

How emotions impact the interactive value formation process during problematic social media interactions

How emotions impact the IVF process

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Abstract

Purpose – Previous research has studied interactive value formation (IVF) using resource- or practice-based approaches but has neglected the role of emotions. This article aims to show how emotions are correlated in problematic social media interactions and explore their role in IVF.

Design/methodology/approach – By combining a text mining algorithm, nonparametric Spearman's rho and thematic qualitative analysis in an explanatory sequential mixed-method design, the authors (1) categorize customers' comments as positive, neutral or negative; (2) pinpoint peaks of negative comments; (3) classify problematic interactions as detrimental, contradictory or conflictual; (4) identify customers' main positive (joy, trust and surprise) and negative emotions (anger, dissatisfaction, disgust, fear and sadness) and (5) correlate these emotions.

Findings – Despite several problematic social interactions, the same pattern of emotions appears but with different intensities. Additionally, value co-creation, value no-creation and value co-destruction co-occur in a context of problematic social interactions (peak of negative comments).

Originality/value – This study provides new insights into the effect of customers' emotions during IVF by studying the links between positive and negative emotions and their effects on different sorts of problematic social interactions.

Keywords Interactive value formation, Emotions, Value co-destruction, Value co-creation, Value no-creation, Social media

Paper type Research paper

Introduction

Social media are internet-based applications that allow customers and companies to interact by creating, sharing or exchanging information. Social media have transformed the nature and

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practice of online interaction, allowing companies to engage with customers by sharing information in brand communities. Companies invest in social media and establish brand fan pages, conveying brand-related content (i.e. brand posts) that users can like, comment on and share (Elsharnouby *et al.*, 2021). This phenomenon has drawn the interest of the interactive marketing academy, that is, “the bidirectional value creation and mutual-influence marketing process through active customer connection, engagement, participation and interaction” (Wang, 2021, p. 1).

When considered in the context of social media, interactive marketing provides the possibility to develop a more customized offer that allows customers to live a deeper and more pleasant interactive process (Wang, 2021). However, social media also have a dark side. They offer users a platform to voice negative customer experiences (Muda and Hamzah, 2021). As Nielsen Company says, 50 per cent of social media users express brand complaints at least once monthly (The Nielsen Company, 2012). The positive and negative experiences lived by customers during social media interactions determine what the literature defines as *interactive value formation* (IVF) (Echeverri and Skälén, 2011, 2021). It refers to a process started by firm–customer interactions in a collaborative social context where actors aim to create value by sharing resources (e.g. knowledge), but value could remain unchanged or even be destroyed (Echeverri and Skälén, 2011). Previous literature has identified a dimension of value associated with positive or negative interaction: emotional value (Mingione *et al.*, 2020). Emotional value is derived from the feelings or affective states generated or aroused by the consumption experience (Sheth *et al.*, 1991). This flow of emotional-based interactions fuels the IVF (Ding and Tseng, 2015). Therefore, interactions between customers and firms are emotionally charged (Echeverri and Skälén, 2011).

Although prior research has focused on the role of emotions in IVF, the process through which the different configurations of IVF (e.g. value co-creation [VCC], value no-creation [VNC] and value co-destruction [VCD]) are impacted by emotions (i.e. positive and negative) remains poorly understood. Nevertheless, few studies suggest how the two main types of emotions (positive and negative) may be correlated and could affect IVF simultaneously (Pappas *et al.*, 2017). The purpose of this study, therefore, is to *expand insights into the simultaneous impact of positive and negative emotions on IVF during problematic social interactions*, which, thus far, has eluded academic interest (Wu *et al.*, 2019). In this theoretical context, the authors try to answer the fundamental question “How do emotions felt during problematic social media interactions impact IVF?”

In doing so, the authors also reply to the call made by Echeverri and Skälén (2021) for employing quantitative methods in the research on IVF and VCD. Therefore, this study adopted an explanatory sequential mixed-method design (Creswell and Clark, 2017) by combining a text mining algorithm, nonparametric Spearman’s rho and thematic qualitative analysis. Furthermore, this research focuses on Huawei Technologies Co., Ltd., by analyzing comments collected from the Huawei Mobile UK Facebook page (from 2011 to 2019).

This research makes two core contributions. First, the authors highlight the role of emotions during IVF. Previous literature has studied VCD mainly by adopting resource and service systems or the practice-based approach (Echeverri and Skälén, 2021). Compared to these two approaches, the role of emotions in IVF has received less academic attention. Thus, by extending former research, the study contributes to determining the effect of emotions in IVF by analyzing the connections between positive and negative emotions and their impacts on different types of problematic social interactions. Second, several studies have theorized that value can be co-created in an adverse context (e.g. Fyrberg Yngfalk, 2013; Cabiddu *et al.*, 2019; Laamanen and Skälén, 2014). Nevertheless, to the best of the authors’ knowledge, no empirical studies support this theory. The results empirically show that value can be no-created or co-created in IVF, even in the context of problematic social interactions such as the peaks of negative social media comments.

Theoretical background

Interactive value formation and problematic customer–firm social interactions

Social interactions involve a series of practices in which customers and a firm have reciprocal actions and influences over time (Cabiddu *et al.*, 2019). Regarding consumer–firm interaction, social media are hubs of brand communities that create opportunities for firms and customers to spread information related to the brand (Wang, 2021). Customers can review products and services, firms can respond and other customers can specify whether the reviews were appreciated.

Furthermore, social media permit firms to review their customers, creating a peer consumer–firm interaction procedure (Sthapit and Björk, 2018). Additionally, websites and mobile apps encourage customers to generate and share content rapidly with acquaintances, friends and family (Izogo and Mpinganjira, 2020). Hence, social media have built-in features that customers can use to interact with firms and other users in dyadic, triadic or multisided communications to build firm–consumer relationships (Lim and Childs, 2020). Interaction-oriented social media such as Facebook provide a great variety of tools for interaction. For example, with an @, customers can connect friends to specific content or use hashtags for cross-referencing (Wang, 2021). Customers may use a platform in different ways according to what they seek: for social and fun purposes or to co-create value with firms (Pelletier *et al.*, 2020; Gligor and Bozkurt, 2021).

Social media also can be used for negative customer–firm interaction. For example, disseminating fake news may trigger brand–community backfire (Elsharnouby *et al.*, 2021; Liao and Wang, 2020). In conclusion, the IVF supported by social media results in VCC, VCD and VNC. The latter reflects that customers' experience of a product or service is in line with their expectations (Makkonen and Olkkonen, 2017; Sthapit and Björk, 2018; Tang *et al.*, 2014).

