THE GOOD, THE BAD, AND THE UGLY – HOW EMOTIONS AFFECT ONLINE CUSTOMER ENGAGEMENT BEHAVIOR

Authors:

Tobias KRAEMER (1)
University of Koblenz-Landau
Institute for Management
Universitaetsstr. 1, 56070
Koblenz, Germany
Phone: + 49 261 287-2542
E-Mail: tkraemer@uni-koblenz.de

Julia DONSBACH (2)
EBS University
Marketing Department
Gustav-Stresemann-Ring 3,
65189 Wiesbaden, Germany
E-Mail: julia.donsbach@ebs.edu

Sven HEIDENREICH (3)
Saarland University
Institute for Technology and Innovation Management
P.O. Box: 151150, 66041
Saarbrücken, Germany
Phone: + 49 681 302-71482
E-Mail: sven.heidenreich@uni-saarland.de

Matthias H.J. GOUTHIER (4)
University of Koblenz-Landau
Institute for Management
Universitätsstr. 1, 56070 Koblenz, Germany
Phone: + 49 261 287-2852
E-Mail: gouthier@uni-koblenz.de

ABSTRACT

During the last years marketing research pays more and more attention to the concept of customer engagement behavior (CEB), which is the customer's behavioral manifestation toward a firm that goes beyond transactions. A central part of CEB are customer's word-out-mouth activities, which nowadays mostly take place in online environments. An important part of this online CEB (OCEB) are online user reviews, in which consumers express experiences with products and services. A wide variety of research addresses effects of online reviews and shows that they essentially influence decision making processes of consumers consulting these reviews. Thus, in many areas, online reviews are the most important information source crucially affecting sales numbers. While, consequences of this form of OCEB are well documented, empirical research on determinants motivating customers to engage online is relatively scarce. Nevertheless, existing research indicates that the expression of positive emotions and the venting of negative emotions related to the consumption experience constitute crucial drivers of OCEB. However, it remains widely unclear how the effects of different basic emotions (e.g. joy, anger, or fear) on OCEB differ. Thus, it could be expected that certain emotions are major drivers of OCEB, while others are negligible. This research tackles this question by proposing a theoretical model that distinguishes basic emotions according to their valence and arousal level and proposes varying effects on OCEB. To test the model we develop a text analysis tool that analyzes online reviews and detects basic emotions. Applying this tool 200,000 reviews from Amazon.com are analyzed and coded before applying ordinary least squares (OLS) regressions to test hypotheses. Results entail crucial theoretical and practical implications.

INTRODUCTION

Although the engagement notion has, in past decades, found far-reaching consideration across a number of academic disciplines, it was applied in marketing research just recently (Brodie *et al.*, 2011, Hollebeek *et al.*, 2014). Thereby, the concept of customer engagement was sought to advance the predictive power and scientific understanding of behavioral outcomes such as customer loyalty (Bowden, 2009, Hollebeek *et al.*, 2014). Customer engagement is assumed to possess cognitive, emotional, and behavioral aspects (Brodie *et al.*, 2011, Hollebeek *et al.*, 2014). This article specifically focuses on the concept's behavioral dimension, also referred to as customer engagement behavior (CEB), which we define as a customer's behavioral manifestation toward a firm that goes beyond transactions and results from a diverse set of motivational drivers (Van Doorn *et al.*, 2010). CEB is assumed to take different forms and to be expressed in a multitude of ways (Van Doorn *et al.*, 2010). For the most part, extant literature differentiates between two major types of CEB. While in interactions with a firm or its representatives the concept has regularly been associated with customer co-creation (e.g. in the context of product innovation), CEB in interactions with peer customers are often associated with customer communication activities (e.g. WOM, recommendations) (Jaakkola and Alexander, 2014, Verleye *et al.*, 2013).

Nowadays, a great share of interactions between the customer and the firm or other customers are being expressed online, particularly on social media websites, websites of online-retailers or on websites hosting user reviews (Bijmolt *et al.*, 2010, Vivek *et al.*, 2014). This specific kind of CEB, which we refer to as OCEB (i.e. online CEB), is in the center of this article. Extant research shows that OCEB, and particular electronic word-of-mouth, which is distributed through online user reviews, essentially influences decision making processes of consumers consulting these reviews. Thus, online reviews have become the most important information source in many areas, particularly in e-commerce, substituting or complementing offline word-of-mouth-communication (Chevalier and Mayzlin, 2006, Yin *et al.*, 2014). Accordingly, it is not surprising that online reviews crucially affect sales numbers of products and services (Forman *et al.*, 2008, Ludwig *et al.*, 2013). Furthermore, existing research shows that customers that show positive OCEB have a higher loyalty, while customers that show negative OCEB have low loyalty intentions and often want to harm the responsible company (Brodie *et al.*, 2013). While, the consequences of OCEB are well documented, empirical research on determinants motivating customers to engage online is relatively scarce. Yet, extant research indicates that emotions, which are generally considered an important motivational driver (Oliver *et al.*, 1997), also could be from high relevance for OCEB. Particularly, results from Hennig-Thurau *et al.* (2004) provide anecdotal evidence that the expression of positive emotions and the venting of negative feelings related to either a very positive or negative consumption experience constitute crucial drivers of OCEB. However, there is no empirical evidence that specifies the role emotions play with regard to OCEB. Thus, it remains unclear if effects of positive and negative emotions on OCEB differ. Furthermore, it has not been investigated if the different distinct emotions within these categories vary in their relevance. Thus, for instance, it could be expected that different negative emotions, like anger and sadness, are not equally important for OCEB. In addition to that, existing research indicates that the effects of emotions on consumer behavior strongly depend on the respective service/product category (e.g., Chitturi *et al.*, 2008). Thus, for example, an emotion like joy could play a different role for OCEB in a product category in which utilitarian benefits are central compared to a product category in which hedonic benefits are in the center of attention. Hence, in spite of the outlined research gaps and the elevated relevance and wide-reaching consequences of nowadays' online interactions, an in-depth empirical examination of the relative importance of customer emotions in driving OCEB appears to be essential.

