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Decomposing the effects of online customer reviews on brand, price, and product attributes

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A B S T R A C T

Online customer reviews (OCRs) have become a major source of information for customers in the Internet. Understanding the impact of OCRs on customers' decisions is an important challenge for academics and practitioners. We apply a choice-based conjoint experiment that combines all relevant levels of the OCR dimensions (valence, volume, and variance) and that estimates the effect of OCRs on choice. The experimental setting allows us to estimate the direct effects but also the interaction effects of the OCR dimensions, which have been largely neglected in previous research. The impact of the OCR dimensions is evaluated against the results from a control group that did not face OCRs when making their choices. Therefore, our experiment enables us to investigate the extent to which the presence of OCRs affects customers' consideration of brand, price, and technical product attributes. By contrast to previous findings, our results show that volume and variance do not affect customers' choices directly but that they moderate the impact of valence on customers' choices. Moreover, we find that OCRs decrease the importance of brand for customer purchase decisions, indicating that managing OCRs have become a challenge for brand management.

1. Introduction

Choosing the right product (including services) online can be an exhausting process. The vast variety of products on retailer websites is often overwhelming. To handle such wide-ranging assortments, online customer reviews (OCRs) have emerged as an important information source for customers to evaluate products prior to purchase (Cui, Lui, & Guo, 2012).

OCRs, which are often presented as a summary statistic (e.g., Amazon.com's five-star rating), are a form of electronic word-of-mouth that has become an integral part of the Internet and online retailing in particular (Moe & Trusov, 2011). Through OCRs, customers have quick and easy access to an unprecedented amount of user-generated product information (Duan, Gu, & Whinston, 2008), which can help customers to choose the most appropriate product according to their idiosyncratic preferences based on other customers' experiences (Moe & Trusov, 2011). The experiences and opinions from other customers can contribute information about the quality and value of a product and can therefore reduce customers' choice risk (Cui et al., 2012; Zhu & Zhang, 2010) and complement other forms of business-to-customer communication (Chevalier & Mayzlin, 2006).

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The practical relevance of OCRs is underscored by previous research demonstrating the strong influence of OCRs on sales (e.g., Chevalier & Mayzlin, 2006; Cui et al., 2012). Accordingly, previous research mainly focuses on explaining or predicting sales, revenue, or sales growth through the consideration of OCRs. However, these studies provide mixed findings with respect to the effects of the three different dimensions that characterize OCRs, namely, valence, volume, and variance. Additionally, the vast majority of present research neglects the potential interaction effects among the OCR dimensions. A recent study by Sun (2012), however, demonstrates the importance of considering these interaction effects.

Moreover, OCRs represent an additional information source for customers that can be used as a quality indicator to decrease uncertainty in the decision process—a role that has traditionally been assigned to brand (e.g., Erdem & Swait, 1998) but also to product price (e.g., Völckner, 2008). However, research investigating the effect of OCRs and brand is limited. Notable exceptions are Ho-Dac, Carson, and Moore (2013), who analyze the effect of OCRs on sales considering brand strength, and Lovett, Peres, and Shachar (2013), who analyze which brand characteristics stimulate word-of-mouth. However, although both studies investigate the relationship between brand and word-of-mouth, they do not analyze whether the presence of OCRs affects the role of brand in a choice situation (e.g., selecting a product online). Given the (monetary) effort that firms invest in building brands and in establishing price perceptions in the mind of customers, it is important to understand how customers adapt to a changing information set due to OCRs.

Based on a conceptual framework that links the effect of OCRs and product attributes (i.e., brand, price, and technical attributes) to customers' choice probabilities, this study aims to address the stated gaps in the literature. Specifically, i) we decompose OCR into valence, volume, and variance and investigate their interactions, and ii) we examine the impact of OCRs on customers' valuation of brand, price, and technical attributes of products.

A unique feature of our study is that we investigate the effect of OCRs on customer choice in a comprehensive choice-based conjoint experiment (Louviere & Woodworth, 1983). One reason for the aforementioned mixed empirical findings in previous research might be that most existing studies are based on analyses of market data. Determining the effect of OCRs on customer behavior with market data may be difficult because of complex challenges such as endogeneity issues (e.g., Amblee & Bui, 2011), reviews by experts in parallel (Ho-Dac et al., 2013), concurrent marketing activities (e.g., advertising; Chintagunta, Gopinath, & Venkataraman, 2010), or the low frequency of OCRs providing poor evaluations (Chevalier & Mayzlin, 2006). Our choice-based conjoint experiment has the advantage of containing a balanced number of all relevant combinations of the OCR dimensions that account for the interaction effects among valence, volume, and variance. Our experimental setting further enables us to observe and analyze individual choice behavior instead of aggregated observed market data. Individual choice behavior conducted within an experiment does not suffer from endogeneity or other volatile marketing activities, such as advertising, because external effects are implicitly held constant during the experiment.

A few of our key empirical findings are as follows. By contrast to other studies, our results show that volume and variance operate as moderators of valence and that they do not have a direct effect on customer choice. Only valence exerts the expected direct effect on customer choice behavior in our experiment.

Furthermore, we find that OCRs reduce the influence of brand and price on customers' choices in our choice-based conjoint experiment. It seems that OCRs, as indicators of a brand's online reputation, reduce the impact of a brand's general reputation once they are displayed together. This finding indicates that OCRs present an emerging challenge for brand management in e-commerce. Brand managers should care about their online reputation, which can be enhanced by increasing the number of positive OCRs about their products or by building a loyal brand audience that stays with their brand because of the emotional benefits associated with it. Loyal customers may ignore other brands and may therefore simply disregard unfavorable OCRs related to their brand.

Our results are also of interest to managers, as they provide insight into the transformation of the online buying process since OCRs are available in nearly every online store. We investigate the changing impact of brands in such a digital environment and discuss options for handling OCRs.

Given the impact of prices in demand, the results indicate that OCRs reduce decision risk for customers, decreasing customers' price sensitivity and increasing customers' willingness to pay (WTP). On average, one additional rating star on a five-star scale (i.e. a one-unit increase in valence,) increases the WTP for an eBook reader by €48.96 (price range in our study = €99–€139).

The remainder of the paper is organized as follows. We next present the conceptual framework for our study, including related literature and hypotheses. Then, we describe our experimental setting and present the results of the empirical analyses. We conclude by discussing our results and by proposing directions for future research in the last section.

2. Conceptual framework and hypotheses

2.1. Online customer reviews

OCRs can be divided into two groups: qualitative and quantitative OCRs (Sridhar & Srinivasan, 2012). Qualitative OCRs provide a written description of the usage experience. In qualitative reviews, the customer is completely free to choose how to describe, criticize, and evaluate the product (Jiménez & Mendoza, 2013).

In the case of a quantitative OCR, the customer is forced to summarize his or her evaluation in a single rating or grade, and the single ratings from customers are usually pooled together into a summary statistic. This paper focuses on quantitative OCRs.

According to Chintagunta et al. (2010), a quantitative OCR can be decomposed into the following three elements:

1. Valence, which is the average rating and represents average customer satisfaction;

2. Volume, which is the number of customer ratings for each valence level and the total number of ratings; and
3. Variance, which is the variation in ratings along the rating scale and is observable through the number of customer ratings for each valence level. Variance represents the degree of disagreement or heterogeneity among customers' evaluations.

2.2. Conceptual framework

On retailers' websites, customers receive different information about products through product attributes (provided by the manufacturer or retailer) and OCRs (provided by other customers). In our conceptual framework (see Fig. 1), we assume that these two information sources, namely, information from product attributes and information from OCRs, determine customers' choice probability.

In a classical choice scenario, without OCRs, a customer's choice is completely determined by the attributes of the product, such as the brand, price, and technical attributes (e.g., battery lifetime) and the customer specific error term. In the presence of OCRs, information about product attributes will undoubtedly remain a crucial element that influences customer product choice. We therefore account for the influence of product attributes on customer choice in our framework.

However, considering retailer websites, one can hardly observe classical choice scenarios anymore. OCRs are present on the vast majority of websites, and customers use OCRs to find products that match their preferences (Chen & Xie, 2008) and to satisfy their search for quality information (Zhu & Zhang, 2010). Thus, we consider OCRs to be a second source of information that influences customer choice probability. Similar to Chintagunta et al. (2010), we decompose OCRs into the dimensions of valence, volume, and variance to assess the individual impact of each dimension on customer choice and their interaction in influencing customer choice. However, in our framework, we assume that volume and variance act only as moderators of the impact of valence and that they do not have a direct effect on customers' choice probability. We detail the explanation for this assumption below when we discuss related research and develop our hypotheses.

