The importance of functional and emotional content in online consumer reviews for product sales: Evidence from mobile gaming market

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ABSTRACT

Prior research on online consumer reviews (OCRs) has focused more on the volume and valence of all OCRs as a whole and less on their individual contents. This paper investigates the importance of multidimensional OCR contents, in terms of functional and emotional dimensions, in online marketing. Utilizing a rich dataset of four million online postings and weekly sales for 342 mobile games, this study identifies subcategories of functional OCRs – product quality, product innovativeness, price acceptability, and product ease-of-use – and emotional OCRs – anger, fear, shame, love, contentment, and happiness. The results show that the volume of product quality and ease-of-use OCRs drives more sales than the valence, while the valence of product innovativeness and price OCRs outperforms the volume. Furthermore, both negative and positive emotion-related OCRs moderate the relationship between functional OCRs and product sales. This study offers guidance to firms in managing specific OCR content for superior marketing outcomes.

Keywords: online consumer reviews; functional; emotional; volume; valence; product sales.

1. Introduction

Customers' product purchase decisions are influenced by the opinions of other consumers (Simonson & Rosen, 2014) because online reviews can reduce not only the risks associated with a purchase but also the search costs associated with the decision-making process (Hennig-Thurau, Gwinner, Walsh, & Gremler, 2004). Millions of product reviews posted daily on online review boards represent aggregate consumer preference data (Decker & Trusov, 2010). Online consumer reviews (OCRs), also referred to as electronic word of mouth (eWOM), can be evaluated by quantitative (or "how much people say") and qualitative (or "what people say") dimensions. Whereas quantitative dimensions of OCRs include numerical attributes such as the number of online reviews, qualitative dimensions include experience attributes such as assessments of product quality as well as positive and negative emotions.

From the qualitative perspective, OCRs can be classified into two groups – functional (cognitive) and emotional (affective) – because both functional and emotional OCRs influence consumers' purchase decisions (Lovett, Peres, & Shachar, 2013). Functional OCRs relate to positive and negative attributes and beliefs about a product, while emotional OCRs pertain to feelings and emotions in response to the product experience. Prior studies show that perceptions of both functional and emotional dimensions should be considered to investigate their effects on online shopping behavior (Lovett et al., 2013; Van der Heijden, 2004). Surprisingly, little OCR research has quantified the multidimensional contents of qualitative OCRs, such as functional (e.g., quality, innovativeness) and emotional (e.g., anger, happiness) dimensions, which may predict future consumers' purchase decisions.

To fill these abovementioned gaps, this study attempts to investigate the impact of "what people say" (the in-depth multidimensional aspects of the qualitative OCR content), in terms of volume, valence, and content, on product sales. Specifically, we developed defensible measurements of OCRs by executing a comprehensive empirical text analysis, measuring the volume and valence of each subcategory of functional and emotional OCR, and evaluating the effects of these subcategories on product sales. To this end, we analyzed a large dataset of OCRs of the 342 most talked-about smartphone games from seven different genres over a thirty-month period from August 2010 to February 2013. We utilized the Mano and Oliver (1993)'s three-dimensional post-consumption experience (product evaluation, product-elicited emotions, and product satisfaction) as a framework to classify OCRs into functional and emotional dimensions, which further affect product purchases (Chiu, Wang, Fang, & Huang, 2014).

Our study contributes to the academic literature in several ways. First, based on the multidimensionality of post-consumption experience, we identified the role of functional and emotional OCRs (Keller, 2012; Kervyn, Fiske, & Malone, 2012) for maximizing the market outcomes of a product. Second, this study also identified the different heuristic attributes in the OCRs by decomposing functional OCRs into the volume and valence across four attributes of a product (i.e. quality, innovativeness, price, and ease-of-use). Finally, our analysis of simultaneous association between functional and emotional OCRs suggests that the two sets of OCR information have mixed effects on potential consumers' behaviors (Shen, 2012; Verhagen & van Dolen, 2011).

Those findings provide practical contributions to online marketing managers. First, this study guides managers to utilize the "quantified qualitative OCR" information to predict future product sales more accurately. Furthermore, this study shows that although online review management software is used for monitoring OCRs, managers should add advanced features to collect specific content-level (e.g. functional and emotional subcategories) volume and valence information. Finally, this study indicates that managers should keep in mind that emotional OCRs should be combined with the functional OCR information to better understand their combinative effects on consumers' overall product evaluations.

2. Conceptual framework and hypotheses

2.1. Previous OCR research

Researchers have studied OCRs of utilitarian products such as software (Duan, Gu, & Whinston, 2009; Zhou & Duan, 2016) and printers (Esmark Jones, Stevens, Breazeale, & Spaid, 2018), hedonic products such as TV shows (Godes & Mayzlin, 2004) and video games (Zhu & Zhang, 2010), and both utilitarian and hedonic products such as books (Berger, Sorensen, & Rasmussen, 2010) and hotels (Jang & Moutinho, 2019). Although evaluations of hedonic products are emotional, subjective, and personal (Dhar & Wertenbroch, 2000), most studies of hedonic products have focused on overall OCRs, with some studies exploring emotional OCRs (e.g. Gopinath, Thomas, & Krishnamurthi, 2014; Yin, Bond, & Zhang, 2014).

In addition, early OCR studies have paid attention to the effects of volume and valence of OCRs, not their content, on market outcomes (Chevalier & Mayzlin, 2006; Godes & Mayzlin, 2004; Liu 2006). recent studies have identified the importance of specific contents in overall OCRs (Liu, Singh, & Srinivasan, 2016; Onish & Manchanda, 2012), functional OCRs (Gopinath et al., 2014; Jang & Moutinho, 2019), and emotional OCRs (Ren & Nickerson, 2018; Yin et al., 2014). However, these studies have focused more on either (1) the quantitative aspects of OCRs than the qualitative (i.e. content) or (2) the aggregate-level qualitative OCRs than the disaggregate-level (i.e. subcategories). Little OCR research has quantified the multidimensional qualitative contents of OCRs, such as the functional (e.g.

quality, innovativeness) and emotional (e.g. anger, fear) dimensions, which may predict future consumers' purchase decisions. Table 1 provides a summary of past studies.

[Insert Table 1 about here]

2.2. OCR information processing framework

Product satisfaction is naturally tied to both cognitive judgements and affective reactions evoked through the consumption of a product (Mano & Oliver, 1993). A number of studies posit that a product's design and performance influence both consumers' cognition and emotions. Keller (2012) argues that functional aspects are critical to how consumers evaluate products; Kervyn et al. (2012) also emphasize the important link between product functionality and consumer emotions. Consumer's attitudes, evaluations, and purchase decisions can be based on functional and emotional experiences (Chiu et al., 2014). As OCRs with informational and emotional support have positive effects on consumers' trust and brand loyalty (Mazzucchelli et al., 2018), marketers attempt to use communication messages that contain functional and/or emotional factors (Haddock, Maio, Arnold, & Huskinson, 2008). Consumers tend to first seek to understand a product's functionality before engaging in its hedonic benefits, which can be defined as its aesthetic, experiential, and enjoyable dimensions (Chitturi, Raghunathan, & Mahajan, 2007; Noseworthy & Trudel, 2011).

Building on these ideas, we propose that functional and emotional OCRs provide clear input for potential consumers to process product-related information, and that the combined information from these OCRs influences consumers' behavioral intentions. Functional OCR messages include positive and negative evaluations of a product's functionality, while emotional OCR messages include positive and negative discrete emotions. For quantifying qualitative OCR contents, we employ three measures – volume (the total word count), valence (the ratio of the positive word count to the total word count), and share (the ratio of a specific content-related word count to the total word count). We introduce the new term "share" for emotional OCRs because emotion-expressing messages have distinct values and cannot be classified as a specific topic (e.g. anger can be the opposite expression for either love or happiness), whereas function-evaluating messages can be classified according to topics (e.g. positive or negative opinions about product quality). Like the study of Tirunillai and Tellis (2014) applying the Herfindahl index to measure OCR concentration on specific dimensions, we use share rather than valence to measure the dominance of specific emotions relative to the total volume of emotional OCRs.

This research focuses not only on the direct effect of the volume and valence of disaggregate-level functional OCRs on product sales but also on the moderating effect of the share of emotional OCRs on the functional OCR-sales relationship. As shown in Fig. 1, we first classify OCRs into (1) the two aggregated dimensions functional and emotional and (2) multiple subcategories. Functional OCRs are classified into four subcategories (product quality, product innovativeness, price acceptability, and product ease-of-use) and emotional OCRs into six subcategories including negative dimensions (anger, fear, shame) and positive dimensions (love, contentment, happiness). The detailed characteristics of functional and emotional OCRs and the related hypotheses are explained in the following sections.