Accordingly this paper strives to contribute to this stream of research (1) by determining the relative importance of all basic emotions for OCEB, (2) by providing a theoretical framework that explains the varying effects of the different basic emotions and allows for an integration of findings into existing research on emotions and OCEB, and (3) by accounting for differences in product/service categories that allow for more precise predictions to which extend the different basic emotions foster OCEB.

To pursue these contributions this paper proceeds as follows. First, we develop a theoretical framework that makes predictions on the relevance of different emotions for OCEB. Building on Plutchik's (1980,1982) wheel of emotions, we identify eight basic emotions and use the dimensions of valence and arousal to explain varying effects on OCEB. Second, the framework is extended by integrating moderating effects of the respective product/service category (i.e. utilitarian vs. hedonic). Third, for our empirical investigation we develop a text analysis tool that analyzes online reviews and automatically detects distinct basic emotions. Applying this tool a large sample of 200,000 online reviews of eight product/service categories from Amazon.com were analyzed and coded before applying ordinary least squares (OLS) regressions to test the research hypotheses. Fourth, building on our theoretical development and empirical analysis, theoretical and practical implications are derived and directions for future research on emotions and OCEB are provided.

CONCEPTUAL DEVELOPMENT

Classification of Emotions

A lot of work has been conducted in the field of emotion research, highlighting the emotion concept as vital element and important driver of human behavior and, more specifically of customer behavior (Gaur *et al.*, 2014). Thereby, emotions are often regarded as "mental state of readiness that arises from cognitive appraisals of events or thoughts", that "[…] is often expressed physically (e.g., in gestures, posture, facial features) and may result in specific actions to affirm or cope with the emotion […]" (Bagozzi *et al.*, 1999; p. 184). There is a great number of emotions that can be distinguished. Academic literature has mostly utilized two major approaches for categorizing emotions (Havlena and Holbrook, 1986): basic emotional categories (e.g., Izard, 1977, Plutchik, 1980) and underlying dimensions of affective states (e.g., Mehrabian and Russell, 1974, Russell, 1980). One of the most prominent emotional typologies was introduced by Robert Plutchik (1980) and has provided the conceptual framework for a multitude of empirical investigations into the subject (e.g., Havlena and Holbrook, 1986). Based in evolutionary processes, Plutchick (1980; 1982) defines emotions in terms of a complex stimulus-reaction sequence, and focuses on only eight basic emotional categories. Building the foundation for all more complex secondary emotions, the array of basic or primary emotions include anger, joy, trust, surprise, fear, sadness, disgust and anticipation (Plutchik, 2001). An overview is provided in Table 1. Plutchik (1982; 2001) arranges the emotions in a circumplex manner with bipolar pairs allocated opposite to each other. He argues that different kinds of dyads (primary, secondary, or tertiary) may result from the combination of any two either directly or indirectly adjoined emotions. Assumed to involve different levels of intensity or arousal, emotions, further, may as a result eventually lead to dissimilar behavioral manifestations (Plutchik, 1991). This is also in line with basic assumptions involved in affect theory, claiming affective states to be best represented in terms of continuous underlying dimensions of valence and arousal (or activation) (e.g., Mano and Oliver, 1993, Mehrabian and Russell, 1974, Russell, 1980, Russell and Barrett, 1999). Similar to their depiction in basic categories, emotions in the multi-factor based representation are assumed to occur in a circumplex manner. Arranged around orthogonal axes, emotions thus, are suggested to exist not only in bipolar categories but also in different levels of intensity (Bagozzi *et al.*, 1999, Reisenzein, 1994), leading to a diverse set of associated behaviors. A comprehensive investigation of the role of emotions for OCEB thus has not only to account for all different basic emotions but also for their valence and respective arousal level. While previous empirical studies relied on one emotion or the other when examining consequences for OCEB, no empirical study exists yet that follows a comprehensive approach taking all distinct basic emotions and their valence and arousal level into account. Consequently, we rely on Plutchik's (1980) comprehensive typology of emotions to address these shortcomings of previous empirical research on emotions and OCEB. Therefore, it is necessary to categorize Plutchik's basic emotions according to their valence (positive, neutral, negative) and their arousal level (low, high). Considering the wide variety of approaches that categorize emotions on the basis of these two dimensions, which however not all include all of Plutchik's basic emotions, it was necessary to develop a new typology that categorizes all eight basic emotions along the dimensions valence (positive, neutral, negative) and arousal (high, low). Therefore, various categorization approaches (Bagozzi *et al.*, 1999, Reisenzein, 1994, Russell and Barrett, 1999, Smith and Ellsworth, 1985) were assessed and discussed by an expert group of researchers with an academic background in marketing and/or psychology. The expert group went through the existent categorization approaches, assessed the relevance and applicability of every typology and specified in each case their detailed understanding of each basic emotion with respect to its valence and arousal level. Table 1 illustrates the resulting allocation of basic emotions on the dimensions of valence and arousal.

-Insert Table 1 about here-

In the following we outline theoretical rationales how the valence and arousal level of distinct basic emotion affect how frequently these emotions are expressed in online reviews and how strong the impact of these emotions is on the level of OCEB. Furthermore, we outline possible interaction effects between emotions and OCEB with respect to the primary benefit (hedonic/utilitarian) of product/service categories.

Valence of Emotions

The classification of emotions along the dimensions of positive and negative affect (i.e. valence) has found frequent application in past research (e.g., Edell and Burke, 1987, Laros and Steenkamp, 2005, Smith and Ellsworth, 1985). For example, research has utilized valence as one basic dimension to delineate the emotional reality (Russell, 1980). Generally, valence describes the level of pleasantness individuals feel, when they experience a certain emotion (Bagozzi *et al.*, 1999). Typically, with regard to valence, three kinds of emotions are differentiated: positive, neutral, and negative emotions (Danner *et al.*, 2001). It can be expected that especially positive and negative emotions show major differences. Depending on their valence, emotions are assumed to influence an individual's action and goal attainment (Bagozzi *et al.*, 1999). In general, expressions of positive emotions in public are, in contrast to the expression of negative emotions, mostly supported due to their positive impact on social interaction (Kim and Gupta, 2012). Additionally, average product ratings, which are in most cases very high (Chevalier and Mayzlin, 2006), suggest that consumers predominantly experience positive consumption emotions. Negative emotions instead entail stronger action tendencies than positive emotions (Fredrickson, 2001). For example, anger urges individuals to attack the source of anger. Positive emotions instead tend to enhance the thought-action repertoire of individuals and entail a greater tendency for sharing or maintaining positive experiences (Bagozzi *et al.*, 1999). Accordingly, we hypothesize:

Hypothesis 1a: Positive emotions are more frequently expressed in reviews than negative or neutral emotions.