2.3. Related literature

Using different methods and types of data and focusing on different research questions, scientists reported different findings regarding the effects of valence, volume, and variance (Cui et al., 2012). In the following, we summarize the major findings of related research that applies to our study (see Table 1).

Valence and volume are considered in all the studies that are presented in Table 1, albeit with mixed findings. Most studies report a significant positive effect of valence (Chevalier & Mayzlin, 2006; Chintagunta et al., 2010; Clemons, Gao, & Hitt, 2006; Cui et al., 2012; Dellarocas, Zhang, & Awad, 2007; Dhar & Chang, 2009; Sun, 2012); however, some do not find a significant effect (Amblee & Bui, 2011; Duan et al., 2008). A limitation of these studies is that in practice, products with a low valence generally do not survive long enough to be observed frequently (Chevalier & Mayzlin, 2006). Nevertheless, OCRs with low valence exist, and they are informative about the true impact of valence on customer choice behavior.

Previous literature also presents mixed findings with respect to volume. Several studies find a significant positive relationship between volume and the dependent variable (Amblee & Bui, 2011; Chevalier & Mayzlin, 2006; Cui et al., 2012; Dellarocas et al., 2007; Duan et al., 2008; Sun, 2012), whereas others do not find a significant effect (Chintagunta et al., 2010; Clemons et al., 2006). The direct effect of volume is attributed to the increased likelihood that prospective customers will become aware of a product owing to increased volume (Dellarocas et al., 2007; Duan et al., 2008).

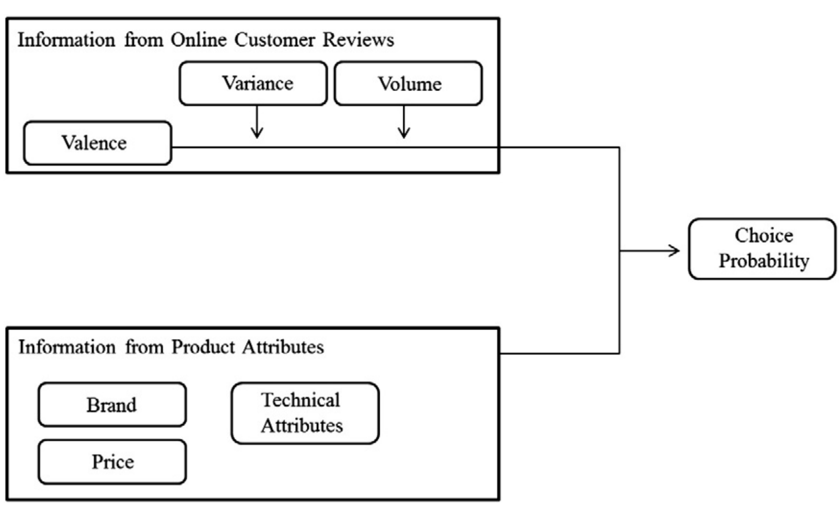


Fig. 1. Conceptual framework.

Table 1
Overview of previous literature on OCR dimensions.

Study	Object of study	Online Customer Review				Key findings regarding online customer reviews	Product	Type of good[a]	Experimental data[b]
		Valence	Volume	Variance	Inter-action				
Amblee and Bui (2011)	Effect of reviews on sales rank	X	X			• Valence not significant • Volume significant	Short stories	e	
Chen et al. (2011)	Differential and interaction effects of WOM and observational learning	X	X			• Negative word-of-mouth more influential than positive WOM • Observational learning has a positive effect on sales, whereas negative observational learning has no effect • WOM shows a diminishing effect over lifetime	Cameras	s	
Chevalier and Mayzlin (2006)	Effect of reviews on relative sales	X	X			• Relative sales improve with better valence for Amazon but not for BN • Volume improves relatives sales for Amazon	Books	e	
Chintagunta et al. (2010)	Impact of reviews on box office sales	X	X	X	x	• Valence is important in the prediction of sales, not volume and variance • Interactions are not important	Movies	e	
Clemons et al. (2006)	Predictive power of electronic WOM for product sales growth	X	X	X		• Logarithm of volume is not significant • Variance is significantly correlated with sales growth • Average valence is significant • After splitting valence, only mean top quartile remains significant	Beer	e	
Cui et al. (2012)	Effect of online reviews on new product sales (search vs. experience good)	X	X			• Valence and volume are significant • Valence has a stronger impact than volume on search goods • For experience goods, this relation switches	Consumer electronics & video games	e/s	
Dellarocas et al. (2007)	Ability of electronic WOM to forecast box office sales	X	X			• Valence and volume show a significant relationship with future box office sales	Movies	e	
Dhar and Chang (2009)	Predicting sales with electronic WOM	X	X			• Valence significant for a one week-ahead prediction in a fixed effects model • Volume (of customer reviews) is not implemented in the model	Music albums	e	
Duan et al. (2008)	Impact of electronic WOM on box office revenue	X	X			• Valence does not influence sales Volume is significantly associated with revenue	Movies	e	
Ho-Dac et al. (2013)	Explanatory power of OCRs and brand equity for Blu-Ray and DVD revenue	X	X			• OCRs have a significant impact on the sales of weak brands • OCRs have no significant impact on the sales of strong brands • OCRs aid the transition from a weak to a strong brand	Blu-Ray & DVD	s	
Jang et al. (2012)	Influence of reviews on consideration set and choice; estimation of the monetary value of review change	X	X	X		• Monetary value of increase in valence is positive • Monetary value of increase in volume (less important) and impact of variance depends on prior perceived quality	Hotels	e	ed
Kostyra and Reiner (2012)	Impact of OCRs design on OCRs evaluation	X				• Valence has a significant and positive effect on choice	Games	e	ed
Moe and Trusov (2011)	Dynamics of online product ratings	X	X	X		• Rating dynamics can substantially affect future ratings • Rating dynamics can have direct and indirect effects • Positive direct effect of valence on sales • No direct effect of variance and volume on sales	Bath, fragrance, and beauty products	e/s	
Sun (2012)	Effect of reviews on sales rank	X	X	X	x	• Impact of volume is positive and significant for Amazon • Valence is significant for Amazon but not for BN. • Interaction of valence and variance is	Books	e	

Table 1 *(continued)*

Study	Object of study	Online Customer Review: Valence	Volume	Variance	Inter-action	Key findings regarding online customer reviews	Product	Type of good[a]	Experimental data[b]
						significant; higher variance increases relative sales when valence is low, and higher valence increases relative sales when variance is low			
Zhu and Zhang (2010)	Impact of OCRs on sales	X	X	X		• Valence and variance are significant for less popular games with an online mode • Volume is significant for popular and less popular games with an online mode	Console games	e	
This Study	Effect of OCRs on product choice	X	X	X	X	• Valence has a positive, direct effect on product choice • Volume positively moderates high valence (only) • Variance negatively moderates high and medium valence • Online customer reviews draw importance from brand relevance, price sensitivity, and technical product characteristics • Average willingness-to-pay for a one-star increase in online customer reviews is €48.96 for an eBook reader	eBook reader	s	ed

BN = Barnes & Noble; WOM = word-of-mouth.
OCRs = online customer reviews.
[a] e = experience good and s = search product.
[b] ed = experimental data are used.

However, Duan et al. (2008) question whether the effect of volume on customer product awareness applies to OCRs that are posted on retail websites (in contrast to online discussion forums), as they consider product awareness to be a precondition for page visits or product searches on retail websites. A positive direct effect through volume seems plausible only for products with network externalities because an indication of the actual number of users through volume would help a potential customer to estimate the value or utility of the entire network (e.g., multiplayer online games; Yang & Mai, 2010; Zhu & Zhang, 2010).

Variance has not been the focus of most published studies (often because of the OCR design on the observed website), but the results have differed from where it has been examined. A significant influence of variance is reported by Clemons et al. (2006) and Sun (2012), whereas Zhu and Zhang (2010) identify a significant effect only for less popular games with an online mode. Chintagunta et al. (2010) do not find a significant effect of variance.

Only two studies explore the interaction of the OCR dimensions (Chintagunta et al., 2010; Sun, 2012). A significant interaction effect of valence and variance is only documented by Sun (2012), who finds a significant moderation effect of variance on the impact of valence on sales. These results underpin our assumption that the interaction effects among the OCR dimensions must be considered to decompose the impact of OCRs on customer choice.