[Insert Fig. 1 about here]

2.3. The classification and role of functional OCRs

Previous studies suggest that functional values such as product quality and price acceptability (Hall, Robertson, & Shaw, 2001) influence consumers' brand purchases (Tsai, 2005). Product quality is defined as a product's superiority over other products in the customers' eyes based on quality, delivered benefits, and economic advantage (Gatignon & Xuereb, 1997). Price acceptability is the consumers' judgment about whether the branded product's price is fair and affordable (Tsai, 2005). In addition to these two factors, we add two more factors for functional values: product innovativeness and product ease-of-use. Product innovativeness refers to the meaningful newness of a product from the customer's perspective (Garcia & Calantone, 2002). Furthermore, product ease-of-use is the degree to which a customer believes that using a particular product would be free of physical and mental effort (Moore & Benbasat, 1991), which is a fundamental determinant of customer acceptance (Davis, 1989). In sum, the basic premise of this research is that four subcategories of functional OCRs – product quality, product innovativeness, price acceptability, and product ease-of-use – can influence consumers' purchase behavior, leading to further product sales.

Although some studies show that the volume of OCRs has no relationship with market outcomes (Chintagunta, Gopinath, & Venkataraman, 2010; Gopinath et al., 2014), most extant research suggests that volume has a positive effect (e.g. Godes & Mayzlin, 2004; Liu, 2006; Jang & Chung, 2015). OCR volume indicates a product's popularity and credibility because it represents the number of consumers who have bought the product (Liu, 2006) and strengthens consumers' confidence in a product, leading to a greater willingness to pay for it (Brynjolfsson & Smith, 2000). Moreover, two-sided messages, which illustrate both positive and negative aspects of a particular product, generate relatively high levels of attention and motivation to process because they are novel, interesting, and credible (Crowley & Hoyer, 1994). Hence, when the volume of a specific category-related OCR increases, potential consumers are likely to regard such rich information as more credible and more objective (Wang, Lu, Chi, & Shi, 2015), therefore triggering more positive responses (Chiou & Cheng, 2003) and greater purchase intentions (Brynjolfsson & Smith, 2000). Consistent with previous studies, we expected that the volume of OCRs containing product function-related expressions would have a distinct, positive impact on product sales. Specifically, we hypothesized the following:

H1: The volume of functional OCRs related to (a) product quality, (b) product innovativeness, (c) price acceptability, or (d) product ease-of-use has a positive effect on product sales.

Research on the effects of OCR valence has yielded mixed results. Some studies claim that OCR valence does not have a significant impact on sales (e.g. Chung, 2011; Godes & Mayzlin, 2004), whereas other studies have found valence to have a positive impact on market outcomes (e.g. Chevalier & Mayzlin, 2006; Chintagunta et al., 2010). These inconsistencies can be attributed to the fact that OCR valence is reflected by the aggregated scores of all OCRs. In this study, the valence of functional OCRs is further decomposed into multiple categories, depending on a product's specific function. The OCR valence of a product's specific category can provide information of high quality, which is crucial for potential consumers' evaluation and purchase decisions (Setia, Venkatesh, & Joglekar, 2013). Consumers infer the quality of a product through functional OCRs to reduce purchase risk and uncertainty about the product (Berger et al., 2010; Liu, 2006). Thus, the valence of a specific category-related functional OCR may signal overall product performance (Kostyra, Reiner, Natter, & Klapper, 2016) compared to other competitors and appears to be an excellent instrument for measuring product or service satisfaction (Liu et al., 2017). Accordingly, we hypothesized the following:

H2: The valence of functional OCRs related to (a) product quality, (b) product innovativeness, (c) price acceptability, or (d) product ease-of-use has a positive effect on product sales.

2.4. The classification and moderating role of emotional OCRs

Researchers have classified emotions in several ways: (1) as simply positive or negative (Oliver, 1993); (2) as pleasure or arousal (Olney, Holbrook, & Batra, 1991), and (3) as eight negative emotions (anger, discontent, worry, sadness, fear, shame, envy, and loneliness) and seven positive emotions (romantic love, peacefulness, contentment, optimism, joy, excitement, and surprise) (Richins, 1997). Laros and Steenkamp (2005) also suggest that emotions can be grouped into clusters with a hierarchical structure in which specific emotions are similar or represent particular nuances of underlying basic emotions. Although a comprehensive set of specific emotions (Richins, 1997) was utilized initially, we adopted a hierarchical set of emotional components comprised of three negative categories (anger, fear, and shame) and three positive categories (love, contentment, and happiness), an approach suggested by Laros and Steenkamp (2005). This classification scheme not only captures the arousal factor – the different level of emotionality expressed in texts (Ren & Nickerson, 2018; Warriner, Kuperman & Brysbaert, 2013) but also prevents the issues of multicollinearity among variables and model overfitting.

Research frequently emphasizes the importance of investigating the role of emotions in consumers' processing of OCR information (Yin et al., 2014). A single source of information such as emotional OCRs does not lead to a greater intention of product purchase but needs to be combined with other sources of information (e.g. functional OCRs) (Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2016). Previous research also supports the interaction between functional and emotional OCRs because the functional performance of products can affect both consumer cognition and emotions (Kervyn et al., 2012; Keller, 2012). When two sources of OCR messages are revealed to potential customers, their perceived diagnosticity of the OCR information will determine the usefulness of the information; this is called information accessibility-diagnosticity theory (Feldman & Lynch, 1988). Accessibility is the contextual ease of retrieving a piece of information from memory into a judgment, and diagnosticity is the extent to which that piece of information is relevant for that judgment (Feldman & Lynch, 1988; Meyvis & Janiszewski, 2004). According to this theory, consumers will be reluctant to use the less accessible and less diagnostic information to make decisions when more accessible and more diagnostic information emerges (Herr et al., 1991).

In this study, we regard two sets of OCRs – functional OCRs (i.e. the volume and valence of functional OCR subcategories) and emotional OCRs (i.e. the share of emotional OCR subcategories) – as two pieces of information for consumers' decision making (Shen, 2012). However, the simultaneous association of two sets of OCRs may lead to mixed effects on market outcomes due to their accessible and diagnostic difference. For example, if functional OCRs are more accessible/diagnostic than emotional OCRs, positive functional OCRs can affect consumers' behavior positively in combination with positive emotional OCRs (Pappas, Kourouthanassis, Giannakos, & Chrissikopoulos, 2014), or with both positive and negative emotions (Verhagen & van Dolen, 2011). On the other hand, if consumers perceive emotional OCRs more accessible/diagnostic, they may regard a high share of negative emotion-related OCRs as more credible and helpful for purchase decisions (Crowley & Hoyer, 1994; Yin et al., 2014). In addition, when a highly positive valence of functional OCRs is associated with a high share of negative emotional OCRs, this mixed information can affect market outcomes positively (Verhagen & van Dolen, 2011).

Such mixed interactive effects can be explained by the consistency theory (Osgood &

Tannenbaum, 1955), which is used to predict the changes in consumers' original attitude to maintain their internal consistency when new information is received. That is, OCRs are filtered by consumers according to their consistency with previous evaluation criteria (Wilson & Hodges, 1992) or may change consumers' attitude; inconsistent information can convince them to change the initial attitude (Jain & Maheswaran, 2000). Hence, emotional OCRs about a product may encourage or discourage consumers to undertake a comprehensive, analytic, and cognitive assessment of product-related information from functional OCRs (Meyers-Levy & Malaviya, 1999). Based on the information accessibility-diagnosticity theory and the consistency theory, we propose that the effects of the volume and valence of functional OCRs on product sales can vary depending on emotional OCRs. Hence, our hypotheses as follows:

H3: Emotional OCRs will moderate the effect of the volume of functional OCRs on product sales.

H4: Emotional OCRs will moderate the effect of the valence of functional OCRs on product sales.

3. Method

3.1. Data collection and sample

To test the four hypotheses, we obtained rich data on online reviews of mobile games and their unit sales from a leading mobile app market in South Korea. Research has demonstrated the importance of OCRs in predicting product sales and revenues across various product categories, including books (Chevalier & Mayzlin, 2006), movies

(Chintagunta et al., 2010; Liu, 2006), and hotels (Gavilan, Avello, & Martinez-Navarro, 2018). Mobile games were selected for the subject of this study because game consumers give feedback in the online user community inside the digital platforms (Jeppesen & Frederiksen, 2006; Kim, Kim, & Mattila, 2012); half of mobile game users leave online reviews after positive experiences, while two-thirds leave reviews after negative experiences (Levenson, 2015). Recently, researchers have examined the effectiveness of OCRs in the digital gaming market (Jang & Chung, 2015; Zhu & Zhang, 2010).

Online review text was collected from the 342 most talked-about mobile games across 8 genres (action, arcade, puzzle/board, role playing, shooting, simulation, sports) for each week between August 2010 and February 2013 and classified into different functional and emotional categories. Because each mobile game has its own age rating (i.e. 12, 15, 18, adult), young players of a 15-rated game can neither purchase 18-rated or adult games nor access OCRs of 18-rated or adult games. Each review was classified by three independent human coders for validation. In order to produce the final dataset based on detailed dimensions of functional and emotional OCRs according to our conceptual framework, we first performed the following five steps by using a lexical analysis (Onishi & Manchanda, 2012).

First, each sentence of every review (4,147,187 sentences total) was parsed into words. Because many reviews were not delimited into words, this step was important. We then classified the words according to lexical categories (e.g. nouns, adjectives, verbs), totaling 645,406.