Hypothesis 1b: Negative emotions have a greater impact on OCEB (i.e. length of review) than positive or neutral emotions.

Arousal Level of Emotions

Arousal refers to the degree of activation the experience of a certain emotion causes for an individual (Bagozzi *et al.*, 1999). Thus, in addition to their valence, emotions may differ in their level of evoked arousal or activation (Smith and Ellsworth, 1985). Regularly, research differentiates between low- and high-arousal emotions (Bagozzi *et al.*, 1999). Constituting not only a vital aspect of emotions but also of the behavior related to emotions (Bagozzi *et al.*, 1999), arousal has been suggested to be an important motivational driver of an individual's emotional and behavioral reaction to stimuli. As such, it has been argued, that the likelihood of action tendencies resulting in actual behaviors are highly interrelated and, thus, dependent on the particular level of emotional arousal (Chitturi *et al.*, 2008). In particular may the relative intensity of emotions be a determinant for associated socially consequential behaviors (Reisenzein, 1994). Constituting a state of mobilization (Berger and Milkman, 2012), it can be expected, that independent from the valence of an emotion, high levels of activation cause stronger memorability and motivation for the individual to react to the stimulus that caused the emotion, than do low levels of activation. In particular, the level of psychological arousal has been suggested to directly influence individuals' likelihood to engage in some sort of activity. Especially high-arousal emotions have been suggested to positively influence activities such as sharing content in an online environment (Berger and Milkman, 2012). In the context of this study, the stimulus that caused the emotion is a consumption experience with a product or service, and the corresponding reaction is a customer's OCEB. Hence, we hypothesize:

Hypothesis 2a: High-arousal emotions are more frequently expressed in reviews than low-arousal emotions.

Hypothesis 2b: High-arousal emotions have a greater impact on OCEB (i.e. length of review) than low-arousal emotions.

Interaction between Valence and Arousal Level of Emotions

The depiction and investigation of the emotional reality based on the dimensions of valence and arousal have found repeated application in the extant literature

(Mehrabian and Russell, 1974, Olney *et al.*, 1991). For example, Russell (1980) suggests affective states to be best represented in a continuous two-dimensional bipolar space, with the dimensions of pleasantness-unpleasantness and arousal-sleep providing the basis for any delineation and combination of components. In contrast, Watson and Tellegen (1985) introduce the dimensions of high positive affect-low positive affect and high negative affect-low negative affect for the accurate depiction of emotions. Following the logic of Russell (1980) and Watson and Tellegen (1985), both intensity level of arousal of affect (high-low) and valence of affect constitute decisive components of the emotional reality. Both high-arousal positive and negative emotions are not only suggested to lead to greater actual behavioral outcomes (Chitturi *et al.*, 2008) but also to be particularly viral in an online environment (Berger and Milkman, 2012). Yet, in contrast to the common belief that particularly negative word of mouth is more frequently passed along, especially positive word-of-mouth often is socially transmitted (Berger and Milkman, 2012). As we expect positive emotions to be expressed more frequently than negative emotions, and high-arousal emotions more frequently than low-arousal emotions, we predict that positive high-arousal emotions (i.e. the basic emotion joy) are the most frequently expressed in reviews. Based on the particularly strong action tendencies of negatively valenced emotions (Fredrickson, 2001) we similarly suggest that negative valence and high-arousal drive OCEB. Therefore, we assume that negative high-arousal emotions have the greatest effect on OCEB. Consequently, we hypothesize:

Hypothesis 3a: Positive high-arousal emotions (i.e. joy) are the emotions that are most frequently expressed in reviews.

Hypothesis 3b: Negative high-arousal emotions (i.e. anger, disgust, and fear) have the greatest impact on OCEB (i.e. length of review).

Moderating Effects of Primary Benefits of Products/Services

Categorizing products and services on basis of primary benefits seems particularly useful, and has previously been highlighted by research (Chitturi *et al.*, 2008, Ng *et al.*, 2007, Uhrich *et al.*, 2013). Primary benefits refer to the underlying reasons of consumers to use products or services; that is, consumers may seek either for hedonic gratification or for the fulfillment of utilitarian needs (Uhrich *et al.*, 2013). As such, hedonic motivated consumption focuses specifically on the fulfillment of psychological needs related to the experience of personal pleasure, enjoyment or delight during consumption (Cooper-Martin, 1992, O'Shaughnessy and O'Shaughnessy, 2002). Based on affective states resulting from the consumption experience of hedonic products or services, evaluations are mostly based on affect-based factors. In contrast, utilitarian motivated consumption primarily aims at fulfilling rational and functional needs, and bases evaluations of the consumption experience predominantly on cognitive processes (Ng *et al.*, 2007). Thus, while the consumption of hedonic benefits is primarily related to evoking high-arousal promotion emotions, utilitarian benefits primarily evoke low-arousal prevention emotions (Chitturi *et al.*, 2008). Qualitatively different in their type and intensity of emotional experience, the consumption of hedonic and utilitarian benefits leads to dissimilar levels and interrelationships with associated behavioral outcomes (Chitturi *et al.*, 2008). Therefore, we hypothesize:

Hypothesis 4: High-arousal emotions are more frequently expressed in reviews *(H4a)* and have a greater impact on OCEB (i.e. length of review) *(H4b)* in categories in which hedonic benefits dominate compared to categories in which utilitarian benefits dominate.

Hypothesis 5: Low-arousal emotions are more frequently expressed in reviews *(H5a)* and have a greater impact on OCEB (i.e. length of review) *(H5b)* in categories in which utilitarian benefits dominate compared to categories in which hedonic benefits dominate.