Interactive marketing research has extensively analyzed social interactions, categorizing them as beneficial or destructive for IVF. Different authors have focused their research on problematic social interactions (e.g. Echeverri *et al.*, 2012; Vafeas *et al.*, 2016; Frau *et al.*, 2018; Nam *et al.*, 2018; Cabiddu *et al.* 2019), classifying them into misbehavior, contradictory, conflictual or negative (i.e. detrimental, as the authors renamed it not to create confusion with the negative comment, which is only a part of the interaction). The first, *misbehavior*, is defined as the intentional, candid or covert actions of customers that disrupt functional interactions by violating the accepted norms of conduct (Echeverri *et al.*, 2012; Kashif and Zarkada, 2015). The second, known as *contradictory interaction*, occurs when the customers involved in a relationship have divergent opinions that effectively mar their interactions (e.g. structural tension) (Vartiainen and Tuunanen, 2016). The third, defined as *conflictual interaction*, results from divergent opinions. However, such interaction leads to customer conflicts (Vafeas *et al.*, 2016). Finally, the fourth category, *detrimental interaction*, is a mechanism triggered by customers who seek social support to spread their negative experiences within a community (Smith, 2013; Nam *et al.*, 2018). Such classification is functional to examine the impact of emotions on IVF and helped to summarize the literature according to the type of problematic social interaction (Table 1).

While there is a large body of research that scrutinizes how social interactions moderate IVF (Smith, 2013; Nam *et al.*, 2018; Echeverri *et al.*, 2012; Kashif and Zarkada, 2015; Vafeas *et al.*, 2016; Frau *et al.*, 2018), none of the previous studies clearly explained how problematic social interactions trigger VCC, VNC or VCD. Some interactive marketing researchers consider IVF's problematic social interactions a VCD determinant (Echeverri and Skálén, 2011; Worthington and Durkin, 2012; Lombardo and Cabiddu, 2017) or value diminution (Vafeas *et al.*, 2016). Other researchers endorse this view and maintain that misbehavior, contradictory, conflictual and detrimental interactions encourage the misuse of resources (Kashif and Zarkada, 2015; Smith, 2013), which acts as VCD input. In contrast, some

Table 1.
Summary of the
literature on IVF
according to the type
of problematic social
interaction

Problematic social interaction article	Misbehavior	Contradictory	Conflictual	Detrimental
Echeverri and Skälén (2011)			×	
Echeverri <i>et al.</i> (2012)	×			
Worthington and Durkin (2012)		×		
Fyrberg Yngfalk (2013)		×		
Smith (2013)			×	×
Laamanen and Skälén (2014)		×	×	
Kashif and Zarkada (2015)	×	×		
Frau <i>et al.</i> (2018)	×			
Jmour and Hmida (2017)	×			
Nam <i>et al.</i> (2018)		×	×	×
Vartiainen and Tuunanen (2016)		×		
Vafeas <i>et al.</i> (2016)			×	
Lombardo and Cabiddu (2017)		×	×	×
Makkonen and Olkkonen (2017)			×	×
Tang <i>et al.</i> (2014)		×	×	
Cabiddu <i>et al.</i> (2019)	×	×	×	×

interactive marketing scholars debate that contradictions and conflicts might be a source of VCC (Fyrberg Yngfalk, 2013; Laamanen and Skälén, 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. Consistent with previous studies, Laamanen and Skälén (2014) suggested that conflicts encourage innovation and creativity because conflicts are inherent in human interactions. Such interactions are “neither positive nor negative.” In conclusion, recent interactive marketing studies highlighted that interaction episodes accumulated in a relationship combined with neutral social interactions also could drive IVF to VNC (Makkonen and Olkkonen, 2017; Tang *et al.*, 2014).

Interactive value formation and the role of emotions

The interactive marketing literature considers pivotal the links between emotions and IVF to identify VCC, VCD and VNC (Sthapit and Björk, 2018). According to Moreau and Herd (2010), positive emotions such as pride can elicit VCC (Wu *et al.*, 2019), while Baron *et al.* (2005) suggested that negative emotions such as anger (Smith, 2013) and guilt (Sugathan *et al.*, 2017) may result in VCD. Moreover, failures in co-creating products differ from general situations of failure in IVF since unsuccessful co-created products generate self-directed emotions such as guilt, shame and self-pity in customers (Sugathan *et al.*, 2017). However, these emotions are moderated by the degree of co-creation (Sugathan *et al.*, 2017). Therefore, failure attributed to customers increases their motivation to co-create in the future (Sugathan *et al.*, 2017). Other studies on IVF found that, on average, trust, joy and anticipation are dominant emotions in reviews (Felbermayr and Nanopoulos, 2016). Customers’ voice and share emotions via emojis, which reflect the primary human emotions (Wang, 2021). Nevertheless, unfavorable reviews, when expressed by trustworthy customers (e.g. customers who do a high number of reviews), can destroy value by spreading negative electronic word of mouth (Muda and Hamzah, 2021). Besides, due to social media’s quickness, traditional negative word of mouth is even more threatening, evolving into word-of-click. This happens when customers advise against firms’ posts, e.g. by clicking on the “angry” emoji (Xue, 2019).

Additionally, firms’ lack of emotions, such as empathy in IVF, is a driver of VCD, which is reflected in poor customer service. This shortcoming destroys customer value in terms of losses of time and financial resources (Sthapit and Björk, 2019). Furthermore, firms’ misbehavior and

terrible customer experiences in IVF could prompt emotions such as anger, betrayal, dissatisfaction, frustration, disappointment and hostility (Jmour and Hmida, 2017).

Despite valuable findings regarding the link between IVF and emotions, none of the previous studies investigated how the conjoint action of positive and negative emotions affects IVF (see Figure 1). Previous studies focused only on positive emotions such as pride, trust and joy (Moreau and Herd, 2010; Wu et al., 2019; Felbermayr and Nanopoulos, 2016) or merely on negative emotions such as anger, guilt, shame, self-pity, revenge, lack of empathy, betrayal, dissatisfaction, frustration, disappointment and hostility (Smith, 2013; Sugathan et al., 2017; Sthapit and Björk, 2019).

Methods

This study adopted the explanatory sequential mixed-method research design to analyze the role of emotions in problematic social interactions during IVF (Creswell and Clark, 2017). The authors use the dyadic interaction as a unit of analysis, which involves comments posted by the parties of the dyad (firm–customer and customer–customer). The mixed-methods approach is helpful because quantitative methods categorize comments into positive, neutral or negative, identifying peaks of negative comments in which the main customer emotions are pinpointed, and identify correlations between emotions. However, they do not detail the type of problematic interactions characterizing those peaks. The qualitative analysis explores the IVF and finds associations between emotions and types of problematic interactions (Figure 2).