Second, independent human coders who had a deeper knowledge of mobile gaming developed a dictionary for mobile game reviews. Based on high-frequency and category-specific words used by mobile game users, they created the dictionary of 18,430 sets made up of 1,887 object words and 1,823 expression words. For example, the post, “the graphics are good but the sound is ordinary" is coded with the two sets "graphics–good" and "sound–ordinary" from the dictionary. This dictionary was used to classify each expression into a specific, representative category of functional and emotional contents and their subcategories.

Third, after the coders built the dictionary, we extracted the 361 expression words that were relevant to functional and emotional OCRs while eliminating irrelevant and vague words. We then performed a frequency count of all unique words on a weekly basis.

Fourth, we classified each expression word with multiple object words in the dictionary into an appropriate category of functional or emotional content. Among the 361 words, we selected the final 260 words by excluding 101 words that could have multiple meanings in different contexts. For example, this included the word "hot," which could mean either that the game was very exciting or that the device's temperature became high while playing the game. Finally, the 260 words were grouped under 74 representative words, because some words have the same or similar meanings but use different language expressions, mainly due to grammatical errors and inter-gamer idioms.

Finally, we merged the weekly sales data with the OCR data to obtain the final dataset of 1,835 observations; each observation consisted of weekly sales along with volume and valence of functional and emotional OCRs for the focal product. The number of final observations is relatively small because mobile games have short life cycles due to high competition and most functional and emotional OCRs being generated in the early stage of the product's life cycle.

Subsequently, we divided the final dataset into two subsets based on product launch time to enable conducting a predictive validity check (Fig. 2). In-sample data consisted of 1,487 observations (81%) generated from 246 products (72%) launched between August 2010 and April 2012, whereas out-of-sample data consisted of 348 observations (19%) generated from 96 products (28%) launched between May 2012 and February 2013. In-sample data were analyzed and used for hypothesis testing both at the aggregate level and disaggregate level. Out-of-sample data were used to conduct a predictive validity check to investigate which model best predicted future product sales.

[Insert Fig. 2 about here]

3.2. Variables

Consumers express a product's functional performance with a combination of object words (nouns) and expression words (adjectives). This study considers the interrelated issues of the structure and content of functional OCRs by proposing a hierarchy consisting of three levels (Fig. 3). The superordinate level (1) contains positive and negative categories for functional OCRs, the basic level (2) contains four positive and four negative functional OCR subcategories and three positive and three negative emotional OCR subcategories, and the subordinate level (3) contains categories for specific words. For example, mobile game users can express their opinions on a mobile game's functionality positively (e.g. the story is interesting) or negatively (e.g. the screen is defective); these pertain to Level 3. The expression words "interesting" and "defective" belong to the subcategory of product quality (Level 2), which is further classified as a functional OCR (Level 1). As another example, game users may express emotions such as "the price makes me angry" and "the fee is scary" (Level 3), which are classified as the negative emotions anger and fear (Level 2), and further as an emotional OCR (Level 1).

[Insert Fig. 3 about here]

Based on the text analysis and extraction of specific content for functional and emotional dimensions as described earlier, we selected 14 independent variables to use as the OCR subcategories of Level 2, along with their respective subordinate words (Level 3). Table

2 shows the classification results of disaggregate-level functional and emotional OCRs. The number of final representative words was 74, 52 of which were functional and 22 of which were emotional. The specific measurements are described below.

Functional OCRs. We measured eight variables of the functional OCR subcategories: product quality, product innovativeness, price acceptability, and product ease-of-use in both volume and valence. Volume measures are the counts of each component-evaluative words. Valence measures are the ratios of the number of evaluative positive words (e.g. the number of positive product quality-related messages) to the component-evaluative total words (e.g. the number of both positive and negative product quality-related messages). We found that 31 words belonged to product quality – 25 positive words (e.g. appropriate and beautiful) and 6 negative words (e.g. defective and dysfunctional); 11 words belonged to product innovativeness – 8 positive words (e.g. differentiated and distinctive) and 3 negative words (e.g. ambiguous and blatant); 3 words belonged to price acceptability – 2 positive words (i.e. cheap and discounted) and 1 negative word (i.e. expensive); and 7 words belonged to product ease-of-use – 4 positive words (e.g. comfortable and convenient) and 3 negative words (e.g. clumsy and complicated).

Emotional OCRs. Similarly, we classified emotional OCRs into six emotion-related subcategories: anger (e.g. boring and disappointing), fear (e.g. addictive and burdensome), shame (e.g. embarrassed and pitiful), love (e.g. affectionate and fascinated), contentment (e.g. content and satisfactory), and happiness (e.g. amazing and cheerful). These subcategories can capture different levels of negative and positive emotionality (i.e. arousal) (Warriner et al., 2013). We developed six measures for the share of emotional OCRs as a ratio of each emotion-related word (e.g. the number of anger-related messages) to total emotion words (e.g. the number of all emotion-related messages).

[Insert Table 2 about here]

3.3. Model estimation

For the analysis, we developed a hierarchical log-linear model to investigate how the volume and valence of functional OCRs influenced the sales of a product j (Equation 1) at time t+1, denoted by $Y_{j,t+1}$, and how the share of emotional OCRs moderated the functional OCR-sales relationship (Equation 2) as follows:

$$
\begin{aligned}
(1)\ \ln(Y_{j,t+1}) = {} & M(j,t)'_{\text{product quality}}\beta_{1jt} + M(j,t)'_{\text{product innovativeness}}\beta_{2jt} \\
& + M(j,t)'_{\text{price acceptability}}\beta_{3jt} + M(j,t)'_{\text{product ease-of-use}}\beta_{4jt} \\
& + N(j,t)'_{\text{product quality}}\beta_{5jt} + N(j,t)'_{\text{product innovativeness}}\beta_{6jt} \\
& + N(j,t)'_{\text{price acceptability}}\beta_{7jt} + N(j,t)'_{\text{product ease-of-use}}\beta_{8jt} \\
& + \beta_{0jt} + \varepsilon_{jt}, \text{ and}
\end{aligned}
$$

$$
\begin{aligned}
(2)\ \beta_{kjt} = {} & S(j,t)'_{\text{anger}}\alpha_{1k} + S(j,t)'_{\text{fear}}\alpha_{2k} + S(j,t)'_{\text{shame}}\alpha_{3k} + S(j,t)'_{\text{love}}\alpha_{4k} \\
& + S(j,t)'_{\text{contentment}}\alpha_{5k} + S(j,t)'_{\text{happiness}}\alpha_{6k} + \alpha_0 + \delta_{jt}
\end{aligned}
$$

where $M(j,t)'$ and $N(j,t)'$ represent vectors for the volume and valence of the four functional OCR subcategories for product j at time t, respectively; and $S(j,t)'$ refers to the vector for the share of six emotional OCR subcategories for product j at time t. We used a Bayesian estimation for model parameters with diffuse conjugate priors via the Markov Chain Monte Carlo (MCMC) simulation method. Ten thousand draws of each chain were implemented for the burn-in period with convergence tests and were used for the estimation of all model parameters after convergence tests. A full description of priors, posterior joint distributions, and the MCMC algorithm can be obtained from the authors upon request.

3.4. Predictive validity check

We performed a predictive validity check with the holdout sample to identify the most robust model for forecasting product sales with OCRs; for this purpose, we compared the traditional approach with each of our models. Table 3 presents the mean squared error (MSE) for seven different models: (1) the base model consisting of the volume and valence of all OCRs as a whole, (2) the base content model consisting of the volume and valence of all functional OCRs and the share of all emotional OCRs, (3) the functional volume model consisting of the volume of the functional OCR subcategories, (4) the functional valence model consisting of the valence of the functional OCR subcategories, (5) the emotional share model consisting of the share of emotional OCR subcategories, (6) the full functional model consisting of the volume and valence of the functional OCR subcategories, and (7) the full content model consisting of the volume and valence of the functional OCR subcategories and the share of emotional OCR subcategories. Results show that Model (7), including all the disaggregate-level variables, has the smallest MSE value so is the best predictive model; this result implies that the disaggregated model including both functional and emotional OCR subcategories will provide better sales forecasts in the mobile gaming industry than the traditional aggregated models consisting of the volume and valence of all OCRs as a whole.

[Insert Table 3 about here]

4. Results

Table 4 provides descriptive statistics and the correlation coefficients among the study's variables. We find that mobile game consumers, on average, generate 55.20 expressions of a product's quality per week, followed by 11.78 ease-of-use expressions, 5.18 innovativeness-related expressions, and 3.34 price-related expressions. Regarding the valence of functional OCRs, consumers generate positive expressions of a product's quality (90%), innovativeness (85%), and ease-of-use (58%) but less positive expressions of the price (35%). Furthermore, consumers express both positive and negative emotions through OCRs, including happiness (29%), anger (21%), and fear (15%). Finally, the correlation coefficients among the variables are below 0.68, so we detect the potential presence of multicollinearity by calculating the variance inflation factor (VIF). It ranges from 1 to 2.35, indicating that multicollinearity is not a serious problem in the model.