EMPIRICAL ANALYSIS

Data Collection

To test our hypotheses we relied on data from the website of the online-retailer Amazon.com, which provides a large number of customer reviews. The review data was obtained from the Stanford Network Analysis Project (SNAP), which (amongst others) collected Amazon review data from a span of 18 years (June 1995 until March 2013); the data set contains the review text and further information like reviewer names, review ratings and prices (McAuley and Leskovec 2013). While Amazon offers a wide variety of product/service categories, we focused on those categories that were unambiguously identified as being primarily utilitarian or hedonic, which enables us to test our research hypotheses unambiguously. To classify product/service categories we asked three researchers to rate the level of utilitarian and hedonic benefits of all Amazon's product/service categories using scales by Voss, Spangenberg, and Grohmann (2003). Afterwards, we obtained the average scores of the ratings and calculated the difference between the level of utilitarian benefits and the level of hedonic benefits. Product/service categories with the most positive indices can be considered as those which primarily provide utilitarian benefits, while those with the most negative indices can be considered as those which primarily provide hedonic benefits. For data analysis, we choose the four product/service categories with the highest scores (primarily utilitarian benefits) and the four product/service categories with the lowest scores (primarily hedonic benefits). The final categorization of relevant products and services according to their primary consumption benefits is provided in Table 2. For each category the most recent 25,000 reviews from the SNAP data were included in our data set (prior to that duplicates and defective data sets have been removed). Finally, our final data set, comprising 8 categories, consists of 200,000 reviews (including data on reviewer ratings [i.e. the star rating] and prices). When choosing the sample size we strived to guarantee that the sample is large enough to provide reliable and representative results in the data analysis. At the same time we did not include all available reviews (or a considerably larger number of reviews), as this would make the handling of the data critically more difficult without providing additional or more reliable insights.

-Insert Table 2 about here-

Measures

OCEB. To operationalize the level of OCEB of the reviewers, we relied on the length of the respective review. Thus, it can be expected that customers, who are highly engaged (positively or negatively) invest more time to prepare an extensive review, while customers that show a low level of engagement tend to write shorter reviews. Particularly, OCEB is operationalized as adjusted word count, which is defined as the overall word count of the review minus the used emotion words (see below). Emotion words were excluded from the OCEB measure to avoid an overlap of the independent and dependent variable.

Measurement of Emotions – Distinct Emotions Word Count (DEWC). By now different linguistic analysis tools are available (e.g., LIWC; Pennebaker, Francis, and Booth 2001) and frequently used in research. However, none of the existing tools is able to detect (all of the) distinct basic emotions. Therefore, we developed DEWC, which is a computerized text analysis tool that measures the frequency of the eight different basic emotions (that Plutchik [1980] defines) in texts. The heart of DEWC is a dictionary consisting of 180 emotion words, of which each is assigned to one of the basic emotions. The dictionary was developed on basis of two compilations of emotion words: a list of emotion words in consumer research by Laros and Steenkamp (2005) and a list of emotion words in the sentiment dictionary by Wilson, Wiebe, and Hoffmann (2005). The emotion words in these lists were categorized (independently) by three researchers that are experts in the field of emotion research. In a first step, the researchers were asked to rate whether the respective word is an emotion word used in everyday language. If more than one of the raters indicated that this is not the case, the word was eliminated. In a second step the emotion words were assigned to the different basic emotions. Again, the raters independently assigned the words. If at least two of the raters assigned a word to a certain basic emotion, the word was placed in this category; otherwise the word was eliminated. Subsequently, the dictionary was implemented in a computerized text analysis tool. Thereby, a list of search terms was developed to enable a precise identification of the emotion words. For example, the emotion word anger is operationalized by the terms “anger” and “angry”. In addition, we applied search terms that detect negations. If an emotion word is negated it is subtracted from the count. Further, certain negations are scored to the emotion on the opposite site in Plutchik’s wheel of emotions. For example, if the word “fun”, which belongs to the category joy, is negated (e.g., “we didn’t have fun”), it is scored as sadness word. To further improve the detection of basic emotions, we additionally implemented the identification of dyads (words representing dyads were not included in the above-described emotion list). Dyads are emotions that are the result of two basic emotions (e.g., delight consists of joy and surprise) (Plutchik 1980; Plutchik 1982). When a dyad is detected (e.g., delight) both underlying basic emotions (e.g., joy and surprise) receive a score.

Overall the DEWC analysis tool incorporates 2,176 search terms (298 terms to identify emotion words plus 1,878 terms to detect negations). Thereby, DEWC provides functions that commonly used computerized text analysis tools do not feature. Thus, DEWC is able to detect distinct emotions and all basic emotions. Other commonly used computerized text analysis tools are only able (and designed) to detect positive or negative sentiments (e.g., SentiStrength; Thelwall et al. 2010) or only differentiate between few emotions (LIWC divides negative emotions into anger, sadness, and anxiety). Additionally, DEWC accounts for negations when calculating emotions scores (LIWC counts negations but does not reflect negations in the emotion scores). To evaluate the reliability of DEWC we compared its analyses results to the commonly used LIWC tool. Our tests suggests that DEWC performs much better than LIWC in detecting distinct emotions (a comparison was only possible for anger, sadness, and anxiety/fear). To demonstrate the function of DEWC, Table 3 shows the DEWC analysis results for some example sentences. Additionally, to offer a comparison, we illustrate the scores LIWC provides with regard to emotions. According to the comparison, DEWC was not only able to detect emotion words more reliable, in contrast to LIWC, it was also able to further differentiate the emotion words in distinct emotions rather than in emotional categories.