This study focused on Huawei Technologies Co., Ltd., an information and communications technology (ICT) and telecommunications company developing systems, network solutions and technological products globally. Among Apple, Samsung and Huawei, the three largest telecommunication companies for profit, sales and units shipped in 2020 [1], the authors selected Huawei because it was the first to create its Facebook page, on June 16, 2009. The long period of activity of the account allowed to collect data for an extended period and to have a representative description of how the problematic interactions evolved. In addition, within social media, the authors selected Facebook because it is the most popular worldwide, ranked first by the number of monthly active users (2.91 billion in January 2022) [2].

		Interactive Value Formation		
		Value co-creation	Value no-creation	Value co-destruction
Emotions	Positive	<p>Use of positive emotions to study VCC</p> <p>Moreau and Herd (2010) find that positive emotions such as pride could elicit VCC;</p> <p>Felbermayr & Nanopoulos (2016) show that trust and joy are dominant emotions in perceived usefulness in online customer reviews;</p> <p>Sthapit and Björk (2018) used the words good, positive, excellent, great and nice to detect VCC in the IVF process.</p>	<p>Use of positive emotions to study VNC</p> <p>Sthapit and Björk (2018) use the words ok, average, standard, decent and not good not bad to pinpoint VNC.</p>	<p>Use of positive emotions to study VCD</p> <p>Felbermayr & Nanopoulos, (2016) suggest that trust, joy, and anticipation have substantial variance across product categories;</p> <p>Wu et al. (2019) find that positive emotions set optimistic consumers' attitudes toward a brand when they buy using hedonic value. Still, this significant effect does not occur when utilizing utilitarian value.</p>
	Conjoint use of positive and negative emotions	<p>Conjoint use of positive and negative emotions to study IVF</p> <p style="background-color: #cccccc; padding: 10px; display: inline-block;">RESEARCH GAP</p>		
	Negative	<p>Use of negative emotions to study VCC</p> <p>Sugathan et al., (2017) explain that failure attributed to customers increases their motivation to co-create in the future.</p>	<p>Use of negative emotions to study VNC</p> <p>Sugathan et al., (2017) indicate that customer self-directed emotions such as guilt, shame, and self-pity are moderated by the degree of co-creation.</p>	<p>Use of negative emotions to study VCD</p> <p>Baron et al. (2005) and Smith (2013) suggest that negative emotions such as anger result in VCD;</p> <p>Sugathan et al., (2017) found that guilt, shame, and self-pity result in VCD;</p> <p>Xue (2019) show that customers clicking on the angry emoji results into word-of-click a more dangerous evolution of negative electronic word of mouth;</p> <p>Jmour and Hmida (2017) find that customer terrible experiences in IVF prompt emotions like anger, betrayal, dissatisfaction, frustration, disappointment, and hostility;</p> <p>Sthapit and Björk (2018) use negative emotional words (bad, negative, worst, terrible, poor) to find VCD in IVF.</p>

Figure 1. Studies on how positive and negative emotions impact IVF

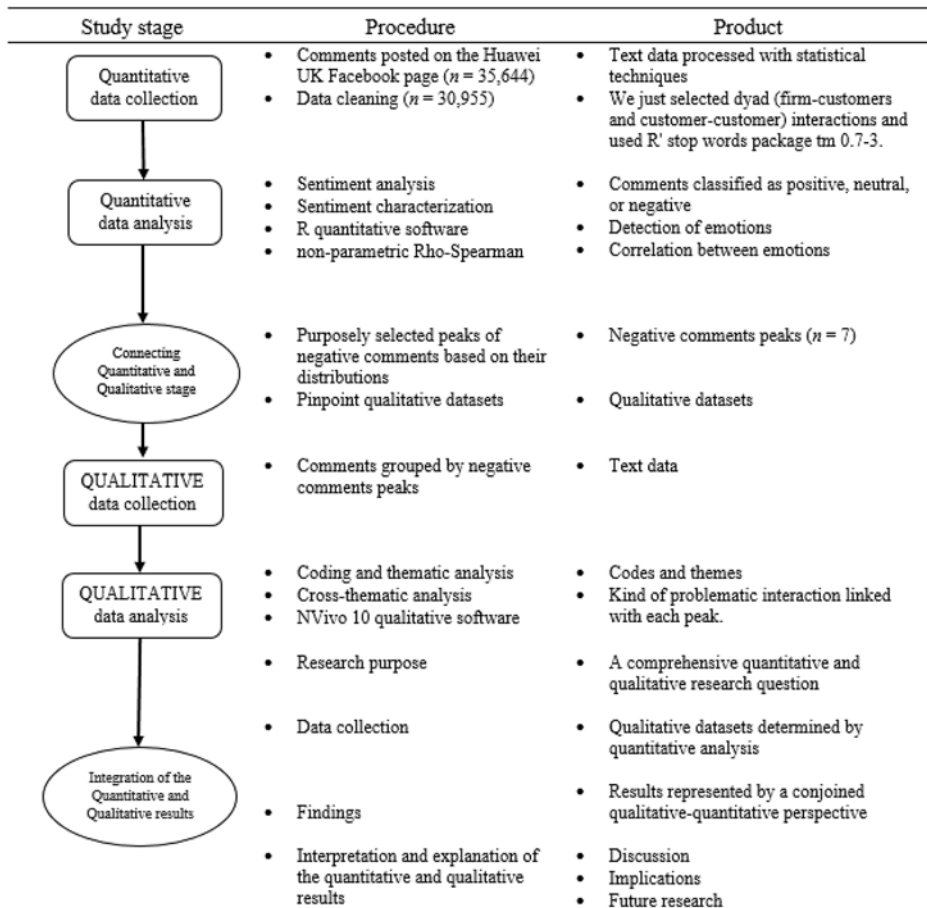


Figure 2. Visual model for the mixed-methods explanatory sequential design study

Data preprocessing

The quantitative dataset comprises 35,644 records: the postings and comments on the Huawei UK Facebook page from September 2011 to May 2019.

Quantitative data cleaning. First, the authors removed 3,125 comments from external pages and their replies because they exclusively considered the dyadic interactions between Huawei Mobile and its customers. Next, they used the vocabulary stored in the “tm 0.7–3” R package (Meyer *et al.*, 2008) to remove articles, conjunctions, prepositions and numbers (considered not significant for the analysis). Finally, they considered only 30,955 of the remaining 32,519 comments for the analysis.

Data analysis

Quantitative analysis: the text mining-based algorithm. The algorithm proposed in this study consists of three main parts, which can (1) discern positive, negative and neutral comments, (2) pinpoint the periods characterized by significant peaks of negative comments and (3) distinguish each topic with its emotions.

