
	"Fugly" (Disgust)	
	"That thing is ugly as hell. It looks like my grandpa's old watch. I'll keep looking at my phone when I need to." (Fear)	

The *third peak* of problematic social interactions is also composed of three main topics: Limited compatibility with network companies; Technical issues; Dislike device features. When users discuss the poor compatibility of the device with network companies, we observed a mix of feelings composed of sadness, lack of expectations and fear. Users express their feelings through negative interactions, exposing the difficulties and compatibility limitations that the device seems to have with some network companies. However, users do not trespass on conflicting, contradictory and misbehaviour interactions. As observed for the same topic in the previously-analysed peak, the interactions regarding the technical problems have generated a set of feelings consisting of disregard of expectations, anger, and disgust. As in the second peak of problematic interactions, also, in this case, the language used in the conversations is offensive and can be traced back to the category of conflictual interactions. Finally, the disappointment and anger caused by the difference between the expectations on the characteristics of the device and the actual revealed by the device, have caused an increase of anger in the interactions which can be considered conflictual.

Table 7: Summary of the third peak of problematic social interactions

Topic	**Quote example (sentiment)**	**Kind of interactions**
1) Limited compatibility with network companies.	"Unfortunately Sprint won't work with this device, because like Verizon, Sprint is on a CDMA network." (Sadness)	Negative interaction
	"Why are the phones sold in 3 store single sim. Bought a P9 Lite from them. Disappointed to find it out that it's only a single sim." (Expectation)	
	"Wish they worked with metro pcs" (Fear)	
2) Technical issues	"Was disappointed with the lack of updates for the Mate 2. I tried you once but never again. Sorry." (Expectation)	Conflictual interaction
	"Got mine but the software is very outdated which is a shame"(Disgust)	
	"Can anyone help? Stupid phone overheats regularly then it gets stuck on the start-up screen. Can't even get into play store to download antivirus Norton. I hate this phone." (Anger)	
3) Disliked device feature	"I'm still waiting for an update on my Ascend Mate 2 that Huawei promised. Smh." (Expectation)	Conflictual interaction

	"Damn! Not much difference except 12mpx camera and extra processors." (Anger)	

5. DISCUSSION

This work contributes to the wider VCC literature since it complements the studies about problematic social interactions which lead to VCD. Previous studies have considerably enhanced our understanding about VCD by explaining the problematic social interactions as customer misbehavior (Echeverri et al., 2012; Kashif & Zarkada, 2015); contradictory interactions; conflictual interactions (Vafeas et al., 2016); and generically as negative interactions (Smith, 2013). Overall considered, this branch of literature has found a link between firm-customer problematic interactions and the VCD process. On the other hand, these explanations lack considering which feelings and emotions are involved in these kinds of interactions. Our study participates in the debate by analyzing five negative emotions (anger, expectation, disgust, fear, and sadness) in a social media setting. For each peak of problematic social interactions, thanks to the quantitative analysis, we identified three topics and precisely pinpointed the mix of negative emotions involved in each conversation. Then, exploiting the qualitative analysis, we found a connection between the mix of negative emotions and the kind of interactions. Finally, by combining quantitative and qualitative analysis, we explained the impact of the emotions mix in terms of VCD. In doing so, this study sheds light on the VCD process by complementing previous literature on firm-customer social interactions (Echeverri et al., 2012; Kashif & Zarkada, 2015; Vafeas et al., 2016; Smith, 2013).

Nevertheless, our work has some limitations. For instance, in the multitude of social media settings, we have run the algorithm on data collected only in Facebook not considering other important online environments such as Twitter. Given the explorative purpose of our investigation, we analysed just a company. Therefore, future research may extend their analysis to a wider range of social media contexts with the aim of identifying differences due to the platform characteristics and involving more than one company in their studies. Concluding, we pointed our attention towards the negative emotions and the relationship with the king of problematic social interactions and the related VCD process. On the contrary, future researches may analyse the role of positive emotions and their effects on firm-customer interactions and VCC.

Finally, our work is a useful managerial tool which helps to monitor the huge amount of positive and negative comments posted by the customers in firms' Facebook pages every day. Moreover, our algorithm can easily identify the trend and peaks of negative comments and the related customers' emotions which can be analysed by the social media managers to understand what caused the increase of negatives comments. In turn, this analysis can also help the social media managers to design response strategies.

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