Therefore, the setting of our choice-based conjoint experiment allows for a combination of all possible levels of the OCR dimensions. Furthermore, our comprehensive and well-balanced data sample provides an appropriate testing ground for the existence of moderation effects among the dimensions. Volume and variance, in particular, are assumed to operate as moderators of the effect of valence on customer choice because volume lends substance to the indication of valence with respect to quality and because variance can be considered to indicate ambiguity among former customers regarding their valence statements. Ignoring these expected moderations can easily result in biased interpretations with respect to the direct impact of volume and variance (see Model 1, 4.1) on customer choice behavior. The previously reported mixed findings regarding the effects of valence, volume, and variance may arise for several reasons. First, analysis of real market data from websites (see Table 1) is common to almost all previous OCR studies that we are aware of (with the exception of Jang, Prasad, & Ratchford, 2012 and Kostyra & Reiner, 2012). Real market data may suffer from endogeneity issues that render assessing the impact of OCR characteristics on the relevance of a product's brand, price, or technical attribute difficulty; that is, retailers will usually not randomly show and hide OCRs without observing negative impacts on customer behavior during day-to-day business. Therefore, endogeneity issues challenge researchers to distinguish between the impact of volume, a critical OCR dimension that describes the number of submitted OCRs on sales, and the impact of sales on volume for sales prediction (Amblee & Bui, 2011; Godes & Mayzlin, 2004; Park, Lee, & Han, 2007). Volume may simply act as a lagged measure of sales and may be misinterpreted to be responsible for future sales. Many researchers have used various approaches to address endogeneity issues in previous research (Duan et al., 2008: simultaneous equation system; Cui et al., 2012:

fixed effects model; Chen, Wan, & Xie, 2011: first difference model; Zhu & Zhang, 2010: differences-in-differences model; Amblee & Bui, 2011: repeated analyses of different periods to monitor consistency; Moe & Trusov, 2011: baseline level of sales for each product during pre-rating period). Further, other researchers have addressed different types of endogeneity (e.g., Chintagunta et al., 2010: correlations across markets as well as number of companies (i.e., theaters) within each market as a result of unobservable knowledge; Feng & Papatla, 2011: relationship between advertising spending and word-of-mouth).

Given the vast types of and possibilities to address endogeneity, we regard the absence of endogeneity issues as an advantage of our experimental approach that increases the internal validity of our results. Further, although real market data may have the advantage of high external validity, it may provide a biased image of the effects of OCRs because of the diversity of concurrent marketing activities, such as advertising (Chintagunta et al., 2010), which also drive sales.

Second, non-experimental studies do not have access to the choice sets that customers considered while purchasing and encountering different OCRs for every product. Therefore, these studies relate the impact of OCRs to downstream variables, such as growth, sales, or revenue, instead of product choice.

Third previous research bases analyses on different definitions of OCRs. For instance, some studies examine only valence and volume, others examine all three dimensions (valence, volume, and variance), and only a few examine the interaction effects among the OCR dimensions.

Previous research on the relationship between brand and OCRs is limited. Lovett et al. (2013) investigate the relationship between brand and word-of-mouth and analyze which characteristics of a brand stimulate word-of-mouth (on- offline). The authors find that social, emotional, and functional drivers of a brand drive word-of-mouth. Ho-Dac et al. (2013) investigate the role of brand strength in the context of OCRs and find that brand equity moderates the relationship between OCRs and sales in both investigated markets (Blue-ray and DVD). They further conclude that OCRs matter more for weak brands and less for strong brands.

However, little research has been conducted to investigate the relationship between price sensitivity and OCRs. Shin, Hanssens, Kim, and Gajula (2011) use online buzz (i.e., qualitative customer reviews) to explain price changes on the MP3 market. They link this finding to a decrease in WTP among customers.

2.4. Development of hypotheses

Based on the presented related literature, we next develop our hypotheses.

Valence: Although the previous literature agrees regarding the theoretical meaning and impact of valence in general, the empirical findings are mixed (see Table 1). Positive opinions are assumed to increase customers' choice probability for a product, whereas negative opinions are assumed to discourage potential customers (Dellarocas et al., 2007). However, some studies do not identify a significant relationship between valence and revenue (e.g., Duan et al., 2008). We argue that valence, as a reference for overall product quality, has a positive direct effect on customer choice probability. Consequently, our first hypothesis is as follows:

H1. Increasing valence has a positive effect on the probability that a customer will choose a product.

Volume: The higher the volume is, the more trustworthy valence becomes. This is because the overall rating converges toward the true value as the volume of ratings increases (Ho-Dac et al., 2013; Zhu & Zhang, 2010). Thus, volume acts as a moderator of the impact of valence (see Fig. 1) on customer choice and only stimulates sales when the valence signal is high. The choice probability for a product should decrease if a greater number of people agree about its inferior quality (i.e., high volume and low valence). If volume is very low, doubts about the trustworthiness of the valence level may arise, and customers may pay less attention to OCRs. Accordingly, we state our second hypothesis:

H2. Volume moderates the impact of valence on customer choice probability, whereby higher volume increases the importance of valence for customer choice.

Assuming that volume moderates the impact of valence leads to an additional assumption about volume: once a certain volume of reviews is reached, trustworthiness is not expected to increase linearly. That is, we expect a diminishing effect of volume on the impact of valence.

Therefore, we assume that the proposed moderation by volume follows a log-linear functional form that reflects diminishing marginal effects when volume increases after a certain point. Therefore, we present our third hypothesis:

H3. An increase in volume has a diminishing marginal effect on the impact of valence on customer choice.

Variance: The variance of an OCR is suggested to measure disagreement or heterogeneity among customers (Jang et al., 2012; Sun, 2012; Zhu & Zhang, 2010). The higher the heterogeneity is, the higher the deviation among the ratings will be because some customers report satisfied preferences (= high valence), whereas others do not (= low valence). Therefore, high variance signals high quality, on the one hand, and high mismatch costs, on the other hand (Sun, 2012). Clemons et al. (2006) put forth a similar argument suggesting that when products are differentiated, some people will find a perfect match for their preferences in a certain product and will reward it with a good rating, whereas other people with different preferences will provide the opposite rating. These differences among customers inevitably lead to greater variation in OCR ratings. For our study, Sun's (2012) assumptions seem most applicable. As long as the valence is low, high variance has a positive impact on customer choice because it raises doubts about bad ratings—some customers seem satisfied. The opposite effect should be found for products with high valence, as high variance challenges the unambiguousness of good ratings. Therefore, low variance establishes valence and strengthens its quality signal, rendering highly rated products even more attractive and low-rated products more unattractive. Thus, we do not expect to find a unidirectional effect (neither strictly positive nor negative) of variance on customer choice; rather, we expect variance to moderate the impact of valence on customer choice. Accordingly, we propose the following two hypotheses:

H4a. Increasing variance decreases the positive impact of high valence on customer choice.

H4b. Increasing variance decreases the negative impact of low valence on customer choice.

Impact of OCRs on brand, price, and technical attributes: OCRs have been shown to influence customer behavior because they communicate information about the quality perceptions of other customers and are perceived as trustworthy (Bickart & Schindler, 2001; Chen & Xie, 2008; Park et al., 2007). To the best of our knowledge, only Ho-Dac et al. (2013) investigate the role of brand strength in the context of OCRs. However, the impact of price and technical attributes on customer choice remains unclear.

Previous research stresses the strong quality signal of brands (Erdem & Swait, 1998). It is likely that product attributes that are used for quality evaluations (e.g., brand) still contribute to customer choice when OCRs are present. However, if OCRs provide additional information about quality, the impact of such product attributes (e.g., brand) should be replaced by OCRs to some extent. If the brand transfers its typical role as a quality signal to OCRs, the impact of brand on customer choice probability will decrease.

Accordingly, we hypothesize as follows:

H5. The importance of a product's brand on customer choice probability decreases in the presence of online customer reviews.

Pricing research provides two contradictory directions for the impact of OCRs on price. First, the impact of OCRs on price can be expected to be negative. A greater importance of price as a quality signal typically leads to lower overall price elasticity and hence higher optimal prices (e.g., Völckner, 2008). Because OCRs are expected to partly replace price as a quality signal, higher price sensitivity can be expected in the presence of OCRs.

Another stream of pricing research, however, indicates that OCRs should decrease price sensitivity, as adding information about quality (online reputation) should decrease uncertainty and perceived risks, leading to a decrease in price sensitivity (Erdem, Swait, & Louviere, 2002). This reduced price sensitivity diminishes the impact of price on customer choice probability and results in lower price elasticity in the presence of OCRs.

To empirically investigate which line of argumentation dominates in the context of OCRs, we formulate our hypothesis in favor of the second stream of research:

H6. The importance of price for customer choice probability decreases when online customer reviews are available.