In the first step, the algorithm classifies the customers' comments as positive, neutral or negative by running a sentiment analysis. Next, the algorithm constructs a document-term matrix from the original comments. Thus, the text is vectorized by creating a map from words to a vector space. Then, the algorithm runs a logistic regression model on the database "sentiment140" (Go *et al.*, 2009), which consists of 1,578,627 records already classified as either positive or negative. Finally, the algorithm applies the model to the collected data and calculates each comment's positivity probability. The probability ranged from 0 (totally negative comment) to 1 (totally positive comment). Then, the algorithm performs a receiver operating characteristic (ROC) analysis to define two thresholds in line with the coordinates of the ROC curve for sensitivity and specificity, respectively, at 0.75 in both cases (Krzanowski and Hand, 2009). This implies that the first threshold separates positive from neutral and negative comments, ensuring that 75 per cent of positive comments are correctly classified. On the other hand, the second threshold separates positive and neutral comments from negative comments, guaranteeing that 75 per cent of negative comments are correctly allocated. This process helps in obtaining three groups of comments (positive, neutral and negative) in line with the literature, which states that such social interactions may trigger VCC, VNC and VCD, respectively, in IVF (Makkonen and Olkkonen, 2017; Tang *et al.*, 2014).

In the second step, the algorithm uses empirical fluctuation tests to identify the time intervals in which the distribution of negative comments shows structural changes. The algorithm recognizes these ranges by testing when the distribution of negative comments differs from a regression model with a null slope: first, a model that captures the fluctuation in terms of the sums of residuals is fitted to the data, and an empirical process is derived. Then, the ranges in which this empirical process is significantly different ($p < 0.05$) from a linear model with null slope are identified as the periods with significant peaks of negative comments. Next, the empirical processes are assumed to be MOVing SUM (MOSUM) processes, and the ordinary least squares-based MOSUM test is performed. Moreover, starting from the 500th recorded day, the algorithm conducts an empirical fluctuation test considering all previous days and that same day. Consequently, the threshold that identifies the peaks changes dynamically according to the data update.

The last step of the algorithm consists of characterizing the identified peaks with appropriate positive (joy, surprise and trust) or negative (anger, dissatisfaction, disgust, fear and sadness) emotions by using a lexicon in the emotion vocabulary "nrc" contained in the "tidytext 0.1.9" R package (Silge and Robinson, 2016). This vocabulary consists of 13,901 words that are associated with emotions. In particular, since each comment is distinguished by a combination of emotions, all the positive and negative emotions within the comment are summarized by a relative frequency table (see Table 2). The result of the three steps also leads to identifying the number of interactions within the peaks (see Table 2). The company always started the interaction by posting content on its social media home page. Then, a customer replies and waits for the firm's and other customers' reactions, keeping the interaction going until the firm and the customers stop commenting.

All the analyses were run using the packages of the statistical language program "R" version 3.4.4 (Team, 2018): text2vec 0.5.1 (Selivanov and Wang, 2016); strucchange 1.5-1 (Kleiber *et al.*, 2002); glmnet 2.0-16 (Friedman *et al.*, 2010) and tidytext 0.1.9 (Silge and Robinson, 2016).

Quantitative analysis: nonparametric Spearman's rho. Due to the nonfulfillment of the r -Pearson correlation analysis requirements, the authors used a nonparametric Spearman's rho analysis to analyze the relationship between negative and positive emotions (Crewson, 2006). The analysis shows the relationship between pairs of variables for all the positive and negative emotions identified in the study (e.g. anger and dissatisfaction, anger and joy). Appendix presents the correlation matrices for all seven peaks of negative comments. The sample size for the correlations performed within a peak is the number of negative

Table 2.
Description of the
seven peaks

Peak no.	Duration		Number of negative comments	Number of interactions	Per cent of negative emotions in the peak			Per cent of positive emotions in the peak			Kind of problematic interactions		
	From	To			Dissatisfaction	Disgust	Sadness	Anger	Fear	Trust		Joy	Surprise
1	25/03/2013	14/04/2013	105	18	22.36	12.42	10.56	9.32	8.70	18.01	11.80	6.83	Confictual
2	13/05/2013	09/06/2013	182	29	17.94	12.3	12.29	11.96	10.96	12.96	13.95	7.64	Contradictory
3	13/06/2013	11/08/2013	1,796	78	16.85	12.53	12.23	11.86	10.57	15.97	11.59	8.40	Detrimental
4	25/10/2015	05/12/2015	718	65	21.12	15.65	10.07	9.03	7.48	21.17	10.47	5.01	Contradictory
5	07/09/2016	21/10/2016	679	49	16.38	12.87	12.23	8.62	6.18	22.66	13.83	7.23	Detrimental
6	02/01/2017	15/05/2017	1,989	183	21.26	12.44	10.91	10.65	7.49	17.84	12.05	7.36	Confictual
7	18/12/2017	27/02/2018	3,320	64	20.83	11.65	11.59	10.61	8.93	16.94	11.95	7.50	Contradictory

comments in that peak (e.g. for Peak 7, it is 3,320; see the fourth column of Table 2). The authors summarized the correlations in Figure 4.

Qualitative analysis. The authors created a qualitative dataset by including the 8,789 negative comments detected in the seven peaks (see the fourth column of Table 2 for the comment distribution). Then, the authors uploaded the selected comments into NVivo 10 for thematic qualitative data analysis (Cabiddu *et al.*, 2018). The qualitative analysis aims to associate the peaks with the appropriate problematic interaction (e.g. misbehavior, contradictory, conflictual and detrimental interaction).

The authors performed a two-phase coding process for the seven peaks. The first coding phase observed the descriptive and interpretative codes. Descriptive codes need little or no data interpretation, whereas interpretative codes indicate the researcher's understanding of the data (Miles and Huberman, 1994). The first phase gives a former collection of structured codes that represent customers' problems with their devices, such as software freezes, fragile devices, network issues, ugly devices and supply problems. Using deductive logic and a literature-driven coding scheme, the authors sought thematic codes in the second coding phase (Miles and Huberman, 1994). The authors compared the definitions of the four forms of problematic interactions to select the interactions that best fit the category. For instance, they classified the following interaction as contradictory: "Huawei, HTC and Vodafone offer some of the worst customer service. All three are best avoided like the plague" [User A]. User B replied, "I've HTC and Huawei. Funny, I've never had a problem at all. So yeah, I disagree." User C added: "I disagree on all the points." Then, they performed a cross-thematic analysis by which they realized whether the problematic social interaction was affecting one or several peaks. For example, the first and sixth peaks are associated with the "conflictual" kind of problematic interaction (see Table 2 for the list). Two coauthors were responsible for the coding activities to reduce subjective interpretation issues. During both coding phases, the coders separately analyzed the data and compared their categorization until they reached an agreement. The authors verified the robustness of the codes by running a *coding comparison query* in NVivo. Then, they discussed the inconsistencies until the value of the k coefficient was above 0.75, which is a very good degree of agreement according to Fleiss *et al.* (2003).