-Insert Table 3 about here-

Emotion Composites. The DEWC analysis tool enables us to detect distinct basic emotions. However, our hypotheses relate to certain dimensions of emotions that are assumed to affect their influence on OCEB. Accordingly, we build different composites, which sum up the scores of the emotions that belong to this category; this approach enables us to test the theory-driven hypotheses. With regard to valence three different composites are created: positive (including joy and trust), neutral (including surprise and anticipation), negative (including anger, disgust, sadness, and fear) (Laros and Steenkamp 2005). With respect to the level of arousal, two composites are build: low-arousal (trust, anticipation, sadness) and high-arousal (joy, surprise, anger, disgust, and fear) (Reisenzein 1994; Russell and Feldman Barrett 1999). Finally, the two dimensions (i.e. valence and arousal) are combined, which results in six different categories. In this classification, every category with the exception of negative high-arousal emotions (i.e. anger, disgust, and fear) represents one basic emotion.

The approach of building emotion composites enables us to gain more general insights on the influence of emotions on OCEB. Thus, there is a wide variety of non-primary (i.e. not basic) emotions that can be rated along the dimensions valence and arousal (e.g., Reisenzein 1994; Russell and Feldman Barrett 1999). Consequently, our results can also be used to estimate the influence of these emotions.

Controls. To provide a stronger test of our hypotheses we incorporated control variables. Particularly, we controlled for the reviewer rating (i.e. the number of stars) and the price of the product/service from the SNAP data. Additionally, we controlled for the linguistic style and content with data that we obtained with LIWC 2015, which is a newer, advanced version of the original LIWC program (Pennebaker, Francis, and Booth 2001). Thereby, we relied on the variables words per sentence, words > 6 letters, references to money, and informal language.

Data Analysis

Our research hypotheses relate to the mean frequencies of different emotions in customer reviews and the effects of different emotion composites on OCEB, which is measured with adjusted word count (see measures). Mean frequencies are compared using a student t-test. Effects of the emotion composites on customer engagement are obtained by applying ordinary least squares (OLS) regression, with adjusted word count as dependent and emotion composites (according to valence, level of arousal, or both) and the controls as independent variables. Thereby, we rely on unstandardized regression coefficients, as these indicate to which extend one emotion word (which is the measure for a particular emotion) affects the adjusted word count (which is the measure for OCEB) in absolute numbers. Thus, when for example, anger shows an unstandardized regression coefficient of 30, it means that for every anger word, the review is averagely 30 words longer. In other words, a one unit increase in anger, leads to an increase of 30 units of OCEB. For our purpose, unstandardized regression coefficients are more meaningful as they are in contrast to standardized regression coefficients not affected by the mean of the independent variables (i.e. the mean frequencies of the emotions).

-Insert Table 4 and Table 5 about here-

Valence of Emotions. H1a suggest that positive emotions are more frequently expressed in reviews than neutral or negative emotions. To test this hypothesis, we compared the mean frequencies of the different emotion composites in a t-test (see Table 4). In accordance with H1a, data analysis shows that positive emotions (M = 2.79, SD = 2.78) are expressed significantly ($p < .001$) more frequently than neutral (M = 0.20, SD = 0.54) or negative emotions (M = 0.58, SD = 1.30). H1b predicts that negative emotions have a stronger impact on customer engagement than positive and neutral emotions. To test this hypothesis we regressed adjusted word count (as measure for OCEB) on positive emotions, neutral emotions, negative emotions and the control variables:

$$\text{ADJUSTED WORD COUNT}_i = b_0 + b_1 * \text{RATING}_i + b_2 * \text{PRICE}_i + b_3 * \text{WORDS/SENTENCE}_i + b_4 * \text{WORDS>6LETTERS}_i + b_5 * \text{REFERENCE TO MONEY}_i + b_6 * \text{INFORMAL LANGUAGE}_i + b_7 * \text{POSITIVE EMOTIONS}_i + b_8 * \text{NEUTRAL EMOTIONS}_i + b_9 * \text{NEGATIVE EMOTIONS}_i + e_i.$$

Table 5 shows that negative emotions (b=29.38, $p<0.001$) have the highest unstandardized regression coefficient and thus a stronger impact on OCEB than positive (b = 11.68, $p < 0.001$) and neutral emotions (b = 22.86, $p < 0.001$). The difference between all regression coefficients is significant for $p < 0.001$, why H1b is supported.

Level of Arousal of Emotions. H2a suggests that high-arousal emotions appear more frequently in reviews than low-arousal emotions. Accordingly, we compare the mean frequencies of high- and low-arousal emotions in a t-test. Results support H2a and outline that high-arousal emotions (M=2.64, SD=2.59) are clearly more frequently expressed (difference significant for $p < 0.001$) than low-arousal emotions (M = 0.92, SD = 1.44). H2b assumes that high-arousal emotions also have a stronger impact on OCEB compared to low-arousal emotions. To estimate the effects, we regressed adjusted word count (as measure for OCEB) on low-arousal emotions, high-arousal emotions, and the controls:

$$\text{ADJUSTED WORD COUNT}_i = b_0 + b_1 * \text{RATING}_i + b_2 * \text{PRICE}_i + b_3 * \text{WORDS/SENTENCE}_i + b_4 * \text{WORDS>6LETTERS}_i + b_5 * \text{REFERENCE TO MONEY}_i + b_6 * \text{INFORMAL LANGUAGE}_i + b_7 * \text{LOW-AROUSAL EMOTIONS}_i + b_8 * \text{HIGH-AROUSAL EMOTIONS}_i + e_i.$$

Results highlight that high-arousal emotions (b = 18.90, $p < 0.001$) clearly have a stronger influence on adjusted word count than low-arousal emotions (b = 11.39, $p < 0.001$). In support of H2b the difference is significant for $p < 0.001$.