We expect that some customers may rely on OCRs to avoid cumbersome evaluations of differences in the technical attributes of alternative offerings. Hence, in general, OCRs should decrease the impact of technical attributes on choice probability. Accordingly, we hypothesize as follows:

H7. The importance of technical attributes for customer choice probability decreases when online customer reviews are available.

3. Methodology and data

To test our conceptual framework, we conducted a choice-based conjoint experiment. We selected the eBook reader category as the subject for our experiment. An eBook reader is an electronic device to read digital texts. This category was selected because (at the time of the survey, early 2012) it represents a rather novel product category that is characterized by fast growth. The novelty of the eBook reader category is a useful property because most customers had a small or medium amount of experience with eBook readers and therefore may rely on OCRs, although some category experts may have already existed. At the same time, the eBook category was sufficiently established that respondents were able to participate in our experiment. The rapid growth of this category is an important indicator of general interest in eBook readers (i.e., the intention to purchase an eBook reader).

Using a pre-study, we confirmed our abovementioned assumptions. In this pre-study, we asked 28 respondents to rate six different electronic products with respect to their category experience, knowledge, interest, and general brand preference. The eBook category was revealed to be the most appropriate category for our experiment. Furthermore, the majority of previous research focuses on experience goods (see Column 9, Table 1). In particular, OCRs for movies, TV shows, and books have been analyzed. Cui et al. (2012) show that the valence of OCRs is more important for search goods than for experience goods. We believe that a closer look at search goods (e.g., eBook reader) is warranted because most studies focus on experience goods.

To ensure the general setting of our experiment, we conducted an additional laboratory experiment ($N = 20$) in which we investigated whether customers indeed make use of OCRs while searching for products. In the laboratory experiment, we asked participants to search online for an eBook reader of their choice. We recorded their search behavior with software that produces a movie of all activities on the screen. To ensure that the participants engaged in serious search behavior, we incentivized their search by a prize competition in which the participants could win the eBook reader that they selected. The laboratory experiment shows that 45% of the customers (i.e., participants in the laboratory experiment) rely on OCRs and actively use them to make buying decisions.

3.1. Setup of choice-based conjoint analysis

For the choice-based conjoint experiment (using DISE; Schlereth & Skiera, 2012), we applied a fractional full factorial design. In the treatment group, every subject made 20 choices between three hypothetical eBook readers and a no-purchase option. To increase the variation within the choice sets with respect to the OCR combinations, we created 12 versions of the online survey, each with 20 different choice sets. In total, 240 unique choice sets were observable. In addition, every respondent answered questions related to his or her need to use OCRs and demographics.

Every eBook reader (stimulus) was described by four product attributes (brand, battery lifetime, type of control, and price) and the OCR dimensions (valence, volume, and variance) (see Table 2). To ensure that the setting was familiar to the respondents, we applied a commonly used five-level design, the standard Amazon.com design.

Amazon's five star rating contains five levels for valence (1 star = worst and 5 stars = best level), a statement for volume (i.e., number of customers who rated the product), and a graphical overview for variance.

To observe the relevant combinations of valence, volume, and variance, we generated 60 different OCR patterns visualized with a unique “Amazon-like” picture presented in each stimulus (compare the example in Table 2).

To test for differences between the choice situations with and without OCR, we used a control group. The control group completed an identical survey except that the choice sets did not contain OCRs.

In total, 771 respondents completed the survey. The treatment group included 601 respondents (i.e., with OCRs in their choice sets), and the control group included 170 respondents who had no OCRs in their choice sets. The sample can be classified as a student sample because the majority (75.84%) of the respondents were students (employed respondents = 20.49%). On average, the respondents were 25.59 years old, and 55.19% were females.

3.2. Model estimation and simulation

To test our hypotheses, we estimated three different models. Table 3 which presents the three models and the corresponding variables, indicates the estimation method for each model, and illustrates which hypotheses are addressed.

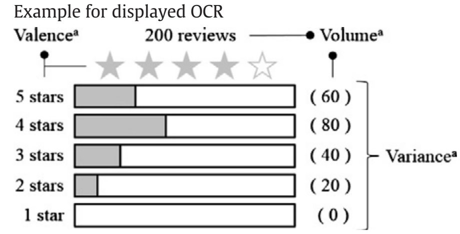
Model 1 contains the product attributes and OCR dimensions, and it represents an interesting benchmark because it replicates the majority of models proposed in previous research (compare Table 1). By contrast to most previous research, we also include the interaction effects among the OCR dimensions in Model 2 to test whether volume and variance moderate the impact of valence. Specifically, we include interactions between volume and variance with valence. The results for Model 2 are used to examine hypotheses H1, H2, H3, H4a, and H4b. Model 3 reveals the effects of OCRs on the relationship between product attributes and choice probability (H5 to H7) by comparing the control group (without OCRs) with the treatment group (with OCRs).

To compare the control group and the treatment group, every product attribute is interacted with a treatment indicator (1 = treatment group, 0 = control group) to indicate the impact of OCRs on brand, price, and technical attributes. If OCRs are irrelevant, no product attribute coefficient should change, and all coefficients for the treatment interactions should remain nonsignificant.

Table 2
Attributes and levels for choice-based conjoint analysis.

	Product attributes				OCR		
Attribute	Brand	Battery lifetime	Control	Price	Valence	Volume	Variance
Level 1	Amazon	10,000 pages[b]	Touch pad	€99	Low, avg. stars: 1.1 to 2.33	6 reviews	Low, sd < 1
Level 2	Sony	15,000 pages	Keyboard	€119	Medium, avg. stars: 3.0 to 3.3	10 reviews	High, sd > 1
Level 3	Pocketbook	20,000 pages		€139	High, avg. stars: 3.67 to 4.9	30 reviews	
Level 4						100 reviews	
Level 5						200 reviews	

Example for displayed OCR



sd = standard deviation; avg. = average.
a: Labels are not displayed in the choice set.
b: Pages = page impressions.

Table 3
Overview of estimated models.

Variables	Model 1	Model 2	Model 3
Brand + price + technical attributes	X	X	X
OCR dimensions (valence, volume, and variance)	X	X	X
OCR interactions		X	X
Control/treatment group indicator			X
Estimation method	Mixed MNL	Mixed MNL	Mixed MNL
To test hypothesis		H1/H2/H3/H4a/H4b	H5/H6/H7

Mixed MNL = random coefficient logit model.

We estimate Models 1–3 with a random coefficient logit model (mixed MNL) that accounts for random taste variations between the subjects (i.e., heterogeneity).

To better understand the effect of each attribute and level and their interactions on choice probability, we also conduct a simulation study (compare to Lewis, 2004). Similar to our empirical analysis, the simulation generates 20 choice sets, whereas the hypothetical products are randomly generated from the levels and attributes presented in Table 2. We use the estimated coefficients (e.g., from Model 2) to calculate the choice probability for each hypothetical product and the no-choice option. We incorporate heterogeneity into the model by drawing from the coefficients' distributions (i.e., from a normal distribution that uses the estimated coefficient as the mean and the estimated standard deviation). We set the nonsignificant estimated coefficients to zero, and we run 5000 iterations (representing 5000 respondents each answering 20 choice sets) to ensure that all cases are equally represented in our data.

The impact of the levels on choice probability is measured by restricting each attribute and level separately. For example, we restrict all the hypothetical products to have the brand "Amazon". All other attributes vary randomly. We then calculate the mean choice probability for this simulation (5000 customers × 20 choice sets). Likewise, we run this simulation for the other two brands. The resulting average choice probabilities for all three brands allow for a comparison of the effect of brand on choice probability.

Table 4
Estimation results for Model 1 and Model 2.