Results

The role of problematic social interactions in IVF

To shed light on the emotions involved in the problematic social interactions during IVF, the authors first need to discern among positive, neutral and negative comments to identify the adverse context: the peaks of negative social media comments. Therefore, the comments' likelihood of positivity lower than 0.4636 was set as negative, and those with a probability of positivity higher than 0.5575 were set as positive. Finally, the comments with a chance between 0.4636 and 0.5575 were considered neutral. These thresholds guarantee that at least 75 per cent of the comments are correctly allocated in the positive, negative and neutral categories. Next, the authors pinpointed the structural changes in the distribution of negative comments and identified the seven peaks from September 2011 to May 2019 that are the context for this study (see Figure 3).

Then, thanks to the algorithm, the authors calculate the probability that the comments contain contents associated with joy, surprise, trust, anger, dissatisfaction, disgust, fear and sadness (see Table 2 for the percentage of negative and positive emotions within a peak).

The combination of quantitative and qualitative analyses revealed that the seven peaks are associated with three of the four problematic interactions identified in the literature: contradictory (Peaks 2, 4 and 7), conflictual (Peaks 1 and 6) and detrimental (Peaks 3 and 5).

From September 2011 to February 2013, there were no peaks in negative comments. In 2013, the Huawei UK Facebook page faced three peaks (1, 2 and 3). Peak 1 is distinguished

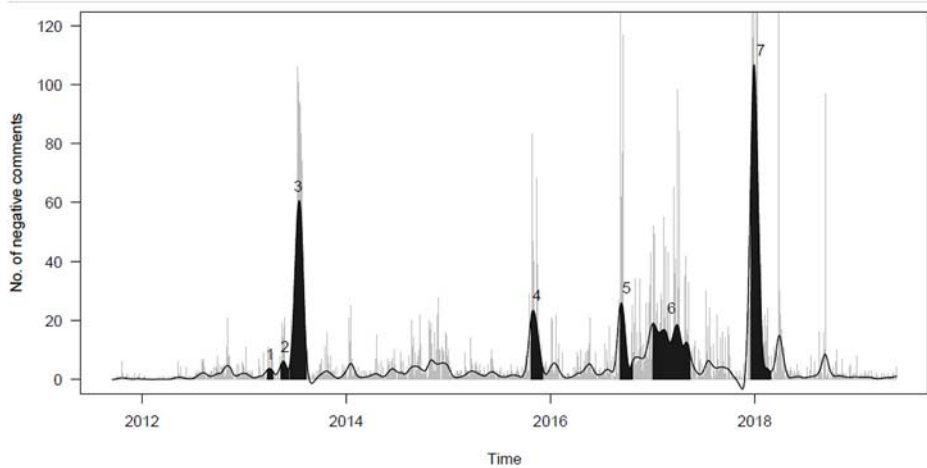


Figure 3.
The negative
comments distribution

Notes: The solid black line is the relative cubic smoothing spline. The darker areas indicate the seven periods characterized by statistically significant structural changes ($p < 0.05$) from a flat trend

by dissatisfaction (22.36 per cent), disgust (12.42 per cent) and sadness (10.56 per cent) but also by a high percentage of the positive emotion trust (18.01 per cent). Concerning Peak 2, the negative emotion percentages show a period of comments not only characterized mainly by dissatisfaction (17.94 per cent) but also influenced by a balanced mix of disgust (12.3 per cent), sadness (12.29 per cent), anger (11.96 per cent) and fear (10.96 per cent). Here, joy (13.95 per cent) plays a predominant role in the positive emotions. Peaks 1 and 2 are shorter (20 and 27 days) and more minor (105 and 182 negative comments) than the other five peaks. Despite similar dimensions, Peaks 1 and 2 differ regarding the type of problematic interactions and IVF dynamics. As detected by the qualitative analysis, Peak 1 is conflictual due to customers' frequent use of bad words and strong negative sentences such as "Terrible bastardized iPhone clone". Peak 2 is a contradictory type of problematic interaction. In this peak, customers, when expressing divergent opinions that mar the IVF, avoid strong negative judgments: "I was told mine [product name] would ship late this week. If there is no shipment by then, I'll be very upset...". Peak 3, the third peak in 2013, accumulated 1,796 negative comments in only 59 days. This peak is categorized as a detrimental interaction because the qualitative analysis detected that customers sought community support to spread their negative experiences on the Facebook page. These social dynamics also might explain Peak 3's fast growth. The quantitative analysis showed that Peak 3 is distinguished by dissatisfaction (16.85 per cent), followed by disgust (12.53 per cent) and sadness (12.23 per cent). In Peak 3, customers keep trying to involve other customers in their negative experience when expressing their criticisms, e.g. asking for users' help rather than calling on the firm's support: "[...] my phone screen cracked yesterday. Can someone help me? Regret getting my phone!". Here, a positive influence in the IVF is played by the firm response that promptly reassured the customers: "[...] After you are a Gold Member, please contact our Technical Support hotline to book for the free screen replacement." This may explain the high percentage of trust (15.97 per cent) discovered in Peak 3.

In 2014, no peak was detected, while the remaining four peaks (Peaks 4, 5, 6 and 7) were identified from 2015 to 2018, one per year. Peaks 4 and 5 are similar in duration (41 and 44 days) and size (718 and 679 negative comments). However, from a deeper qualitative analysis,

Peak 5 shows detrimental interactions that impact the IVF by involving other members of the social media community rather than arguing with them, as detected in Peak 4. The latter is distinguished by negative emotions such as dissatisfaction (21.12 per cent), disgust (15.65 per cent), the highest within the seven peaks, and sadness (10.07 per cent). Once again, trust is the strongest (21.17 per cent) among the positive emotions. However, during the interaction, customers often use impolite expressions, e.g. “Why it’s so fucking smooth?? I cracked my phone!”. In Peak 5, the emotion mix is composed of dissatisfaction (16.38 per cent), disgust and sadness (12.87 and 12.23 per cent). Additionally, the qualitative analysis shows customers trying to attract other customers’ attention and asking for support, e.g. by spreading their mishaps: “One of my handsets has developed a fault & the UK Huawei service team are unwilling to assist. I suggest anyone to choose an alternative brand. Share it!”. Indeed, positive emotions were predominant, with trust and joy at their highest among the seven peaks (22.66 and 13.83 per cent). This is because, except for sporadic uses of imprecations or sarcasm, in Peak 5, the interactions were overall easy, and the IVF remained respectful.