[Insert Table 4 about here]

4.1. The main effects of functional OCRs on product sales

Table 5 reports the means and standard deviations of the parameter estimates. From the volume perspective of the functional OCR subcategories (i), product quality and product ease-of-use have positive effects on product sales ($\beta_1 = 0.493$ and $\beta_4 = 0.232$ respectively), in support of H1a and H1d, whereas price acceptability has a negative effect (β_3 = -0.166) and product innovativeness has no effect, not supporting H1b or H1c. From the valence perspective of the functional OCR subcategories, product innovativeness and price acceptability have positive effects on product sales ($\beta_6 = 0.111$ and $\beta_7 = 0.141$ respectively), in support of H2b and H2c, while the valence of product quality has a negative effect and the valence of product ease-of-use has no relationship. The results do not support H2a or H2d. The results show two important findings. One is that the subcategories of functional OCRs provide additional useful information about how specific components influence product sales. The other is that depending on specific product functionality, either the volume or valence of multidimensional functional OCRs can play a more important role. For example, the volume information about product quality or product ease-of-use is more important than the valence information, while the valence information is critical for product innovativeness and price acceptability.

[Insert Table 5 about here]

4.2. The main and moderating effects of emotional OCRs on product sales

The empirical analysis provides two important findings about the effects of emotional OCRs. Emotional OCRs have no direct (main) effect but some indirect (moderating) effects on product sales. For instance, although the share of fear-related OCRs has no direct effect on product sales, the association of a high volume of price-related OCRs increases sales ($\alpha_{\text{price acceptability volume} \times \text{fear share}} = 0.197$), supporting the moderating effects of emotional OCRs (H3). Whereas the share of anger-related OCRs has no direct effect on product sales, it amplifies the negative effect of the valence of product quality-related OCRs on sales ($\alpha_{\text{product quality valence} \times \text{anger share}} = -0.063$). In addition, the combination of the valence of product ease-of-use OCRs with the share of anger OCRs leads to an increase in product sales ($\alpha_{\text{product ease-of-use valence} \times \text{anger share}} = 0.061$). Finally, the share of happiness-related OCRs also amplifies the positive effect of the valence of price-related OCRs on product sales ($\alpha_{\text{price acceptability valence} \times \text{happiness share}} = 0.106$). While supporting H4, these results recognize the important role of emotions in understanding how the simultaneous association between functional and emotional OCRs influence product sales.

5. Discussion

Numerous studies have discussed the effects of the volume and valence of OCRs as a whole, but little has been studied about the qualitative content of OCRs. It is relevant for both marketing researchers and practitioners to understand how to (1) classify granular OCRs according to specific dimensions, (2) quantify OCR contents with volume, valence, and share, and (3) examine the effects of the quantified OCRs on product sales. Utilizing a rich dataset of four million online reviews of mobile games, this study classifies OCRs into multiple hierarchies of functional and emotional dimensions and further examines the direct and interactive effects of functional and emotional OCR subcategories on product sales. Our findings reveal that consumers generate four types of functional OCRs – product quality, product innovativeness, price acceptability, and product ease-of-use – and six types of emotional OCRs – anger, fear, shame, love, contentment, and happiness. The subcategories of functional OCRs are derived from classifications of brand values (Laros & Steenkamp, 2005; Richins, 1997; Tsai, 2005) and those of emotional OCRs from prior research on emotion (Laros & Steenkamp, 2005; Richins, 1997). These subcategories of OCRs are then measured from three perspectives: volume, valence, and share.

Regarding the effectiveness of functional OCRs, the results reveal that potential consumers tend to regard the volume of product quality and ease-of-use OCRs as more credible than the valence. However, valence plays a more significant role than volume for product innovativeness and price acceptability. Concerning the role of emotional OCRs, it is found that both negative and positive emotions (i.e. anger, fear, and happiness) significantly moderate the relationship between functional OCRs and product sales. The association of the volume of price-related OCRs with the share of fear-related OCRs leads to an increase in product sales. On the contrary, when the valence of product quality OCRs is combined with anger-related OCRs, product sales decrease. In addition, a combination of two positive pieces of information, i.e. the valence of price-related OCRs and the share of happiness-related

OCRs, increases sales. As such, our findings suggest that the impact of functional OCRs on product sales varies across negative emotion-related OCRs (Yin et al., 2014) and positive emotion-related OCRs (Pappas et al., 2014).

5.1. Theoretical implications

This research offers several theoretical implications in the field of OCR literature. First, this study extends knowledge on the multidimensionality of post-consumption experience (Mano & Oliver, 1993) by shedding lights on the identification of the role of functional and emotional OCRs for maximizing the market outcomes. In line with previous research (Keller, 2012; Kervyn et al., 2012), this study demonstrates that the evaluations of product features and product-elicited emotions expressed online by post-purchase consumers influence future consumers' purchase decisions. In addition, different from prior studies focusing on the multiple emotional dimensions (Briesemeister, Kuchinke, & Jacobs, 2014), this research examines the interplay among multidimensional contents of functional and emotional OCRs. Specifically, this study reveals that consumers first perceive a product's functionality and then gain hedonic and emotional benefits (Chitturi et al., 2007; Noseworthy & Trudel, 2011).

Second, this study provides important implications for academics studying the different heuristic attributes contained in the OCRs. While prior studies have focused on volume and valence (e.g. Godes & Mayzlin, 2004; Liu 2006), a more complex theory of OCR sentiment posits three dimensions: volume, valence, and content (e.g. Gopinath et al., 2014; Onishi & Manchanda, 2012). This study extends this knowledge by decomposing functional OCRs into the volume and valence of specific content (i.e. product quality, product innovativeness, price acceptability, and product ease-of-use). Prior research indicates that the volume of functional OCRs often represents both product popularity and credibility, therefore leading to a positive impact on consumers' behavior (Brynjolfsson & Smith, 2000; Chiou & Cheng, 2003). However, our results show mixed effects. It indicates that consumers tend to prefer volume over valence for product quality and ease-of-use OCRs, but valence over volume for product innovativeness and price OCRs. These results can be explained by the fact that consumers may have subjective views on good or bad quality and ease-of-use (North & Hargreaves, 1995). Because consumers often obtain sufficient quality-related OCRs, they can separate the price-quality inferences easily and interpret positive price-related OCRs as positive information (Erickson & Johansson, 1985).

Finally, our analysis of the simultaneous association between functional and emotional OCRs contributes to the information accessibility-diagnosticity theory. This study investigates how two pieces of information – functional and emotional OCRs – affect potential consumers' purchase behaviors and further product sales (Shen, 2012). The results indicate that potential consumers' purchase decisions are influenced by interactions among the OCRs. Such mixed results can be explained by the difference of consumers' perceived diagnosticity of the OCR information (Yan et al., 2014) and the consumers' different evaluation criteria (Jain & Maheswaran, 2000). If functional OCRs are more diagnostic than emotional OCRs, the positive valence of functional OCRs can influence consumers' behavior positively, regardless of emotional OCRs (either positive or mixed) (Pappas et al., 2014; Verhagen & van Dolen, 2011). Conversely, if emotional OCRs are more diagnostic, negative or positive emotions are more influential when combined with functional OCRs (Pappas et al., 2014; Yin et al., 2014). Furthermore, the results of this study reinforce the notion that negative OCRs (e.g. anger- and fear-related) play a more influential role in future consumers' information processing than positive emotion-related OCRs (Yin et al., 2014).

5.2. Managerial implications

The findings provide digital marketing managers with several guidelines based on utilizing multidimensional OCRs and the uncovered interrelationship of OCR subcategories and product sales. This study finds evidence to support the notion that multidimensional OCRs can predict future product sales more accurately than collective OCRs. This study's results demonstrate that the disaggregate-level model, which includes both functional and emotional OCR subcategories, performs better than the traditional model that includes all OCRs as a whole (see Table 3). For maximizing product sales, managers should set a goal for reaching a certain volume (total number of reviews) and a certain valence score (ratio of positive reviews to total reviews). Specifically, managers can create and implement a review program that engages consumers and encourages them to leave their feedback actively on product quality and product ease-of-use. In addition, due to consumers' sensitivity to the innovativeness and price aspects, product managers should keep in mind that product uniqueness and sophisticated pricing schemes (e.g. prices of in-game virtual goods) can differentiate their products from rivals' and further increase positive feedback.

When firms can use online review management software to monitor OCRs on a real-time basis, managers should implement advanced features to collect volume and valence information related to specific content, such as functional and emotional subcategories. One limitation of such tools is that they present a product's OCR status only, without capturing the effect of OCRs on product sales. In order to understand the effectiveness of multidimensional OCRs, the collected OCR contents need to be combined with transaction data. Our findings reveal that consumers' functional and emotional expressions on online review boards are important explanatory factors on product sales. If a firm relies on an OCR monitoring tool, managers may focus only on generating positive reviews and discouraging negative reviews. However, this positivity bias may lead OCRs to appear less credible and authentic.