Interaction of Valence and Level of Arousal of Emotions. To test H3a and H3b, which relate to the interaction of valence and level of arousal we proceed as previously. Comparing mean frequencies of the composites shows that positive high-arousal emotions (i.e. the basic emotion joy; M = 2.22; SD = 2.16) appear most frequently and significantly more often than any other emotion composite (differences significant for $p < 0.001$). Accordingly, H3a is supported. Results further reveal that positive low-arousal emotions (i.e. trust; M = 0.57, SD = 1.03) and negative high-arousal emotions (i.e. anger, fear, disgust; M = 0.34; SD = 0.91) are the next most frequent emotions. To test H3b, we regressed adjusted word count on the 6 emotion composites and the controls:

$$\text{ADJUSTED WORD COUNT}_i = b_0 + b_1 * \text{RATING}_i + b_2 * \text{PRICE}_i + b_3 * \text{WORDS/SENTENCE}_i + b_4 * \text{WORDS>6LETTERS}_i + b_5 * \text{REFERENCE TO MONEY}_i + b_6 * \text{INFORMAL LANGUAGE}_i + b_7 * \text{POSITIVE LOW-AROUSAL EMOTION}_i + b_8 * \text{POSITIVE HIGH-AROUSAL EMOTION}_i + b_9 * \text{NEUTRAL LOW-AROUSAL EMOTION}_i + b_{10} * \text{NEUTRAL HIGH-AROUSAL EMOTION}_i + b_{11} * \text{NEGATIVE LOW-AROUSAL EMOTION}_i + b_{12} * \text{NEGATIVE}$$

HIGH-AROUSAL EMOTION$_i$ + e_i.

Results from regression analysis support H3b. Thus, negative high-arousal emotions (i.e. anger, disgust, fear; $b = 31.52$, $p < 0.001$) have the greatest effect on OCEB.

Multi-Group Analysis. H4 and H5 propose different frequencies and different effects of the emotion composites in different markets (utilitarian vs. hedonic). To test these hypotheses, we build on the previously presented procedure but perform separate analyses for the two subsamples. H4 predicts that high-arousal emotions are more frequently expressed in reviews (H4a) and have a greater impact on OCEB (H4b) in categories in which hedonic benefits dominate compared to categories in which utilitarian benefits dominate. Data analysis supports both proposition made in H4: high-arousal emotions are clearly more frequent in hedonic ($M = 2.92$, $SD = 2.88$) than in utilitarian categories ($M = 2.37$, $SD = 2.24$; difference significant for $p < 0.001$); high-arousal emotions have a greater influence on OCEB in hedonic ($b = 19.91$, $p < 0.001$) than in utilitarian categories ($b = 17.97$, $p < 0.001$; difference significant for $p < 0.001$). H5 assumes that low-arousal emotions are more often expressed in reviews (H5a) and have a stronger influence on OCEB (H5b) in utilitarian than in hedonic categories. Results reject H5a and show that low-arousal emotions are less frequent in utilitarian ($M = 0.79$, $SD = 1.33$) than in hedonic categories ($M = 1.05$, $SD = 1.54$; difference significant for $p < 0.001$). Additionally, findings reject H5b by showing that low-arousal emotions are less influential in utilitarian ($b = 11.20$, $p < 0.001$) than in hedonic categories ($b = 12.30$, $p < 0.001$; difference significant for $p<0.001$).

Additional Analysis—The Influence of Negative High-arousal Emotions

When the primary emotions are categorized along both regarded dimensions—valence and level of arousal—each emotion composite represents one particular basic emotion, with the exception of negative high-arousal emotions. This composite includes the three basic emotions: anger, disgust, and fear. As this composite has a strong influence on customer engagement and it remains unclear which of the three emotions is most important, we conduct an additional analysis. Thereby, we regress adjusted word count on all basic emotions and the control variables. Among the three negative, high-arousal emotions, anger clearly has the strongest impact on OCEB ($b = 37.83$, $p < 0.001$), followed by fear ($b = 26.82$, $p < 0.001$), and disgust ($b = 24.16$, $p < 0.001$). Furthermore, we found that anger ($b_{Util} = 32.17$, $p>.001$; $b_{Hed} =41.84$, $p < 0.001$) and disgust ($b_{Util} = 21.62$, $p > 0.001$; $b_{Hed} = 26.62$, $p < 0.001$) are more important in hedonic than in utilitarian product categories, while fear ($b_{Util} = 29.96$, $p > 0.001$; $b_{Hed} = 25.52$, $p < 0.001$) is more important in utilitarian than in hedonic categories.

CONCLUSION

Discussion of Results

The results of the empirical analysis highlight that the different basic emotions vary substantially with regard to their effects on OCEB. As expected, a lot of this variance can be explained, when the emotions are categorized with regard to their valence and their level of arousal. Our results show, that positive emotions, which are those emotions that are experienced as pleasant feelings, are expressed essentially more often in customer reviews than neutral or negative emotions. This can be explained with the fact that customer experiences nowadays are predominately positive. In line with this argumentation, the average star rating in the reviews we analyzed was

4.16 stars (out of five stars) and more than 60% of the reviews have a 5-Star rating. However, negative emotions that customers experience create decisively higher levels of OCEB than positive (and neutral) emotions. This finding can be explained with the notion that negative emotions entail stronger action tendencies than positive emotions (Fredrickson 2001). Additionally, it can be assumed that since positive consumption experiences are the usual case, negative emotions (caused by negative experiences) are more outstanding and thus cause higher levels of OCEB. Furthermore, our results show that the level of arousal essentially influences how frequent different basic emotions occur in online reviews and how strong their impact is. Particularly, we find that high-arousal emotions occur crucially more often in online reviews and have a decisively greater impact on OCEB. These findings can be explained with notion that high-arousal emotions are better remembered due to their higher level of activation and that this higher level of activation also creates a stronger motivation to react to the stimulus (i.e. the consumption experience) (Berger and Milkman 2012).

Combining the above presented findings it can be expected that positive high-arousal emotions are the emotions that occur most frequently in online reviews and that negative high-arousal emotions are the emotions that have the greatest impact on OCEB. Our results support this conclusion and show that joy, which is the only positive high-arousal emotion among the basic emotions, occurs clearly most often in customer reviews; negative high-arousal emotions have the strongest impact on OCEB. However, three basic emotions (i.e. anger, disgust, and fear) can be categorized as negative high-arousal emotions and an additional analysis shows that they vary in their influence on OCEB. Thus, anger clearly has the highest impact on OCEB, followed by fear, and disgust. As our theoretical development delivers no explanation for the differences in the effects of these emotions, it should be subject to future research.