Peak 6 lasted 133 days, the most prolonged peak of the observed timeframe. This peak grouped 1,989 negative comments, making it the second-largest. The qualitative analysis categorized Peak 6 as conflictual. For its size, duration and problematic interactions, Peak 6 had one of the most negative impacts on IVF. Its mix of negative emotions is composed of dissatisfaction (21.26 per cent), disgust (12.44 per cent) and an equivalent level of sadness and anger (respectively, 10.91 and 10.65 per cent). The positive mix of emotions consists of trust (17.84 per cent), joy (12.05 per cent) and surprise (7.36 per cent), which plays a minor role. Customers appear even more hostile than in contradictory peaks (e.g. Peaks 2 and 4). They often use rude language, which could generate customer conflicts and negatively affect IVF, e.g. “Oil is a natural substance you fucking asshole. It’s not manmade. Kill yourself.” or with the company: “Junk phones and no customer service at all...good luck growing as a company with shit you do..”

The last peak, the seventh, is the most populated. It grouped 3,320 negative comments in 72 days. The quantitative analysis shows that Peak 7 is characterized by a high percentage of dissatisfaction (20.83 per cent), followed by disgust (11.65 per cent) and sadness (11.59 per cent). However, the highest positive emotions detected in Peak 7 are trust (16.94 per cent) and joy (11.95 per cent). The qualitative analysis categorized Peak 7 as contradictory because, as observed in Peaks 2 and 4, the interactions are offensive but not as destructive as the conflictual ones (detected in Peaks 1 and 6). An example of a contradictory comment within Peak 7 is “People only care about Samsung and iPhone”

How emotions influence IVF

The authors used relationship matrix analysis to show the relationships between positive and negative emotions (see [Appendix](#)). The analysis shows three areas of dependence: (1) negative vs. negative, (2) negative vs. positive and (3) positive vs. positive. According to the analysis, each area corresponds to a region of the IVF in which the value is mainly co-destroyed (1 VCD Area), not created (2 VNC Area) or co-created (VCC Area, see [Figure 4](#)).

Correlations are between negative emotions in the first area, which the authors labeled the VCD area. Dissatisfaction does not occur with any of the other negative emotions, not resulting in the occurrence of the other negative emotions. Being dissatisfied therefore causes neither anger, disgust, fear nor sadness. Thus, dissatisfaction in the IVF does not lead to solid VCD interactions, such as extreme negative interactions expressed in the customers’ comments on Facebook, e.g. “My [mobile model] is disappointing. It never recognizes my fingerprint. I’m nothing but dissatisfied.” The authors assumed dissatisfaction is within the area of the customer’s tolerable emotions. Therefore, an unsatisfied customer does not escalate problematic interactions unless provoked by other customers or an unsatisfactory firm reply.

Emotions	Anger	Dissatisfaction	Disgust	Fear	Sadness	Joy	Surprise	Trust	
Anger	1 VCD area	negve 4	positive 7	positive 7	positive 7	negative 3	positive 4	negative 3	2 VNC area
Dissatisfaction	negative 4***		negve 6	positive 1	negative 5	positive 4	positive 7	positive 5	
Disgust	positive 7***	negative 1*, 5***		positive 6	positive 4	negative 4	positive 2	negative 6	
Fear	positive 1**, 6***	positive 1***	positive 2**, 4***		positive 7	negative 1	positive 2	negative 2	
Sadness	positive 1*, 1**, 5***	negative 2**, 3***	positive 4***	positive 7***		negative 2	positive 1	negative 4	
Joy	negative 3*	positive 4***	negative 1*, 3***	negative 1*	negative 1*, 1***		positive 7	positive 7	3 VCC area
Surprise	positive 1**, 3***	positive 1*, 3**, 3***	positive 1*, 1**	positive 1**, 1***	positive 1**	positive 2**, 5***		positive 7	
Trust	negative 1*, 1**, 1***	positive 1*, 2**, 2***	negative 1*, 2**, 3***	negative 1*, 1**	negative 1*, 1**, 3***	positive 7***	positive 2*, 5***		

1 Value co-destruction area

2 Value no-creation

3 Value co-creation area

Figure 4. Negative and positive correlations: the map of IVF emotions

Notes: The cells of the upper triangle (top-right) report the number of peaks until seven, where the correlation between emotions is statistically significant. The dark gray cells stand for negative correlations, while the light gray ones stand for positive correlation. See Appendix for correlation coefficients. The cells of the lower triangle (bottom-left) show their significance levels using asterisks to indicate whether $p < 0.05$ (*), $p < 0.05$ (**), or $p < 0.001$ (***)

For example, User A claimed, “100 pounds for a phone omg come-on guys stop whining. People talking about quality should spend 500 on an iPhone,” and User B reacted with “even at £100 you expect some sort of satisfaction. Why don’t you update to ICS, then try to contact the customer service and then you see why Huawei’s customers are so angry.”

In comparison, the remaining negative emotions are correlated with each other (e.g. anger, disgust, fear and sadness), the least frequent being disgust and sadness, detected in four peaks. This result shows the significant role of extreme emotions in negative IVF, such as VCD. Therefore, moving the customer beyond dissatisfaction causes stronger problematic interactions in which intertwined negative emotions efficiently prompt VCD. For example, “Disgusted with Huawei. I bought my wife a multiactivity sports watch that is water resistant. She swam once in a swimming pool and now doesn’t work properly. Phoned customer services and they say that chemicals in the swimming pool may have damaged it. Where do you expect people to swim, you utter fools!!”

In the second area of the IVF, the VNC area, the authors identified positive relationships between positive and negative emotions. Anger is moderately correlated with surprise and trust, and dissatisfaction occurs along with surprise in all seven peaks. Fear and sadness commonly correlate with dissatisfaction, and sadness moderately sustains trust. However, it is worth noting that the correlations achieved were low (Spearman’s rho < 0.2). This means the authors are dealing with an intermediate state where VCC and VCD are compensating and balanced. Thus, the combined action of positive and negative emotions after the IVF process has led the value to no specific increase or decrease, e.g. “Good phone, but bad video quality.” As an alternative interpretation, the value in Area 2 is not destroyed but is not created. For instance, “[mobile model] leaves me indifferent.” Consequently, the authors can distinguish the factors of VNC. Here, correlations include dissatisfaction not interfering with joy, surprise or trust, and, less frequently, anger does not affect surprise. The lack of correlation between dissatisfaction and the remaining negative emotions is reinforced by a positive relationship with positive emotions such as joy, surprise or trust. Thus, it can be concluded that in IVF, dissatisfaction does not cause strong negative emotions and supports positive emotions, e.g. “there are many things that I’m happy that machines will never be able to perform satisfactorily, and the writing of beautiful music is one of them”. Moreover, dissatisfaction is not negatively correlated with positive emotions,

so it does not weaken them. Dissatisfaction, therefore, does not foster strong negative emotions and does not weaken positive emotions. Importantly, *this happens for all peaks, which means that it does not matter the kind of problematic social interactions that prevail in the IVF* (e.g. contradictory, conflictual and detrimental interaction).