This study's findings imply that the dominance of negative emotions, such as anger and fear, does not represent the "purely negative" aspects of a product. For example, when the volume of functional OCRs (e.g. price-related messages) is large, the dominance of fear-related emotions (e.g. addictive) would not affect potential consumers negatively; such a combination may represent a product's positive characteristics, such as being attractive and well-designed. Furthermore, a high level of product ease-of-use may lead experienced consumers to generate anger-related messages. However, such a combination can lead to an increase in product sales because ordinary consumers ignore the experienced consumers' angry reviews and purchase the easy-to-use product. As such, managers should combine functional and emotional dimensions of OCRs for examining their impact on product sales because the combined information influences potential consumers' overall product evaluations.

5.3. Limitations and future research directions

Although this study provides numerous insights related to the OCR-sales relationship, it suffers from some limitations that can be addressed with future work in this area. First, the analyses and results of this study are limited to a pool of mobile game products, which are hedonic products and therefore influenced by emotional factors. A study of utilitarian products, which are less impacted by emotions, would have different results. Researchers have found that the effect of OCRs (volume, valence, and arousal) on product sales can vary depending on product type (utilitarian or hedonic) (Ren & Nickerson, 2018). Thus, future research could take a similar approach to examine the detailed classification and differential roles of OCRs on various types of products, including utilitarian products.

Second, the OCR data were collected from a marketplace in a single country that may be influenced by a group-oriented cultural background (Hofstede, 1980). Consumers in the sample tend to be more motivated to conform to the norms of a group than those from individualistic cultures (Yau, 1986). Because personal and group-oriented attitudes can affect behavioral intentions (Lee & Green, 1999) and consumers' shopping goals and online flow vary cross culture and language groups (Bridges, 2018), further research should study how consumers in different social, cultural and economic settings collect, create, and disseminate information through OCRs (Tang et al., 2019; Yoon, 2018).

Finally, this study examines four million online postings by using a lexical analysis to predict product sales based on both quantitative and qualitative OCR information (with the assistance of human coders). However, in order to extract a more sophisticated level of OCR valence (e.g. arousal), future research should employ an unsupervised method, latent Dirichlet allocation (LDA), which can handle both big data and highly disaggregate time periods with sparse data. Researchers can use the results of LDA for advanced analysis to capture context-specific valence such as extracting latent dimensions of the valence quality and analyzing heterogeneity among consumers' reliance on dimensions and perceptual maps of competing brands (Tirunillai & Tellis, 2014).

Nevertheless, this empirical research makes an important contribution to the growing literature on OCRs. Little attention has been paid to how to quantify qualitative OCR content for predicting product sales, which can be described as "how much people say about what they say." Based on rich data on OCRs and sales related to mobile games, this study fills the gap by conducting multidimensional OCR classification considering content (functional and emotional), volume, and valence (positive, negative).

References

Berger, J., Sorensen, A. T., & Rasmussen, S. J. (2010). Positive effects of negative publicity: When negative reviews increase sales. *Marketing Science*, 29(5), 815-827.

Bridges, E. (2018). Hedonic and utilitarian shopping goals: A decade later. *Journal of Global Scholars of Marketing Science*, 28(3), 282-290.

Briesemeister, B. B., Kuchinke, L., & Jacobs, A. M. (2014). Emotion word recognition: Discrete information effects first, continuous later? *Brain Research*, 1564(May), 62-71.

Brynjolfsson, E., & Smith, M. D. (2000). Frictionless commerce? A comparison of internet and conventional retailers. *Management Science*. 46(4), 563-585.

Chevalier, J., & Mayzlin, D. A. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, 43(August), 345-354.

Chintagunta, P. K., Gopinath, S., & Venkataraman, S. (2010). The effects of online user reviews on moive box performance: Accounting for sequential rollout and aggregation across local markets. *Marketing Science*, 29(5), 944-957.

Chiou, J. S., & Cheng, C. (2003). Should a company have message boards on its web sites? *Journal of Interactive Marketing*, 17(3), 50-61.

Chitturi, R., Raghunathan, R., & Mahajan, V. (2007). Form versus function: How the intensities of specific emotions evoked in functional versus hedonic trade-offs mediated product preferences. *Journal of Marketing Research*, 44(November), 702-714.

Chiu, C. M., Wang, E. T., Fang, Y. H., & Huang, H. Y. (2014). Understanding customers' repeat purchase intentions in B2C e-commerce: The roles of utilitarian value, hedonic value and perceived risk. *Information Systems Journal*, 24(1), 85-114.

Chung, J. (2011). Investigating the roles of online buzz for new product diffusion and its cross-country dynamics. *Journal of Business Research*, 64(11), 1183-1189.

Crowley, A. E., & Hoyer, W. D. (1994). An integrative framework for understanding two-sided persuasion. *Journal of Consumer Research*, 20(4), 561-574.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, 13(3), 319-340.

Decker, R., & Trusov, M. (2010). Estimating aggregate consumer preferences from online product reviews. *International Journal of Research in Marketing*, 27, 293-307.

Dhar, R., & Wertenbroch, K. (2000). Consumer choice between hedonic and utilitarian goods. *Journal of Marketing Research*, 37(1), 60-71.

Duan, W., Gu, B., & Whinston, A. B. (2009). Informational cascades and software adoption on the Internet: An empirical investigation. *MIS Quarterly*, 33(1), 23-48.

Erickson, G. M., & Johansson, J. K. (1985). The role of price in multi-attribute product evaluations. *Journal of Consumer Research*, 12(2), 195-199.

Esmark Jones, C. L., Stevens, J. L., Breazeale, M. & Spaid, B. I. (2018). Tell it like it is: The effects of differing responses to negative online reviews. *Psychology & Marketing*, 35, 891-910.

Feldman, J. M., & Lynch, J. G. (1988). Self-generated validity and other effects of measurement on belief, attitude, intention, and behavior. *Journal of Applied Psychology*, 73(3), 421-435.

Garcia, R., & Calantone, R. (2002). A critical look at technological innovation typology and innovativeness terminology: A literature review. *Journal of Product Innovation*

Management, 19(2), 110-132.
Gatignon, H., & Xuereb, J.-M. (1997). Strategic orientation of the firm and new product performance. *Journal of Marketing Research*, 34(February), 77-90.
Gavilan, D., Avello, M., & Martinez-Navarro, G. (2018). The influence of online ratings and reviews on hotel booking consideration. *Tourism Management*, 66, 53-61.
Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, 23(4), 545-560.
Gopinath, S., Thomas, J. S., & Krishnamurthi, L. (2014). Investigating the relationship between the content of online word of mouth, advertising, and brand performance. *Marketing Science*, 33(2), 241-258.
Haddock, G.,Maio, G. R., Arnold, K., & Huskinson, T. (2008). Should persuasion be affective or cognitive? The moderating effects of need for affect and need for cognition. *Personality and Social Psychology Bulletin*, 34(6), 769-778.
Hall, J., Robertson, N., & Shaw, M. (2001). An investigation of perceived value and consumable goods. *Asia Pacific Advances in Consumer Research*, 4, 350-354.
Hennig-Thurau, T., Gwinner, K.P., Walsh, G., Gremler, D.D. (2004). Electonic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, 18(1), 38-52.
Herr, P.M., Kardes, F., & Kim, J. (1991). Effects of word-of-mouth and product-attribute information on persuasion: An accessibility-diagnosticity perspective. *Journal of Consumer Research*, 17(4), 454-462.
Hofstede, G. (1980). *Culture's consequences*. Beverly Hills, CA: Sage.
Jain, S., & Maheswaran, D. (2000). Motivated reasoning: A depth of processing perspective. *Journal of Consumer Research*, 26(4), 358-371.
Jang, S., & Chung, J. (2015). How do interaction activities among customers and between customers and firms influence market performance and continuous product innovation? An empirical investigation of the mobile application market. *Journal of Product Innovation Management*, 32(2), 183-191.
Jang, S. & Moutinho, L. (2019). Do price promotions drive consumer spending on luxury hotel services? The moderating roles of room price and user-generated content. *International Journal of Hospitality Management*, 78, 27-35.
Jeppesen, L.B., & Frederiksen, L. (2006). Why do users contribute to firm-hosted user communities? The case of computer-controlled music instruments. *Organization Science*, 17(1), 45–63.
Keller, K. L. (2012). Understanding the richness of brand relationships: Research dialogue on brands as intentional agents. *Journal of Consumer Psychology*, 22(2), 186-190.
Kervyn, N., Fiske, S. T., & Malone, C. (2012). Brands as intentional agents framework: How perceived intentions and ability can map brand perception. *Journal of Consumer Psychology*, 22(2), 166-176.
Kim, S. J., Kim, K, H., & Mattila, P. (2012). The role of fashion in the characters of online games. *Journal of Global Fashion Marketing*. 3(2), 81-88.
Kostyra, D. S., Reiner, J., Natter, M., & Klapper, D. (2016). Decomposing the effects of online customer reviews on brand, price, and product attributes. *International Journal of Research in Marketing*, 33(1), 11-26.

Laros, F. J. M., & Steenkamp, J.-B. E. M. (2005). Emotions in consumer behavior: A hierarchical approach. *Journal of Business Research*, 58, 1437-1445.