A multi-group analysis that differentiates between product/service categories, which primarily provide utilitarian and those, which primarily provide hedonic benefits, provides more insights on the relationship between the different basic emotions and OCEB. In accordance with existing studies (e.g., Chitturi, Raghunathan, and Mahajan 2008), which propose that hedonic benefits are primarily related to evoking high-arousal emotions, we find that high-arousal emotions occur significantly more frequently and more strongly affect OCEB in hedonic than in utilitarian categories. However, we cannot support the hypothesis that low-arousal emotions are more frequently expressed and create higher levels of OCEB in utilitarian than in hedonic categories. In this regard it can be expected that consumption experiences in hedonic product categories are much more emotional than in utilitarian categories. Thereby, particularly high-arousal emotions are created and are the main driver for OCEB. However, due to the high emotionality in hedonic product categories, also low-arousal emotions occur more often and are more important for OCEB compared to utilitarian categories.

Implications

Theoretical Implications. Understanding how basic emotions as response to consumption experience influence OCEB is crucial to companies that aim to successfully manage their customer relationships. As past research has predominantly centered on the investigation of consequences of OCEB including customer conversion and sales implications (Ludwig *et al.*, 2013, Zhu and Zhang, 2010), an examination of potential drivers of OCEB is particularly valuable and still missing from the academic literature. Especially the investigation of the role and consequences of customer emotions for driving OCEB notably adds to the current understanding and conceptualization of OCEB, and allows for providing a better comprehension of how to foster and better manage OCEB in order to benefit from associated positive outcomes. With the results of our study, we are able to do both validate as well as challenge extant research and previous findings.

In our study, we find that particularly positive emotions experienced as pleasant feelings (e.g. joy), are expressed a lot more frequently in online customer reviews than are neutral or negative emotions. On the one side, this is in line with the results of previous research, suggesting positive content to be considerably more viral in an online environment than negative content (Berger and Milkman, 2012). On the other side, these findings contradict the common believe, that it is especially negative WOM that spreads particularly well (Godes *et al.*, 2005). Particularly considering previous research highlighting (positive) online WOM to exhibit positive impacts on a company's sales (Ho-Dac *et al.*, 2013, Zhu and Zhang, 2010), these results are important to be recognized by future research. In addition, as our study results further suggest, it is particularly negative emotions that create decisively higher levels of OCEB and thus, exhibit significantly greater effects on customers' engagement behaviors online than positive or neutral emotions. These findings particularly contradict previous research results, suggesting particularly positive emotions to enhance the thought –action repertoire of individuals and thus, to be more likely to be shared and maintained (Bagozzi *et al.*, 1999). Overall, in contrast to previous research, our results show that differentiation between the consequences of positive and negative emotions on OCEB. This is particularly important, considering past research suggesting that mere exposure to affective content (positive and negative) may be sufficient to also heavily impact other customer thinking and behavioral manifestations (Lau-Gesk and Meyers-Levy, 2009, Ludwig *et al.*, 2013).

Supporting previous research findings, the results of our study indicate that the level of arousal underlying an emotional expression plays a major role in driving OCEB. Notwithstanding the valence of the emotion, we find particularly high-arousal emotions to foster elevated levels of OCEB among customers. This is in line with previous research highlighting the importance of arousal for driving social transmission. As such, regardless of the prevailing valence of emotions (positive or negative), particularly high-arousal emotions are assumed to lead to particularly elevated levels of virality of online content (Berger and Milkman, 2012). Notably, the current findings add to extant literature in that they empirically demonstrate the increased impact of positive high-arousal emotions on OCEB in hedonic consumption. As our study suggests, high-arousal emotions are particularly relevant for product categories in that hedonic characteristics are in the center of attention. Thus, we adopt the view that product/service characteristics can significantly moderate between arousal level and OCEB.

Managerial Implications. This research outlines various practical suggestions for companies aiming to engage their customers in an online environment. Overall, our results suggest that companies that want to foster (positive) OCEB should particularly aim at creating interesting and joyful experiences for customers. Especially by creating experiences of specifically high levels of arousal among their customers, companies are expected to foster elevated levels of OCEB. Yet, while the experience of positive high-arousal typically leads to a more frequent expression of positive emotions, experiencing negative high-arousal emotions rather leads to particularly remarkable effects on OCEB.

Thus, companies need to understand that clear distinctions between different emotional states and expressions need to be made in order to effectively manage OCEB. By the careful evaluation of customer emotions as response to a consumption experience, in terms of both valence and intensity, companies may be able to better assess potential (positive and negative) behavioral outcomes and associated consequences. For example, although evoking feelings of trust can be utilized to establish long-lasting relationships (Chaudhuri and Holbrook, 2001), it is unlikely to create high levels of OCEB. Moreover, companies need to understand that differences exist in the creation of OCEB with regard to individual product/service categories. For example, while emotions may be particularly useful in fostering OCEB in some product categories, they may be less effective in others. Thus, companies are obliged to understand which specific emotions are required in their particular business to create positive OCEB and which ones may lead to negative OCEB among their customers. As the previously presented results show, fostering OCEB with interesting, joyful experiences for customers works particularly well in product categories or markets in which hedonic benefits are in the center of attention. In contrast, consumption experiences that cause anger and fear create intensive negative OCEB. This is especially true when customers show high interest in the product (category). Notably, it can be assumed that such high levels of OCEB can hardly be reached with positive consumption emotions. In addition, it can be expected that when various customer show negative OCEB that is driven by anger and/or fear, it can have devastating consequences for companies as such feedback negatively influences evaluations of other customers and sales (Chevalier and Mayzlin, 2006, Kim and Gupta, 2012).