		Model 1			Model 2		
Attribute	Parameter	Coefficient	SE	Sig.	Coefficient	SE	Sig.
Brand	Amazon	.310h	.049	***	.291h	.050	***
	Sony	.274	.048	***	.223	.050	***
Battery	Batt_10	−.821	.063	***	−.876	.069	***
Lifetime	Batt_15	−.283h	.049	***	−.306h	.051	***
Control	Keyboard	−.855h	.055	***	−.891h	.058	***
Price	Price	−3.200	.163	***	−3.115	.169	***
Online	Val_high	3.895	.142	***	3.680	.172	***
Customer	Val_med	1.796h	.089	***	1.814h	.153	***
Review	Var_high	−.495h	.046	***	.351	.108	**
	Vol_10	.212h	.073	**	.068	.190	
	Vol_30	.482	.062	***	−.014	.172	
	Vol_100	.897	.066	***	.227	.156	
	Vol_200	.962	.069	***	.231	.155	
	Val_high X Vol_10				.377	.207	
	Val_high X Vol_30				.703h	.191	***
	Val_high X Vol_100				.996	.181	***
	Val_high X Vol_200				1.196h	.179	***
	Val_med X Vol_10				.070	.201	
	Val_med X Vol_30				.386	.198	
	Val_med X Vol_100				.100h	.209	
	Val_med X Vol_200				.297	.192	
	Val_high X Var_high				−1.168	.125	***
	Val_med X Var_high				−.473	.124	***
	no_choice	−1.188	.161	***	−1.269	.198	***
	Number of cases		48,080			48,080	
	Log Likelihood		−11,993			−11,896	

Reference categories: pocketbook, batt_20, touch pad, val_low, vol_6, var_low.
Batt_10 = battery lifetime is 10,000 page impressions; val = valence, vol = volume; var = variance.
Price has been divided by 100 for the estimation.
Sig. = significance level. SE = standard error.
Heterogeneity is modeled by using 100 Halton draws under the assumption of a normal distribution. 'h' indicates significant heterogeneity at the 5% level.
*** = p-value < .001; ** = p-value < .01; * = p-value < .05.

4. Empirical analysis

4.1. Replicating previous research

Model 1 reflects a model structure that is suggested by the majority of previous research on OCRs (compare Table 1): main effects for all product attributes and all OCR dimensions (valence, volume, and variance). The estimation results for Model 1 are presented in Table 4.

As expected, Amazon and Sony have positive coefficients because the reference category (Pocketbook) is neither popular nor perceived as a high-quality brand. The impact of battery lifetime is related to performance. The lowest level of battery lifetime is least attractive, followed by the second level, which is less attractive than the longest battery lifetime (the reference category). The participants prefer a touchpad control over a classical keyboard. The price coefficient is negative, as expected. All effects are highly significant.

Valence exerts a strong positive impact on choice probability. This result supports our assumption because higher valence indicates a superior product; ceteris paribus, customers chose products with higher quality.

Volume (i.e., the number of ratings) shows a positive effect with decreasing effect size on choice probability. The coefficients indicate a diminishing marginal effect (i.e., a log–linear functional form).

This result is face valid because once a critical number of ratings exists, the valence converges toward the true value, and additional reviews provide little benefit (Zhu & Zhang, 2010). However, the positive effect of volume is questionable. If increasing numbers of people agree on the inferiority of a product, the choice probability should not increase. The positive effect for volume in Model 1 (and, subsequently, for variance as well) arises because of the allocation of choice counts to the corresponding level of valence. We find that only 4.27% of all observed choice counts belong to low-valence products, whereas 47.98% of all observed choice counts belong to high-valence products. Because Model 1 does not consider interaction effects between high valence and volume, the estimation is biased in favor of the positive direct effect of volume. It simply outweighs the excluded interaction between low valence and volume (see Model 2). This finding highlights the importance of considering interaction effects; otherwise, the main effects of volume and variance may be biased owing to unbalanced choice observations.

High variance has a significant negative effect on choice probability (reference = low variance). A negative effect for high variance indicates that customers avoid uncertainty. The higher the disagreement about a products' quality is, the more likely a customer is to decide not to purchase that product and to choose another product or nothing at all. Although this insight seems plausible at first glance, it is not meaningful for all possible situations. Products with low valence should be more preferable with an increase in variance. Because high variety in OCRs increases mistrust in a low level of valence, high variance should increase choice probability for products with low valence.

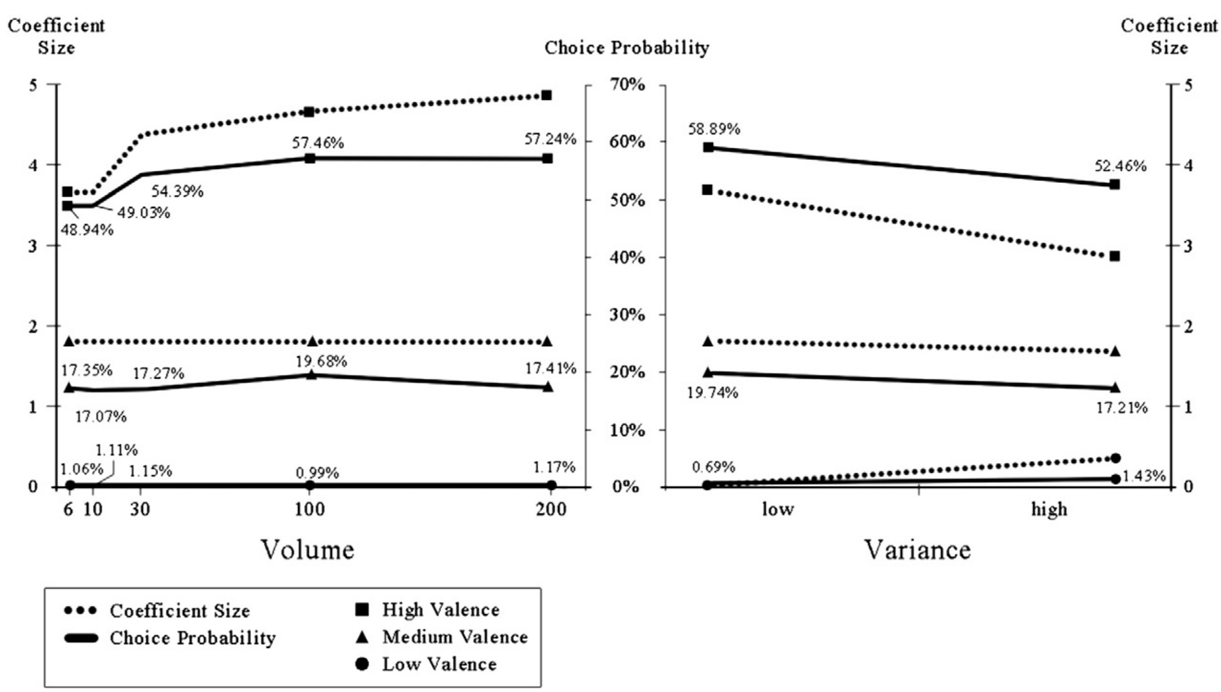


Fig. 2. Illustration for the interactions of valence–volume and valence–variance.

4.2. Decomposing online customer reviews into valence, volume, variance, and their interactions

To overcome the shortcomings of Model 1, we estimate Model 2, which incorporates the valence–volume and valence–variance interactions into Model 1, as proposed in our conceptual framework (Fig. 1). Model 2 thus allows us to test hypotheses H1, H2, H3, H4a, and H4b.

Comparing the coefficients for valence between Model 1 and Model 2, we find that valence has a significant impact on choice probability. This robust result is in line with the stated positive direct effect of valence on choice probability (H1). A higher product rating always increases customer choice probability. The coefficients of all product attributes remain almost unchanged.

However, Model 2 reveals different implications for the effect of volume on choice probability (see Table 4 and Fig. 2). In line with Model 2 and in contrast to Model 1, volume has no continuously positive effect on choice probability. This is only true for high-valence eBook readers. The more that customers agree with a high valence rating, the higher the likelihood of choice will be. The marginal effect of volume on high-valence eBook readers diminishes when volume increases. Therefore, the effect of volume follows a log–linear functional form (see Fig. 2), as proposed in H3. Volume has no effect on low- and medium-valence products.

Hence, H2 is only partially supported (p-value < .01) because although volume increases the importance of valence at a high level, it has no significant moderation effect for medium- or low-valence eBook readers. The missing but expected moderation effect between volume and low valence leaves room for speculation about the existence of the aforementioned awareness effect (Dellarocas et al., 2007; Duan et al., 2008) or any other direct and positive effect of volume. The negative impact of low valence might simply compensate for the positive effect of volume, leaving no measurable effect at all. However, we doubt that this interpretation holds (in line with Duan et al., 2008), as we also find no moderation effect for medium valence with high volume. Medium valence, in contrast to low valence, has a positive effect and therefore cannot cancel out the effect of volume. It appears more rational that given the very low choice count for low valence products in the experiment, volume simply has no impact because all customers generally avoid choosing low valence products.

The interpretation for variance also changes. Fig. 2 shows the influence of valence moderated by variance. In line with the effect of variance in Model 1, adding high variance to a high- or medium-valence eBook reader decreases choice probability. This effect is very strong for high valence and is notable for medium valence (in line with H4a, p-value < .01), but if the valence is low, the opposite effect arises. As a result, the purchase probability increases (in line with H4b, p-value < .01). Although the findings of Sun (2012) are not entirely in line with our results, at this point, we do agree with her conclusion regarding the relationship between valence and variance. Variance does not have a unidirectional effect on choice; it moderates the impact of valence. Variance per se is neither good nor bad. It depends on the valence level of the product.