Lee, C., & Green, R. (1999). Cross-cultural examination of the Fishbein behavioral intention model. *Journal of International Business Studies*, 22(2), 289-305.

Lehmann, E., & Casella, G. (1998). *Theory of Point Estimation (2nd ed.)*. New York: Springer.

Levenson, H. (2015). How important are app ratings and reviews to users? Appsee. Retrieved from https://blog.appsee.com/how-important-are-app-ratings-and-reviews-to-users/. (27 February, 2019).

Liu, Y. (2006). Word-of-mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, 70(July), 74-89.

Liu, X., Singh, P. V., & Srinivasan, K. (2016). A structured analysis of unstructured big data by leveraging cloud computing. *Marketing Science*, 35, 368-388.

Liu, Y., Teichert, T., Rossi, M., Li, H., & Hu, F. (2017). Big data for big insights: Investigating language-specific drivers of hotel satisfaction with 412,784 user-generated reviews. *Tourism Management*, 59, 554-563.

Lovett, M. J., Peres, R., & Shachar, R. (2013). On brands and word of mouth. *Journal of Marketing Research*, 50(August), 427-444.

Mano, H., & Oliver, R. L. (1993). Assessing the dimensionality and structure of the consumption experience: Evaluation, feeling and satisfaction. *Journal of Consumer Research*, 20(3), 451-466.

Mazzucchelli, A., Chierici, R., Ceruti, F., Chiacchierini, C., Godey, B., & Pederzoli, D. (2018). Affecting brand loyalty intention: The effects of UGC and shopping searches via Facebook. *Journal of Global Fashion Marketing*, 9(3), 270-286.

Meyers-Levy, J., & Malaviya, P. (1999). Consumers' processing of persuasive advertisements: An integrative framework of persuasion theories. *Journal of Marketing*, 63, 45-60.

Meyvis, T., & Janiszewski, C. (2004). When are broader brands stronger brands?: An accessibility perspective on the success of brand extensions. *Journal of Consumer Research*, 31(4), 346-357.

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, 2(3), 192-222.

North, A. C., & Hargreaves, D. J. (1995). Subjective complexity, familiarity, and liking for popular music. *Psychomusicology*, 14, 77-93.

Noseworthy, T. J., & Trudel, R. (2011). Looks interesting, but what does it do? Evaluation of incongruent product form depends on positioning. *Journal of Marketing Research*, 48(December), 1008-1019.

Oliver, R. L. (1993). Cognitive, affective, and attribute bases of the satisfaction response. *Journal of Consumer Research*, 20(3), 418-430.

Olney, T., Holbrook, M. B., & Batra, R. (1991). Consumer responses to advertising: The effects of ad content, emotions, and attitude toward the ad on viewing time. *Journal of Consumer Research*, 17(4), 440-453.

Onishi, H., & Manchanda, P. (2012). Marketing activity, blogging and sales. *International*

Journal of Research in Marketing, 29, 221-234.
Osgood, C. E., & Tannenbaum, P. H. (1955). The principle of congruity in the prediction of attitude change. *Psychological Review*, 62(1), 42-55.
Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2014). Shiny happy people buying: The role of emotions on personalized e-shopping. *Electronic Markets*, 24(3), 193-206.
Pappas, I. O., Kourouthanassis, P. E., Giannakos, M. N., & Chrissikopoulos, V. (2016). Explaining online shopping behavior with fsQCA: The role of cognitive and affective perceptions. *Journal of Business Research*, 69, 794-803.
Ren, J., & Nickerson, J. V. (2018). Arousal, valence, and volume: How the influence of online review characteristics offers with respect to utilitarian and hedonic products. *European Journal of Information Systems*, 28(3), 272-290.
Reimer, T., & Benkenstein, M. (2016). When good WOM hurts and bad WOM gains: The effect of untrustworthy online reviews. *Journal of Business Research*, 69, 5993-6001.
Richins, M. L. (1997). Measuring emotions in the consumption experience. *Journal of Consumer Research*, 24(2), 127-146.
Setia, P., Venkatesh, V., & Joglekar, S. (2013). Leveraging digital technologies: How information quality leads to localized capabilities and customer service performance. *MIS Quarterly*, 37(2), 565-590.
Shen, J. (2012). Social comparison, social presence, and enjoyment in the acceptance of social shopping websites. *Journal of Electronic Commerce Research*, 13(3), 198-212.
Simonson, I., & Rosen, E. (2014). What marketers misunderstand about online reviews. *Harvard Business Review*, (January-February), 23-25.
Tang, Y., Zhong, M., Qin, H., Liu, Y, & Xiang, L. (2019). Negative word of mouth about foreign lands: Dimensions of the shared discomforts narrated in travel blogs. *Journal of Global Fashion Marketing*, 29(3), 311-329.
Tirunillai, S., & Tellis, G. J. (2014). Mining marketing meaning from online chatter: Strategic brand analysis of big data using latent dirichlet allocation. *Journal of Marketing Research*, 51(August), 463-479
Tsai, S. -P. (2005). Utility, cultural symbolism and emotion: A comprehensive model of brand purchase value. *International Journal of Research in Marketing*, 22(3), 277-291.
Van der Heijden, Hans (2004), “User Acceptance of Hedonic Information Systems,” *MIS Quarterly*, 28 (4), 695-704.
Verhagen, T., & van Dolen, W. (2011). The influence of online store beliefs on consumer online impulse buying: A model and empirical application. *Information & Management*, 48(8), 320-327.
Wang, M., Lu, Q., Chi, R. T. & Shi, W. (2015). How word-of-mouth moderates room price and hotel stars for online hotel booking. *Journal of Electronic Commerce Research*, 16(1), 72-80.
Warriner, A. B., Kuperman, V., & Brysbaert, M. (2013). Norms of valence, arousal, and dominance for 13,915 English lemmas. *Behavior Research Methods*, 45(4), 1191-1207.
Wilson, T. D., & Hodges, S. D. (1992). Attitudes as temporary constructions. In L. L. Martin & A. Tesser (Eds.), *The construction of social judgments* (pp. 37-65). Hillsdale, NJ, US: Lawrence Erlbaum Associates, Inc.

Yau, O. H. (1986). Chinese cultural values and their marketing implications. In: Hseh, R. T., Scherling, S. A. (Eds.), *Proceeding of the Academy of International Business Southeast Asia Regional Conference. National Chiao Tung University, Taipei*.

Yin, D., Bond, S., & Zhang, H. (2014). Anxious or angry? Effects of discrete emotions on the perceived helpfulness of online reviews. *MIS Quarterly*, 38(2), 539-560.

Yoon, S.-J. (2018). Social-cultural-psychological perspectives on future word-of-mouth research. *Journal of Global Scholars of Marketing Science*, 28(2), 166-174.

Zhou, W., & Duan, W. (2016). Do professional reviews affect online user choices through user reviews? An empirical study. *Journal of Management Information Systems*, 33(1), 202-228.

Zhu, F., & Zhang, X. M. (2010). Impact of online consumer reviews on sales: The moderating role of product and consumer characteristics. *Journal of Marketing*, 74(March), 138-148.

Table 1
Exemplar research related to online customer reviews.

Year	Study	Products	Product type (U: utilitarian, H: hedonic)	Type of OCR				Response variable	OCR-response variable relationship
				Volume	Valence	Content	Classification		
2004	Godes and Mayzlin	TV shows	H	✓	✓	None	OOCR	Rating	Positive in volume, but insignificant in valence
2006	Chevalier and Mayzlin	E-books	U & H	✓	✓	None	OOCR	Sales	Positive in volume and positive valence, but negative in negative valence
2006	Liu	Movies	H	✓	✓	None	OOCR	Sales	Positive in volume, but insignificant in valence
2009	Duan, Gu, and Whinston	Software	U	None	✓	None	OOCR	Sales	Positive for non-popular software
2010	Berger, Sorensen, and Rasmussen	Books	U & H	None	✓ (Negative)	None	OOCR	Sales	Positive for unknown products but negative for established products
2010	Chintagunta, Gopinath, and Venkataraman	Movie	H	✓	✓	None	OOCR	Revenue	Positive in valence, but insignificant in volume
2010	Zhu and Zhang (2010)	Video games	H	✓	✓	None	OOCR	Market share	Mixed depending on product characteristics
2012	Onishi and Manchanda	Movie, cell phone service	U & H	✓	✓	✓	OOCR	Sales	Positive in volume and valence
2014	Gopinath, Thomas, and Krishnamurthi	Cell phones	U & H	✓	✓	✓	FOCR, EOCR	Sales	Insignificant in volume, but positive in only the valence of recommendation
2014	Yin, Bond, and Zhang	Online shopping	U & H	None	✓	✓	EOCR	Review helpfulness	Positive in negative valence (i.e. anger and anxiety)
2015	Jang and Chung	Mobile games	H	✓	None	None	OOCR	Sales	Positive in volume
2016	Liu, Singh, and Srinivasan	TV shows	H	✓	✓	✓	OOCR	Rating	Insignificant in both volume and valence, but positive in content
2016	Ullah, Amblee, Kim, and Lee	Multiple products	U & H	None	✓	✓	EOCR	*None*	Difference in EOCR across search and experience goods
2016	Zhou and Duan	Software	U	✓	✓	None		Sales	Positive in both volume and valence
2017	Candi, Jae, Makarem, and Mohan (2017)	Coffee mugs, watches	U & H	✓	None	✓	FOCR, EOCR	Product consideration	Positive in volume and negative in valence
2018	Esmark Jones, Stevens, Breazeale, and Spaid	Printers	U	None	✓	✓	OOCR	Satisfaction and attitude	Positive under a fellow customer's responses to negative OCRs
2018	Gavilan, Avello, and Martinez-Navarro	Hotels	U & H	✓	✓	✓	OOCR	Product consideration	Positive in volume and negative in valence
2018	Ren and Nickerson	Multiple products	U & H	✓	✓	✓	EOCR	Sales	Varying depending on product type
2019	Jang and Moutinho	Hotels	U & H	✓	✓	✓	FOCR	Consumer spending	Mixed depending on price promotions
	This research	Mobile games	H	✓	✓	✓	FOCR, EOCR	Sales	Mixed depending on OCR categories

Notes: OCR refers to online consumer review. OOCR, FOCR, and EOCR deonote overall OCR, functional OCR, and emotional OCR, respectively.