Limitations and Research Avenues

This research presents a new approach to analyzing the role of basic emotions in fostering OCEB and provides valuable novel insights. However, there are also some limitations to our approach that need to be highlighted. First, we can only analyze those customers who wrote reviews. Thus, in every of the analyzed cases the customers showed at least a small level of OCEB. Consequently, future research should examine whether or not consumption emotions play a different role when it comes to motivating customers to engage at all. Second, we looked at two of the central dimensions on which emotions can be categorized- valence and level of arousal. However, there is a wide variety of additional dimensions that have been highlighted in the literature and that could be important in this regard (e.g., Smith and Ellsworth, 1985). Such dimensions could help to shed additional light into the role neutral emotions such as surprise and anticipation play in driving OCEB. Third, we were not able to analyze how potentially important individual characteristics such as socio-demographics or personality factors influence the relationships proposed in our conceptual model. Thus, future research should expand investigations taking into account individual attributes possibly impacting research findings. Past research has, for example, highlighted the importance of customer s' internet experience when it comes to relying on online reviews (Zhu and Zhang, 2010). Fourth, this research is based on a sample of reviews originating from the US site of the online retailer Amazon. Thus, in order to increase validity and to enhance the generalizability of our findings, future research should test the proposed relationship with reviews from additional sources (i.e. other online retailers and independent review websites). In addition, customer reviews from other countries and cultural backgrounds should be analyzed, as there is a good chance of culture significantly influencing the expression and effects of emotions with regard to OCEB. In order to test and further support the stability of our research findings, future investigations should also test our hypotheses in other product/service categories which, given the scope of this paper, have not yet been examined.

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FIGURES AND TABLES

Table 1: Allocation of basic emotions on the dimensions of valence and arousal.

Valence/Arousal	Low	High
Positive	Trust	Joy
Neutral	Anticipation	Surprise
Negative	Sadness	Anger, Fear, Disgust

Table 2: Product/services according to primary consumption goal

	Primarily Utilitarian	Primarily Hedonic
Product/Service Category	Office Products Home & Kitchen Tools & Home Improvement Software (excluding games)	Instant Video Video Games Movie & TV Jewelry

Table 3: DEWC analysis results in comparison to LIWC analysis results.

Text	**DEWC**	**LIWC**
We were really surprised[a]. The game is great[b]! Our kids have so much fun[b] with it. I also really trust[c] in the quality of the materials.	Surprise[a] = 1 Joy[b] = 2 Trust[c] = 1	Positive emotions = 4
I really regret[a] buying this drill. The quality is surprisingly[b] poor[a]. Using it seems really dangerous[c]!	Sadness[a] = 2 Surprise[b] = 1 Fear[c] = 1	Negative emotions = 3 (sadness = 1)
The movie isn't fun[a] at all! It's actually really distasteful[b].	Sadness[a] = 1 (reverse joy) Disgust[b] = 1	Positive emotions = 1
Not what I hoped for. The album is disappointing[a].	Dissappointment[a] = 1 (dyad) → Sadness = 1 + Surprise = 1	Positive emotions = 1 Negative emotions = 1 (sadness = 1)

Please note that the LIWC output provides scores relative to the word count; e.g. positive emotions = number of positive emotion words/ number of overall words*100; this table provides absolute scores of the word count to provide more transparency with regard to the scoring mechanism.

Table 4: Mean frequencies of emotions in reviews

	Overall	**Utilitarian Products/Services**	**Hedonic Products/Services**
Words	70.60	75.18	66.01
Emotion Words:			
All Emotions	3.57	3.16	3.98
Valence:			
Positive Emotions	2.79	2.40	3.19
Neutral Emotions	0.20	0.18	0.22
Negative Emotions	0.58	0.58	0.57
Level of Arousal			
Low-Arousal Emotions	0.92	0.79	1.05
High-Arousal Emotions	2.64	2.37	2.92
Valence and Level of Arousal			
Positive Low-Arousal Emotions (i.e. trust)	0.57	0.45	0.68
Positive High-Arousal Emotions (i.e. joy)	2.22	1.94	2.51
Neutral Low-Arousal Emotions (i.e. anticipation)	0.11	0.10	0.12
Neutral High-Arousal Emotions (i.e. surprise)	0.08	0.07	0.09
Negative Low-Arousal Emotions (i.e. sadness)	0.24	0.23	0.25
Negative High-Arousal Emotions (i.e. anger, fear, disgust)	0.34	0.35	0.32

Table 5: Regression analyses adjusted word count: Unstandardized regression coefficients

	Model: Controls Only			Model: Valence			Model: Arousal			Model: Valence and Arousal		
	Overall	Util	Hed.	Overall	Util	Hed.	Overall	Util	Hed.	Overall	Util	Hed.
Rating	-6.22***	-6.15***	-5.65***	-3.58***	-3.23***	-2.69***	-10.48***	-9.15***	-10.24***	-4.69***	-4.63***	-3.66***
Price	0.10***	0.12***	0.07***	0.07***	0.09***	0.02***	0.07***	0.09***	0.02***	0.06***	0.08***	0.02***
Words/Sentence	1.90***	2.07***	1.78***	1.18***	1.43***	0.99***	1.24***	1.51***	1.03***	1.14***	1.41***	0.95***
Words > 6 Letters	0.52***	0.16***	0.81***	0.18***	0.09**	0.16***	0.30***	0.23***	0.03***	0.06***	0.01	0.05
Reference to Money	-2.40***	-2.56***	-2.36***	-0.79***	-1.49***	-0.41***	-0.83***	-1.62***	-0.40***	-0.92***	-1.73***	-0.43***
Informal Language	-1.99***	-2.12***	-1.81***	-1.61***	-1.47***	-1.44***	-1.68***	-1.23***	-1.67***	-1.72***	-1.41***	-1.62***
Emotions:												
Positive				11.68***	11.23***	12.67***						
Neutral				22.86***	24.25***	22.50***						
Negative				29.38***	27.65***	30.32***						
Low-Arousal							11.39***	11.20***	12.30***			
High-Arousal							18.90***	17.97***	19.91***			
Positive Low-Arousal (i.e.										0.98***	-0.52*	3.09***
Positive High-Arousal (i.e. joy)										15.78***	16.29***	16.02***
Neutral Low-Arousal (i.e. anticipation)										29.38***	30.23***	28.71***
Neutral High-Arousal (i.e. surprise)										12.76***	13.51***	13.97***
Negative Low-Arousal (i.e. sadness)										25.76***	26.23***	24.61***
Negative High-Arousal (i.e. anger, disgust,										31.52***	28.06***	33.88***
R^2	0.088	0.100	0.079	0.531		0.607	0.500	0.428	0.579	0.547	0.476	0.622

* significant for p<0.05. ** significant for p<0.01. ***significant for p<0.001.