Model robustness: To assure the robustness of our estimation results, we additionally estimate several alternative model specifications. Specifically, we estimate a model with the same variables as Model 2 but with "full interaction" among the variables; i.e., we additionally interact volume with variance and allow for three-way interactions between valence, variance, and volume. Furthermore, we estimate a model comparable to Model 2, for which we recorded volume and variance to have an equal number of levels (3 levels; low, medium, high) to check for a potential bias due to level effects. Finally, we estimate two models by using the numerical values for valence, variance, and volume. The first model is estimated according to our conceptual framework, and the second model allows for "full interaction". Overall we find no systematical differences across the estimated models,[3] demonstrating the robustness of our estimation results presented in Table 4.

4.3. Impact of online customer reviews on customers' valuation of brand, price, and technical attributes

In this analysis (Model 3), we investigate the extent to which the presence of OCRs influences the importance of product attributes (i.e., brand, price, and technical attributes), and we focus on testing hypotheses H5, H6, and H7. For Model 3, we pool the data for the control (without OCRs) and treatment groups (with OCRs). Combining the data for the control and treatment groups enables us to measure the impact of OCRs on product attributes. We do so by introducing a binary variable that indicates the treatment group (treatment_indicator = 1). A significant interaction between this variable and a product attribute variable indicates that OCRs significantly influence the consideration of the product attribute among participants in the treatment group. Table 5 reports the results for Model 3. The OCR dimensions (comparable to Model 2) are not reported for brevity here, but they are included in Model 3.

As shown in Table 5 and Fig. 3, all coefficients for the product attributes significantly decrease, indicating that the presence of OCRs decreases the impact of every product attribute on customer choice. This result means that customers deliberately look for quality signals such as those provided by OCRs and use them for purchase decisions.

To underpin this finding, we additionally inspect the change in the decision weights ascribed to the product attributes depending on whether OCRs are present or not (based on Model 3) by normalizing the decision weights of the product attributes in both situations to 100%. The reason for this additional inspection is that additional information (i.e., OCRs) is available to the treatment group, while such information is not present for the control group. The mere existence of additional information might therefore lead to a systematic bias in the part worth estimations for the product attributes. This systematic bias should then be eliminated if the decision weights ascribed to the product attributes are normalized to 100% and thus the decision weights should not change.

[3] Detailed results for all robustness checks are available from the authors upon request.

Table 5
Model 3, estimation results — impact of OCRs on product attributes.

Attribute	Parameter			Coefficient	SE	Sig.
Brand	Amazon			.851[h]	.079	***
	Amazon	X	Treat	−.531	.091	***
	Amazon[C]			.320		
	Sony			.797	.077	***
	Sony	X	Treat	−.557[h]	.092	***
	Sony[C]			.240		
Battery lifetime	Batt_10			−2.086[h]	.115	***
	Batt_10	X	Treat	1.056	.101	***
	Batt_10[C]			−1.030		
	Batt_15			−.738	.070	***
	Batt_15	X	Treat	.378[h]	.085	***
	Batt_15[C]			−.360		
Control	Keyboard			−1.916[h]	.099	***
	Keyboard	X	Treat	.881	.087	***
	Keyboard[C]			−1.035		
Price	Price			−5.755	.263	***
	Price	X	Treat	2.296[h]	.257	***
	Price[C]			−3.459		
	no_choice			−8.090	.357	***
	no_choice	X	Treat	6.559	.365	***
	no_choice[C]			−1.531		

All OCR variables and their interactions according to Model 2 are included in Model 3 but are not reported.
Treat = binary variable (0 = control group; 1 = treatment group with OCRs), SE = standard error, Sig. = significance level. Number of cases = 61,680.
Reference categories: pocketbook, batt_20, touch pad.
Price has been divided by 100 for the estimation.
*** = p-value < .001; ** = p-value < .01; * = p-value < .05.
C: the values marked with c are the calculated parameter values for the treatment group.
Heterogeneity is modeled by using 100 Halton draws under the assumption of a normal distribution. 'h' indicates significant heterogeneity at the 5% level.

The decision weights for the product attributes do show changes, however. Brand (control group 11.89%; treatment group 8.49%; difference = −3.40%-points) and battery lifetime (control group 29.15%; treatment group 27.33%; difference = −1.82%-points) lose importance compared to price (control group 32.17%; treatment group 36.71%; difference = +4.54%-points) and keyboard (control group 26.78%; treatment group 27.46%; difference = +0.68%-points). It seems that OCRs reduce the uncertainty and substitute the traditional function of brand as indicator of product quality. Due to the importance of battery lifetime in other product categories, for example smartphones or Bluetooth devices, the importance of battery life for an eBook reader may be overestimated by consumers who are new to this category. By contrast, control (keyboard vs. touch pad) and price are attributes where customers more easily can make an evaluation (e.g., preferring touch pad over keyboard).

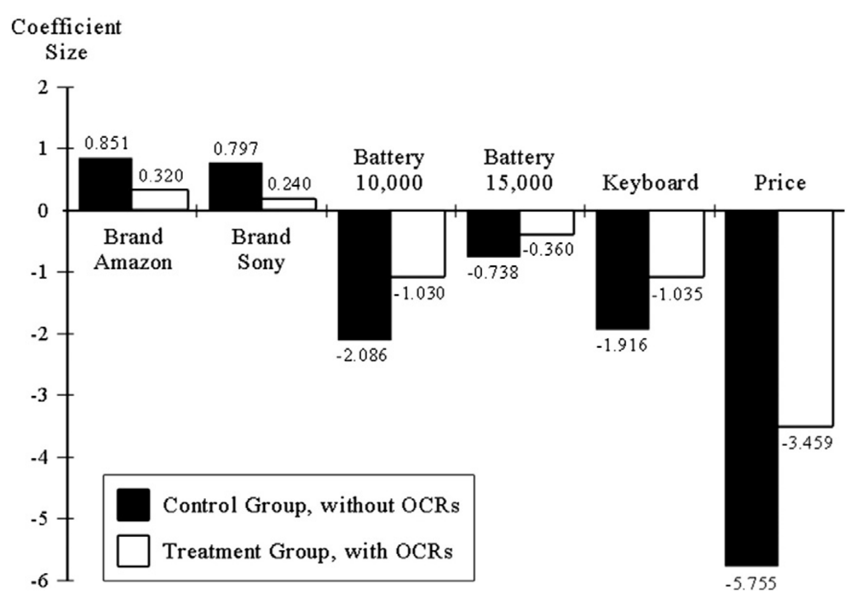


Fig. 3. Coefficients for product attributes for the control (without OCRs) and treatment group (with OCRs). Note: The coefficients are taken from Table 5, and all differences are significant (1% level; see Table 5)

From this additional analysis we cannot conclude that there is a general shift in the part worth estimated due to the mere inclusion of OCRs. Thus, while all product attributes lose importance (see Table 5) because of customers' actual consideration of OCRs, the loss of importance varies for the different product attributes.

Given the results for Model 3, H5 is supported (p-value < .01): the importance of brand for customer choice diminishes when OCRs are available. This finding is good news for no-name brands that are highly rated by customers, as even unbranded products can overcome fears about functional product risks and can find their way to the customer if they have high valence. The challenge is to achieve an initial critical volume of ratings to overcome the brand deficit. One option may be to engage in product sampling or to incentivize OCRs.

The importance of price for customer choice also diminishes when OCRs are provided. This finding is in line with H6 (p-value < .01), suggesting that the perceived risk of a mistaken investment is reduced when the quality of an eBook reader is indicated reliably (as reliably as other customers can assess it). Consequently, OCRs seem to increase prospective customers' WTP.

The technical attributes of battery lifetime and type of control become less important for customer choice when OCRs are available, although these attributes provide an object description of two performance features. This finding may illustrate how customers utilize OCRs to reduce the cognitive effort necessary to compare each product based on their attributes. Customers seem to expect the technical attributes of the most recommended products to sufficiently suit their personal requirements for product attributes and therefore seem to neglect attribute-level comparisons. This result is in line with H7 (p-value < .01).

4.4. Willingness to pay for brand and OCRs

Because our experiment includes the price of the products and a no-purchase option, we are able to calculate the WTP. The WTP is the ratio of the price parameter, which measures the in- or decrease in utility for price changes, to the utility of a certain product attribute. The implemented brands in the experiment (Amazon, Sony, and Pocketbook) are real eBook market participants; therefore, calculating their WTP is valid. Because we use a control group, we can also calculate the WTP in the case that no OCRs are present. The reported WTP values can then be interpreted as the monetary amount that customers are willing to pay to upgrade a product attribute.