Table 2

Classification of functional and emotional OCRs.

Category	Valence	Representative word (number of original words)
Functional OCRs (52, 181)		
product quality (31, 128)	Positive (25, 88)	Appropriate (3), beautiful (10), cute (2), delicious (4), dynamic (2), detailed (9), energetic (2), excellent (2), famous (5), fancy (4), fast (3), friendly (2), harmonious (1), improved (6), interesting (5), luxurious (1), meaningful (3), mysterious (3), optimized (3), polished (3), refreshed (6), sexy (1), soft (5), useful (2), vast (1)
	Negative (6, 40)	Defective (9), dysfunctional (9), heavy-and-slow (3), incomplete (14), unfriendly (4), unnatural (1)
product innovativeness (11, 27)	Positive (8, 20)	Differentiated (1), distinctive (1), exceptional (1), fresh (2), novel (5), outstanding (2), rare (2), unique (6)
	Negative (3, 7)	Ambiguous (2), blatant (1), tedious (4)
price acceptability	Positive (2, 5)	Cheap (3), discounted (2)
(3, 8)	Negative (1, 3)	Expensive (3)
product ease-of-use	Positive (4, 12)	Comfortable (1), convenient (2), easy (4), simple (5)
(7, 18)	Negative (3, 6)	Clumsy (2), complicated (3), overcomplicated (1)
Emotional OCRs (22, 79)		
Negative emotion (13, 39)	*anger* (6, 23)	Boring (7), disappointing (3), hating (2), irritating (1), lousy (9), upsetting (1)
	fear (6, 12)	Addictive (1), burdensome (2), doubtful (1), scary (4), uneasy (2)
	shame (1, 4)	Embarrassed (4), pitiful (2), shame (1)
Positive emotion	*love* (4, 11)	Affectionate (4), fascinated (3), loving (1), romantic (3)
(9, 40)	*contentment* (2, 5)	Content (2), satisfactory (3)
	happiness (3, 24)	Amazing (21)[a], cheerful (1), happy (2)

Notes: The two figures in parentheses represent the number of representative words and the number of total similar words related to the representative word, respectively.

[a] Although consumers may use the word "amazing" to mean a high level of product innovativeness, we classify it as the happiness emotion because, in most cases, consumers are ultimately expressing their strong, positive excitement and surprise about the focal product.

Table 3

Results of predictive validity check.

Variable	Aggregated Models		Disaggregated Models				
	(1) Base model	(2) Base content model	(3) Functional volume model	(4) Functional valence model	(5) Emotional share model	(6) Full functional model	(7) Full content model
Aggregate-level							
overall OCR volume	✓						
overall OCR valence	✓						
functional OCR volume		✓					
functional OCR valence		✓					
emotional OCR volume		✓					
emotional OCR share		✓					
Disaggregate-level							
Functional OCR volume							
product quality			✓			✓	✓
product innovativeness			✓			✓	✓
price acceptability			✓			✓	✓
product ease-of-use			✓			✓	✓
Functional OCR valence							
product quality				✓		✓	✓
product innovativeness				✓		✓	✓
price acceptability				✓		✓	✓
product ease-of-use				✓		✓	✓
Emotional OCR share							
anger					✓		✓
fear					✓		✓
shame					✓		✓
contentment					✓		✓
happiness					✓		✓
Mean Squared Error (MSE)	0.483	0.498	0.481	0.555	0.553	0.470	0.466

Notes: The MSE measures the average of the squares of the difference between the estimator (in-sample) and what is estimated (out-of-sample). The difference occurs because of randomness or because the estimator doesn't account for more accurate information (Lehmann & Casella, 1998). For parsimony, MSEs are calculated after values of in-sample and out-of-sample are standardized.

Table 4

Descriptive statistics and correlation coefficients.

	Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	*sales*	19957.27	29338.15	1													
2	*product quality volume*	55.20	96.73	0.26[a]	1												
3	*product innovativeness volume*	5.18	11.55	0.22[a]	0.68[a]	1											
4	*price acceptability volume*	3.34	6.39	0.01[a]	0.35[a]	0.34[a]	1										
5	*product ease-of-use volume*	11.78	23.34	0.25[a]	0.67[a]	0.62[a]	0.35[a]	1									
6	*product quality valence*	0.90	0.14	0.00	0.05[a]	0.05[a]	0.04	0.05[a]	1								
7	*product innovativeness valence*	0.85	0.22	0.02	0.01	0.02	0.02	0.02	-0.01	1							
8	*price acceptability valence*	0.35	0.20	0.01[a]	-0.22[a]	-0.20[a]	-0.47[a]	-0.21[a]	0.00	-0.03	1						
9	*product ease-of-use valence*	0.58	0.26	0.02	0.00[a]	-0.03	-0.12[a]	0.00[a]	0.05	0.00	0.09[a]	1					
10	*anger share*	0.21	0.24	-0.03[a]	-0.04[a]	-0.02[a]	-0.05	-0.06	0.01	-0.05[a]	0.07	0.05	1				
11	*fear share*	0.15	0.22	-0.01[a]	-0.05[a]	-0.01[a]	0.00[a]	0.01[a]	-0.10[a]	0.01	-0.05[a]	-0.01	-0.21[a]	1			
12	*shame share*	0.00	0.02	-0.01	0.00[a]	0.01[a]	0.00	-0.01[a]	-0.02	0.01	0.02	-0.01	-0.01	-0.01	1		
13	*contentment share*	0.05	0.13	-0.06[a]	0.01[a]	-0.03[a]	0.05[a]	-0.03[a]	-0.01	0.01	-0.07[a]	-0.02[a]	-0.11	-0.12	0.02	1	
14	*happiness share*	0.29	0.27	0.01	0.13[a]	0.06[a]	0.06[a]	0.04[a]	0.06[a]	-0.02	-0.02	0.03	-0.33[a]	-0.26[a]	0.00	-0.07[a]	1

[a] $p < 0.05$.

Table 5

Results of functional and emotional OCR effects.

(i) Results of first-level regression

Variable	Parameter estimate	Variable	Parameter estimate
Functional OCR volume		Functional OCR valence	
product quality	0.493** (0.550)	*product quality*	-0.073** (0.430)
product innovativeness	0.094 (0.570)	*product innovativeness*	0.111** (0.410)
price acceptability	-0.166* (0.550)	*price acceptability*	0.141** (0.450)
product ease-of-use	0.232** (0.560)	*product ease-of-use*	0.024 (0.410)
Intercept	0.076** (0.400)		

(ii) Results of second-level regression

Variable	*First-level intercept*	Emotional OCR share				
		anger	*fear*	*shame*	*contentment*	*happiness*
Second-level intercept	0.076** (0.045)	-0.047 (0.086)	-0.021 (0.078)	0.004 (0.055)	-0.082 (0.076)	-0.079 (0.066)
Functional OCR volume						
product quality	0.493** (0.122)	-0.091 (0.185)	-0.024 (0.213)	0.022 (0.112)	-0.118 (0.178)	-0.121 (0.145)
product innovativeness	0.093 (0.115)	-0.156 (0.180)	0.065 (0.178)	-0.143 (0.127)	0.201 (0.223)	-0.100 (0.167)
price acceptability	-0.166* (0.106)	0.150 (0.146)	0.197** (0.142)	0.030 (0.138)	-0.013 (0.126)	0.146 (0.125)
product ease-of-use	0.232** (0.106)	0.164 (0.209)	-0.099 (0.172)	0.060 (0.182)	-0.084 (0.208)	0.067 (0.169)
Functional OCR valence						
product quality	-0.073** (0.048)	-0.063* (0.050)	-0.055 (0.046)	-0.004 (0.066)	-0.043 (0.041)	-0.032 (0.055)
product innovativeness	0.112** (0.042)	0.029 (0.046)	0.021 (0.045)	0.005 (0.043)	-0.009 (0.044)	-0.008 (0.050)
price acceptability	0.140** (0.061)	0.056 (0.076)	0.046 (0.076)	0.015 (0.092)	-0.013 (0.065)	0.106** (0.069)
product ease-of-use	0.024 (0.041)	0.061* (0.046)	0.036 (0.048)	0.004 (0.043)	-0.046 (0.045)	0.106 (0.046)

Notes: Standard deviations are calculated by averaging the square roots of the corresponding covariance matrix draws obtained from MCMC. In Table 7-ii, the parameter estimates for the main effects of emotional OCR subcategories on product sales are located in the row labeled *second-level intercept*, and those for the moderating effects on the functional OCR-sales link are located in the column labeled “Emotional OCR share.” We used the *love* variable as the reference variable.