There are no negative relationships in the VCC area. This means that positive emotions support each other without exception. Interestingly, even in an adverse context (peaks of negative comments), customers can feel positive emotions during problematic social interactions, e.g. "I'm happy with my [mobile model] apart from the lack of any updates," and those emotions mutually sustain one another in the IVF. These results suggest that even in a VCD environment, VCC occurs. Therefore, *value can be co-created and co-destroyed simultaneously when problematic social interactions occur in IVF*.

Discussion

Building on earlier studies on interactive marketing, this study contributes (1) to a better understanding of the role of positive and negative emotions in different kinds of problematic social interactions and their effects in IVF and (2) to empirically show that in the IVF process, VCC, VNC and VCD simultaneously occur during problematic social interactions.

Problematic social interactions: same emotions, different strengths

Earlier interactive marketing studies have considerably deepened the understanding of IVF, explaining the problematic social interactions according to the intensity of VCD (e.g. Echeverri and Skälén, 2011; Vafeas *et al.*, 2016). Some scholars classify conflictual interactions as the most dangerous kind of problematic social interaction, as they result in divergent opinions and collisions between people (Vafeas *et al.*, 2016). Contradictory interactions are detected when customers have divergent opinions, ruining their interactions (e.g. structural tension) (Vartiainen and Tuunanen, 2016). Last, detrimental interactions are those social mechanisms started by customers looking for help in the community to disseminate their negative experiences (Smith, 2013; Nam *et al.*, 2018). Therefore, former interactive marketing researchers consider problematic social interactions a factor for VCD (Echeverri and Skälén, 2011; Worthington and Durkin, 2012; Vafeas *et al.*, 2016). However, problematic social interactions also might prompt VCC, since contradictory resource integration and interactions are fundamental to initiating innovative solutions (Fyrberg Yngfalk, 2013; Laamanen and Skälén, 2014). While a large body of research examines the effects of social interactions on IVF by employing the resource and service systems approach or the practice-based approach (Echeverri and Skälén, 2021; Smith, 2013; Nam *et al.*, 2018; Echeverri *et al.*, 2012; Kashif and Zarkada, 2015; Vafeas *et al.*, 2016; Frau *et al.*, 2018), and a few studies have pinpointed that the interactions between customers and firms are emotionally charged (Echeverri and Skälén, 2011), the process through which the different configurations of IVF (e.g. VCC, VNC and VCD) are impacted by emotions (i.e. positive and negative) remains poorly understood.

To fill the gap in the literature, the authors focused on positive and negative emotions as antecedents of problematic social interactions and, consequently, as a discriminant of VCC, VNC and VCD. The emotional perspective has received less attention in the academic debate (Mingione *et al.*, 2020) and allows to provide a better gradient of IVF. Therefore, the research contributes to the IVF discussion (summarized in Table 1) by showing clear relationship patterns between emotions in all the analyzed problematic interactions. Furthermore, the analysis unveils that emotions influence IVF, regardless of whether the problematic social interactions have a high (e.g. conflictual) or low level of negativity (e.g. contradictory). Thus, in IVF, emotion has the same impact on one another in conflictual, contradictory and

detrimental interactions. There are differences in the strength of the relationship only in different interaction categories. Compared to previous literature, which mainly focused on the relationships between the kinds of problematic social interactions and the IVF configurations, this study contributes to a better understanding of the emotional antecedents of problematic social interactions. Thus, this study extends former research by investigating the conjunct impact of positive and negative emotions on problematic social interactions.

Emotions in IVF also lead to VCC and VNC, even in an adverse context

Despite the valuable insights regarding the connections between emotions, VCC and VCD, former studies focused only on positive emotions such as pride, trust and joy (Moreau and Herd, 2010; Wu *et al.*, 2019; Felbermayr and Nanopoulos, 2016) or merely negative emotions such as anger, guilt, shame, self-pity, revenge, lack of empathy, betrayal, dissatisfaction, frustration, disappointment and hostility (Smith, 2013; Sugathan *et al.*, 2017; Sthapit and Björk, 2018). This study examines the conjunct impact of positive and negative emotions. In doing so, the research identifies three areas of dependence in IVF: negative vs. negative (Area 1), negative vs. positive (Area 2) and positive vs. positive (Area 3). In the first area of IVF, it is clear that dissatisfaction does not lead to VCD since it does not result in the occurrence of other negative emotions. Thus, dissatisfaction causes neither anger, disgust, fear nor sadness or VCD. In the second area of IVF, the authors identified positive relationships between negative and positive emotions (Wu *et al.*, 2019). This means they are dealing with an intermediary stage of IVF – value is not destroyed but is not created, either. Hence, they distinguish VNC features. Finally, when the authors correlated positive emotions with positive emotions (Area 3), all emotions support each other. Therefore, even in an adverse context – peaks of negative comments – positive emotions may occur, and they are mutually supportive in the IVF. Thus, they can distinguish the factors of VCC.

Previous literature has analyzed only positive emotions to study VCC (e.g. Wu *et al.*, 2019; Felbermayr and Nanopoulos, 2016) or solely negative emotions to investigate VCD (Sugathan *et al.*, 2017; Sthapit and Björk, 2018). Scholars have already theorized the chance to co-create value in an adverse context (Fyrberg Yngfalk, 2013; Cabiddu *et al.*, 2019; Laamanen and Skälén, 2014). However, no empirical studies support the relationship between positive and negative emotions. This research advances previous studies using both valences of emotions to grasp the relationships within them (see Figure 1). Such links cannot be appreciated when using a single emotional perspective. Adopting a double point of view allowed to conclude that not all emotions involved in IVF contribute to only VCC or VCD. However, there are areas of relationships between emotions where value is no-created or co-created rather than co-destroyed (e.g. Areas 2 and 3). The results empirically demonstrate that value also can be no-created or co-created in its formation process, even in the context of problematic social interaction as the peaks of negative social media comments, which is the second contribution of this research.