Compared with Pocketbook, the popular brands show a lower increase in WTP when OCRs are available (€7.15 for Sony (0.223 / (3.115 / 100) = €7.15; see Table 4) and €9.35 for Amazon) than when OCRs are not available (control group: €12.92 for Sony and €15.21 for Amazon). By contrast, the technical attributes are associated with higher WTP; the best levels for the technical attributes are associated with a markup of €28.11 for battery lifetime (control group: €37.03) and €28.61 for control interface (control group: €36.83).

Calculating the WTP for an OCR (e.g., the WTP for a one-star increase) is more complex. First, we look at the different effects due to the interactions among valence, volume, and variance separately. Because volume and variance moderate the impact of valence, the WTP calculation is based on the different combination of valance with volume and variance. We report the respective WTP for all level combinations in Table 6.

High valence is most valuable in terms of WTP. Because low-valence products strongly discourage potential customers, the WTP for better products increases steeply. An increase in volume from 6 to 200 reviews boosts the WTP by €38.41 (€156.56–€118.15) for high-valence products, whereas a change in variance from low to high decreases the WTP (max = −€26.25 (€91.90–€118.15)). High variance can only increase the WTP for a low-valence product by the amount of €11.25.

Second, we need to calculate the intervals between the valence levels. Relating these intervals to the differences in WTP, we can calculate the average WTP per star. The average interval between the valence levels in our survey in terms of review stars (1 star = worst and 5 stars = best level) is 1.325 stars (between low and medium valence) and 1.125 stars (between medium and high valence).

Having calculated the differences in WTP for the valence–volume and valence–variance interaction as well as the intervals of the valence levels, we can combine this information to calculate the average WTP for an increase of an additional star. Regarding the valence–volume combinations (Table 6), one additional OCR star increases the WTP for an eBook reader by between €48.60

Table 6
Willingness to pay for valence & volume and valence & variance combinations.

	Valence		
	Low	Medium	High
Volume			
6	Reference = €0	€58.24	€118.15
10	€0.00	€58.24	€118.15
30	€0.00	€58.24	€140.71
100	€0.00	€58.24	€150.14
200	€0.00	€58.24	€156.56
Variance			
Low	Reference = €0	€58.24	€118.15
High	€11.25	€54.30	€91.90

Estimates originate from Model 2.
Reference category (WTP = €0): valence = low, volume = 6, and variance = low.

(volume = 6) and €65.67 (volume = 200), on average. The WTP is thereby calculated as follows (assuming the situation for a volume of 6): (€118.15 − €58.24) / 1.125 = €53.26 (from high to medium valence) and (€58.24 − €0.00) / 1.325 = €43.95 (from medium to low valence). Taking the mean leads to the result of €48.60.

If the same procedure is applied to all valence–variance combinations (Table 6), the average WTP of an eBook reader for one additional OCR star is between €32.95 (variance = high) and €48.60 (variance = low). Taking the mean over all scenarios (€48.60, €65.67, €32.95, and €48.60) leads to an average WTP of €48.96 (≈$64.20) for adding one star in an OCR. This result is similar to the finding of Jang et al. (2012) that the monetary value of a one-unit increase in valence is between $34.60 and $53.60 for the hotel industry.

Knowledge about WTP is useful for managers, who can adjust their pricing policies according to OCRs on a product during the product's life cycle. When the technology matures (for search goods), OCRs decline, and the quality/price ratio can be revised by management in consideration of the OCRs.

5. Discussion and conclusion

This study aims to investigate the relationship between OCRs and product choice probability. Based on a conceptual framework that builds on an extensive literature review, we test our hypotheses by conducting a choice-based conjoint experiment. Specifically, this study i) decomposes OCR into valence, volume, variance, and investigates their interactions and ii) examines the impact of OCRs on customers' valuation of brand, price, and technical attributes.

Our investigation differs from prior studies because of its experimental character and focus. The use of an experiment permits us to test how OCRs and their dimensions affect customer choice behavior. By contrast, previous OCR research is mainly based on market data (e.g., sales prediction), whereas the results of this study are based on experimental data to gain a deeper understanding of how customers address OCRs in isolation from endogeneity and any external marketing activities (e.g., advertising). This study makes several contributions to the literature. First, we analyze all three OCR dimensions and their interactions in a discrete choice experiment. Valence, representing the average rating, has a strong impact on customer choice: the higher the valence is, the higher the choice probability will be.

Volume, the number of reviews, and variance, the distribution of ratings, moderate the impact of valence on customer choice. Volume increases the positive impact of high valence on customer choice with a diminishing marginal effect; the more people agree with a very good rating, the higher the choice probability will be. Volume exerts no effect on medium- and low-valence products.

High variance increases the choice probability for low valence level but has the opposite effect with medium or high valence. Uncertainty, represented by high variance, is beneficial for poorly rated products and detrimental for highly rated products.

The results of this study are important for any future analysis of or predictions incorporating OCRs in scientific studies as well as decision support systems for marketers. Ignoring these interaction effects could cause biased results and predictions.

Second, the relevance of OCRs for choice decisions is clearly confirmed by our results. By adding a control group, we show how the importance of brand, price, and technical product attributes changes based on the presence of OCRs. According to the results, the importance of all product attributes decrease in the presence of OCRs because information about quality and performance is provided by the OCRs.

In our experimental setting, in particular, the impact of brand on customer choice diminishes in the presence of OCRs. This is a remarkable finding for brands that serve their customers primarily through online retailers. Brand managers have to acknowledge the increasing transparency in competition due to online word-of-mouth. Because OCRs cannot or should not be manipulated, different strategies should be applied to adapt to the new digital environment. For no-name brands, our results suggest that such brands can compensate for their lack of brand equity by investing in product quality, which may subsequently lead to high OCRs. Existing brands are encouraged to implement appropriate expectation management for their customers, because overselling the qualities of a product might backfire later. The importance of implementing proper segmentation and considering segment-specific needs also increases in the presence of OCRs, because a one-fits-all product policy enables niche suppliers to become competitive because of positive OCRs.

Motivating satisfied customers to share their experience becomes essential, and such customers should be incentivized to do so (at least by reminding the customers of their possibility to support the brand). Sampling as a strategy to receive OCRs early after a new product launch could also facilitate the long-term success of a product by becoming an OCR leader. Also buying premium product placement in online stores may pay off twofold by increasing sales immediately and providing positive OCRs for increased sales subsequently.

Another strategy for brand management seems to be effective but is beyond the reach for many brands: become untouchable to electronic word-of-mouth by building a strong brand. Brand loyalty emerges as a crucial factor that may protect brands from being truly evaluated against others based on their OCRs. If loyalty originates from an emotional affinity to the brand rather than functional conviction, then OCRs are more likely to be skipped during purchase decisions, and the new digital world offers many opportunities to strengthen the relationship between a brand and its audience (e.g., social media). Branding in a digitally empowered world therefore means balancing investments in product quality leading to higher OCRs (electronic word-of-mouth) and brand advertising. Brand equity is not a major concern for the reliability of our experiment, as none of the brands had a strong reputation in the eBook reader market by the time that the experiment was conducted (due to the novelty of the category). However, Ho-Dac et al. (2013) show that strong brands seem to be shielded against the impact of OCRs (though strong brands were always backed with many positive OCRs in their study). Further, according to their findings, a brands' transition from weak to strong can be facilitated by positive OCRs, which create a positive feedback loop between sales and OCRs. Therefore, the early stages of the product life cycle are most crucial, when none of the brands in the product category can rely on category reputation.

Furthermore, our results suggest that price sensitivity is reduced when OCRs are available. Because OCRs provide additional reliable information about the true product quality, the perceived risk seems to decrease while the overall WTP rises. Thus, managers might use OCRs as an indicator for future price changes, because OCRs reflect customers' perception of the price–performance ratio. A deterioration of valence might be a signal that new (improved) products have entered the market or that existing competitors have caught up, because better or cheaper substitute products negatively affect the perception of the price–performance ratio. A price reduction by the management could then counterbalance the shifting ratio. This finding is supported by Shin et al. (2011) who investigate the relationship between reviews and the market price of products. Indeed, they report a responsiveness of market prices to positive and negative reviews, whereas prices are assumed to reflect customers' WTP. The monetary value for popular electronic brands in our study is rather low (€7 to €9 in comparison to the least preferred brand), whereas the most appreciated performance features are valued €28 higher than the lowest reference level. Nevertheless, OCRs are most valuable for customers, with an average WTP for an eBook reader of €48.96 for an additional valence unit.