** $p < 0.05$; * $p < 0.1$

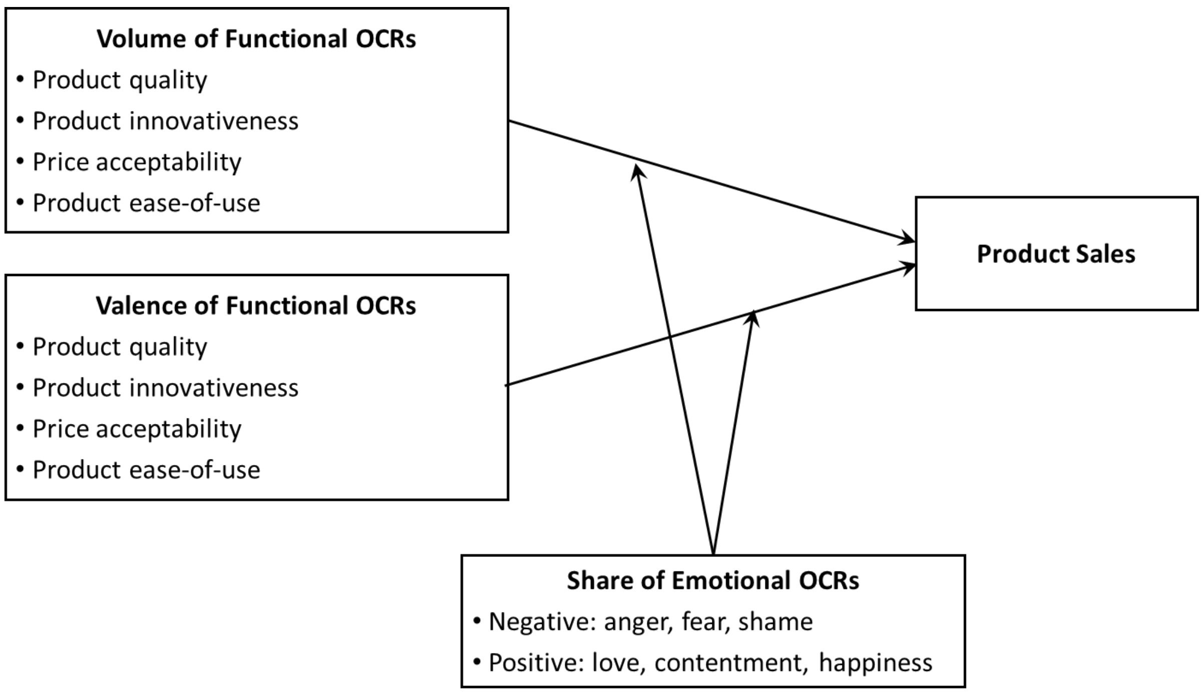

Fig. 1. Conceptual model.

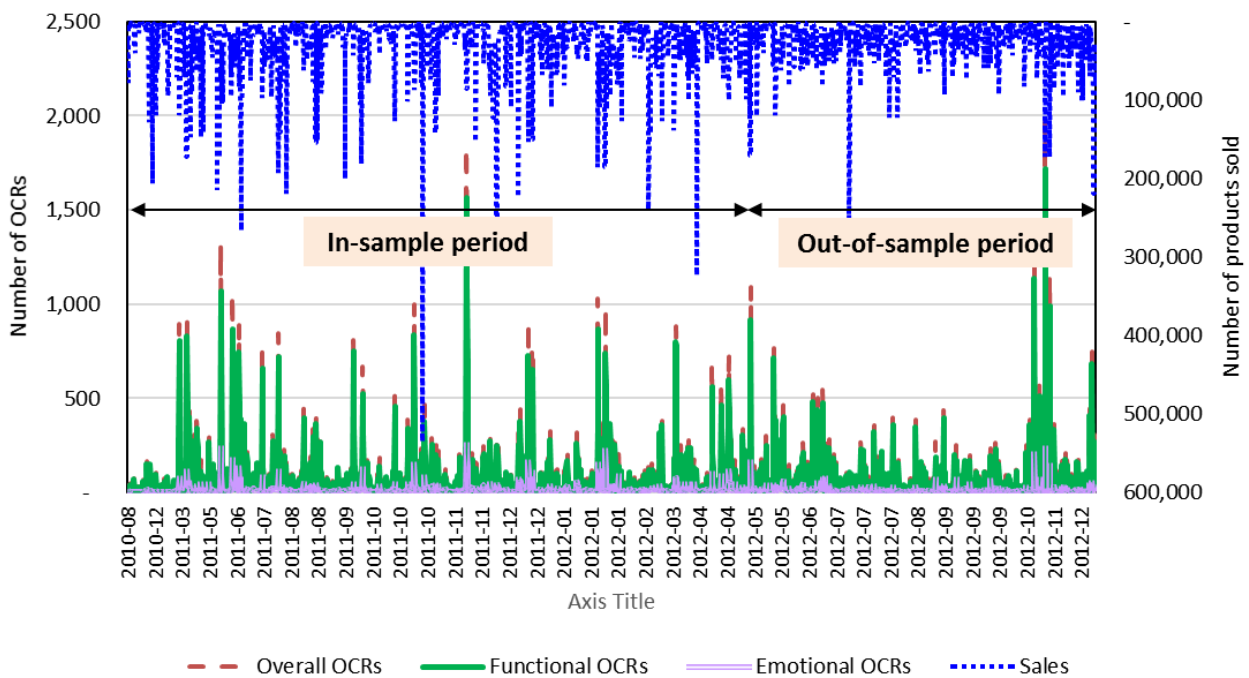

Fig. 2. Volume distribution of OCRs and product sales.

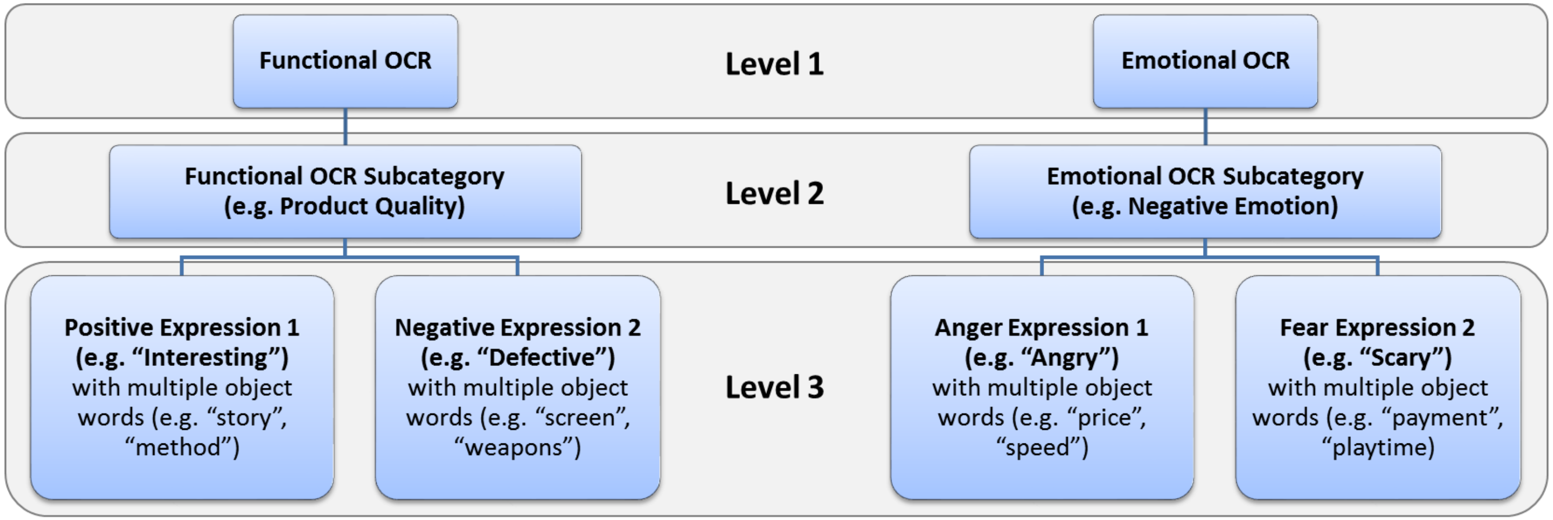

Fig. 3. An example of three levels of OCR classification.