Managerial implications

Practitioners who desire to prevent VCD in their social media might find it interesting that firm customers' problematic interactions are bound tightly with the negative and positive emotions that customers feel when posting their comments in a social media community. The analysis shows that negative and positive emotions desire equal attention. A passive attitude toward negative customer comments allows their emotions to freely influence the IVF, leading to VCD. The analysis shows that when providing information and clear instructions to solve customers' problems, such replies increase the percentage of positive emotions, pushing the IVF to VNC or even VCC results. The positive emotions also may lead the IVF toward neutral

or positive value in the context of peaks of negative comments. In managerial terms, social media managers should expect patterns of emotions with different forces. They also should avoid reacting in a standard way. Conversely, the social media manager who deeply analyses firm–customer interactions and proactively addresses customers’ positive and negative emotions by providing suitable responses also efficiently moves away from VCD.

Limitations and future research

Despite the combined use of quantitative and qualitative methods, this study has limitations, which suggest further theoretical and empirical research opportunities. For instance, the authors focused on data collected only on Facebook, not considering, e.g. Instagram or Twitter. Therefore, future research may extend their analysis to a broader range of social media settings to identify differences in the customers’ mix of emotions and their role in IVF. Additionally, the authors limited the analyses to what occurs within a peak of negative comments. However, investigating what happened before the peaks may help better describe why the emotions’ percentages vary in different peaks, affecting IVF differently. Thus, they suggest that future research focuses on the antecedents of peaks of negative comments.

The choice of a manufacturer ICT and telecommunications company as the study’s empirical setting provides a partial view of IVF in the broader multisector economic field. Nevertheless, future research may involve a higher number and wider variety of companies.

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Notes

1. <https://straitresearch.com/blog/worlds-largest-top-10-smartphone-companies-in-2020>
2. <https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/>

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Conflictual Peak 6, sample size 1,989 negative comments.

		anger	dissatisfaction	disgust	fear	sadness	joy	surprise	trust
Spearman's rho	anger	1,000	-0,133	0,363	0,297	0,23	-0,073	0,109	-0,148
	Correlation Coefficient								
	Sig (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,024	0,001	0,000
	N	964	964	964	964	964	964	964	964
dissatisfaction	Correlation Coefficient	-0,133	1,000	-0,174	-0,063	-0,238	0,172	0,136	0,061
	Sig (2-tailed)	0,000		0,000	0,049	0,000	0,000	0,000	0,060
	N	964	964	964	964	964	964	964	964
disgust	Correlation Coefficient	0,363	-0,174	1,000	0,275	0,33	-0,119	-0,111	-0,188
	Sig (2-tailed)	0,000	0,000		0,000	0,000	0,555	0,734	0,000
	N	964	964	964	964	964	964	964	964
fear	Correlation Coefficient	0,297	-0,063	0,275	1,000	0,506	-0,059	0,019	-0,062
	Sig (2-tailed)	0,000	0,049	0,000		0,000	0,069	0,547	0,054
	N	964	964	964	964	964	964	964	964
sadness	Correlation Coefficient	0,230	-0,232	0,330	0,506	1,000	-0,042	0,084	-0,087
	Sig (2-tailed)	0,000	0,000	0,000	0,000		0,197	0,009	0,007
	N	964	964	964	964	964	964	964	964
joy	Correlation Coefficient	-0,073	0,172	-0,019	-0,059	-0,042	1,000	0,383	0,352
	Sig (2-tailed)	0,024	0,000	0,555	0,069	0,197		0,000	0,000
	N	964	964	964	964	964	964	964	964
surprise	Correlation Coefficient	0,109	0,136	-0,011	0,019	0,084	0,383	1,000	0,275
	Sig (2-tailed)	0,001	0,000	0,734	0,547	0,009	0,000		0,000
	N	964	964	964	964	964	964	964	964
trust	Correlation Coefficient	-0,148	0,061	-0,113	-0,062	-0,087	0,352	0,275	1,000
	Sig (2-tailed)	0,000	0,060	0,000	0,054	0,007	0,000	0,000	
	N	964	964	964	964	964	964	964	964

Contradictory Peak 7, sample size 3,302 negative comments.

		anger	dissatisfaction	disgust	fear	sadness	joy	surprise	trust
Spearman's rho	anger	1,000	-0,138	0,406	0,37	0,21	-0,049093116	0,104	-0,071
	Correlation Coefficient								
	Sig (2-tailed)	0,000	0,000	0,000	0,000	0,000	0,051	0,000	0,005
	N	1574	1574	1574	1574	1574	1574	1574	1574
dissatisfaction	Correlation Coefficient	-0,138	1,000	-0,259	-0,119	-0,301	0,164	0,201	0,066
	Sig (2-tailed)	0,000		0,000	0,000	0,000	0,000	0,000	0,009
	N	1574	1574	1574	1574	1574	1574	1574	1574
disgust	Correlation Coefficient	0,406	-0,259	1,000	0,24	0,512	-0,131	-0,028	-0,157
	Sig (2-tailed)	0,000	0,000		0,000	0,000	0,000	0,261	0,000
	N	1574	1574	1574	1574	1574	1574	1574	1574
fear	Correlation Coefficient	0,37	-0,119	0,24	1,000	0,406	-0,033	0,071	-0,020
	Sig (2-tailed)	0,000	0,000	0,000		0,000	0,186	0,005	0,424
	N	1574	1574	1574	1574	1574	1574	1574	1574
sadness	Correlation Coefficient	0,21	-0,301	0,512	0,402	1,000	-0,124	-0,021	-0,158
	Sig (2-tailed)	0,000	0,000	0,000	0,000		0,000	0,407	0,000
	N	1574	1574	1574	1574	1574	1574	1574	1574
joy	Correlation Coefficient	-0,049	0,164	-0,131	-0,033	-0,124	1,000	0,443	0,43
	Sig (2-tailed)	0,051	0,000	0,000	0,186	0,000		0,000	0,000
	N	1574	1574	1574	1574	1574	1574	1574	1574
surprise	Correlation Coefficient	0,104	0,201	-0,028	0,071	-0,021	0,443	1,000	0,249
	Sig (2-tailed)	0,000	0,000	0,261	0,005	0,407	0,000		0,000
	N	1574	1574	1574	1574	1574	1574	1574	1574
trust	Correlation Coefficient	-0,071	0,066	-0,157	-0,020	-0,158	0,443	0,249	1,000
	Sig (2-tailed)	0,005	0,009	0,000	0,424	0,000	0,000	0,000	
	N	1574	1574	1574	1574	1574	1574	1574	1574

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