Given the high impact of OCRs on customer choice (both positive and negative) and on other product attributes one may think of a dominant management strategy for managing OCRs. OCRs could be displayed whenever valence and volume are both high, and when valence becomes low, OCRs could then be omitted to emphasize the brand. However, such a management strategy is neither promising nor realizable. First, retailers, not manufacturers, decide whether to display OCRs. Second, even if the manufacturer operates its own online store, consistency among products is mandatory. Customer would easily notice the contradiction that OCRs are only present if they are of high valence. In fact, once OCRs become subject to managerial arbitrariness they will lose their trustworthiness and therefore impact. Quite naturally, we strongly encourage every manufacturer to highlight a good OCR for its customers.

6. Limitations and future research

Of course, our study has some limitations. Our empirical analysis is based on a student sample and on a single product category. Although we believe that students represents one of the target groups for eBook readers and although we carefully selected the eBook category for our experimental study, we cannot generalize the results to all product categories. Replications of the study with other product categories and other samples would be useful.

Moreover, in our study, we focus on the quantitative OCRs. Of course, many retailers (e.g., *Yahoo! Movies or bestBuy*) allow for a written statement to back up the rating (e.g., Chakravarty, Liu, & Mazumdar, 2010; Liu, 2006). Thus, often both quantitative and qualitative reviews are available to the customers. Furthermore, qualitative reviews can be found on blogs (Gopinath, Chintagunta, & Venkataraman, 2013) or on forums (Gopinath, Thomas, & Krishnamurthi, 2014). Although the summary statistic (which is used in this study) should summarize the argumentation provided within customers' written text, it may provide additional insight into why a certain rating was chosen; thus, extending our analysis with qualitative OCRs would be interesting.

Hennig-Thurau, Gwinner, Walsh, and Gremler (2004) investigate the motivations of customers who post their opinions online. The authors identify a desire for social interaction, economic incentives, concern for other customers, and the possibility of enhancing one's self-worth as the main drivers. However, little research thus far has addressed the opposite side, namely, personal factors that affect the influence of OCRs during the purchase process. To the best of our knowledge, only Zhu and Zhang (2010) explore the influence of personal characteristics by demonstrating the moderating role of customers' Internet experience on the evaluation of OCRs. However, Internet experience is not related to customers' actual decisions. OCRs constitute external information for potential customers because they are not available through customers' memory. We assume that new external information influences customer choice based on the degree to which the customer needs it, which means that OCRs only affect customer choice when the customer has a need for additional information. The more additional information needed by the costumer to make a decision, the more information will be searched (i.e., external search effort, see Beatty & Smith, 1987). Furthermore, the more that a customer needs certain information to make a satisfactory choice, the more that the customer will consider the information (i.e., OCR) during the choice decision.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.ijresmar.2014.12.004.

References

Amblee, N. F., & Bui, T. (2011). Harnessing the influence of social proof in online shopping: The effect of electronic word of mouth on sales of digital microproducts. *International Journal of Electronic Commerce*, *16*(2), 91–113.

Beatty, S. E., & Smith, S. M. (1987). External search effort: An investigation across several product categories. *Journal of Consumer Research*, *14*(1), 83–95.

Bickart, B., & Schindler, R. M. (2001). International forums as influential sources of consumer information. *Journal of Interactive Marketing*, *15*(3), 31–40.

Chakravarty, A., Liu, Y., & Mazumdar, T. (2010). The differential effects of online word-of-mouth and critics' reviews on pre-release movie evaluation. *Journal of Interactive Marketing*, *24*(3), 185–197.

Chen, Y., Wan, Q., & Xie, J. (2011). Online social interactions: A natural experiment on word of mouth versus observational learning. *Journal of Marketing Research*, *48*(2), 238–254.

Chen, Y., & Xie, J. (2008). Online consumer review: Word-of-mouth as a new element of marketing communication mix. *Management Science*, *54*(3), 477–491.

Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. *Journal of Marketing Research*, *43*(3), 345–354.

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

Clemons, E. K., Gao, G., & Hitt, L. M. (2006). When online reviews meet hyperdifferentiation: A study of the craft beer industry. *Journal of Management Information System*, *23*(2), 149–171.

Cui, G., Lui, H. K., & Guo, X. (2012). The effect of online consumer reviews on new product sales. *International Journal of Electronic Commerce*, *17*(1), 39–57.

Dellarocas, C., Zhang, X., & Awad, N. F. (2007). Exploring the value of online product reviews in forecasting sales: The case of motion pictures. *Journal of Interactive Marketing*, *21*(4), 23–45.

Dhar, V., & Chang, E. A. (2009). Does chatter matter? The impact of user-generated content on music sales. *Journal of Interactive Marketing*, *23*(4), 300–307.

Duan, W., Gu, B., & Whinston, A. B. (2008). Do online reviews matter? — An empirical investigation of panel data. *Decision Support Systems*, *45*(4), 1007–1016.

Erdem, T., & Swait, J. (1998). Brand equity as a signaling phenomenon. *Journal of Consumer Psychology*, *7*(2), 131–157.

Erdem, T., Swait, J., & Louviere, J. (2002). The impact of brand credibility on consumer price sensitivity. *International Journal of Research in Marketing*, *19*(1), 1–19.

Feng, J., & Papatla, P. (2011). Advertising: Stimulant or suppressant of online word of mouth? *Journal of Interactive Marketing*, *25*(2), 75–84.

Godes, D., & Mayzlin, D. (2004). Using online conversations to study word-of-mouth communication. *Marketing Science*, *23*(4), 545–560.

Gopinath, S., Chintagunta, P. K., & Venkataraman, S. (2013). Blogs, advertising, and local-market movie box office performance. *Management Science*, *59*(12), 2635–2654.

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.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer–opinion platforms: What motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, *18*(1), 38–52.

Ho-Dac, N. N., Carson, S. J., & Moore, W. L. (2013). The effects of positive and negative online customer reviews: Do brand strength and category maturity matter? *Journal of Marketing*, *77*(6), 37–53.

Jang, S., Prasad, A., & Ratchford, B. T. (2012). How consumers use product reviews in the purchase decision process. *Marketing Letters*, *23*(3), 825–838.

Jiménez, F., & Mendoza, M. (2013). Too popular to ignore: The influence of online reviews on purchase intentions of search and experience products. *Journal of Interactive Marketing*, *27*(3), 226–235.

Kostyra, D. S., & Reiner, J. (2012). *Does design matter? An empirical investigation into the design-impact of online review systems. Working paper*.

Lewis, M. (2004). The influence of loyalty programs and short-term promotions on customer retention. *Journal of Marketing Research*, *41*(3), 281–292.

Liu, Y. (2006). Word of mouth for movies: Its dynamics and impact on box office revenue. *Journal of Marketing*, *70*(3), 74–89.

Louviere, J., & Woodworth, G. (1983). Design and analysis of simulated choice or allocation experiments: An approach based on aggregate data. *Journal of Marketing Research*, *20*(4), 350–367.

Lovett, M. J., Peres, R., & Shachar, R. (2013). On brands and word of mouth. *Journal of Marketing Research*, *50*(4), 427–444.

Moe, W. W., & Trusov, M. (2011). The value of social dynamics in online product ratings forums. *Journal of Marketing Research*, *48*(3), 444–456.

Park, D. H., Lee, J., & Han, I. (2007). The effect of on-line consumer reviews on consumer purchasing intention: The moderating role of involvement. *International Journal of Electronic Commerce*, *11*(4), 125–148.

Schlereth, C., & Skiera, B. (2012). DISE: Dynamic Intelligent Survey Engine. In A. Diamantopoulos, W. Fritz, & L. Wiesbaden Hildebrandt (Eds.), *Quantitative Marketing and Marketing Management — Festschrift in Honor of Udo Wagner* (pp. 225–243). Gabler Verlag.

Shin, H. S., Hanssens, D. M., Kim, K., & Gajula, B. (2011). Impact of positive vs. negative sentiment on daily market value of high-tech products. *Working paper*.

Sridhar, S., & Srinivasan, R. (2012). Social influence effects in online product ratings. *Journal of Marketing*, *76*(5), 70–88.

Sun, M. (2012). How does variance of product ratings matter? *Management Science*, *58*(4), 696–707.

Völckner, F. (2008). The dual role of price: Decomposing consumers' reactions to price. *Journal of the Academy of Marketing Science*, *36*(3), 359–377.

Yang, J., & Mai, E. S. (2010). Experiential goods with network externalities effects: An empirical study of online rating system. *Journal of Business Research*, *63*(9–10), 1050–1057.

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*(2), 133–148.