Does the length of a review matter in perceived helpfulness? The moderating role of product experience

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Abstract

Purpose – This paper aims to offer a framework explaining how product experience (i.e. think vs feel) and product involvement (high vs low) influence the helpfulness of online reviews. It also reexamined how online consumer review dimensions help to build online review helpfulness under different contexts.

Design/methodology/approach – Data were collected using content analysis on 1,200 online customer reviews on 12 products from four categories to measure the relationships between online review dimensions and the helpfulness of reviews. The regression analysis and analysis of variance (ANOVA) were used to test the hypotheses.

Findings – The findings indicate that the effectiveness of length of a review is moderated by product type; for think products, longer reviews yield higher helpfulness. Furthermore, the level of consistency between individual review ratings and overall product ratings is associated with review helpfulness. The length of product descriptions and product ratings is moderated by the level of involvement. For products with high involvement, longer descriptions yield higher helpfulness.

Originality/value – A conceptual connection to customer interaction is proposed by online customer reviews that vary by product type. The findings provide implications for online retailers to better manage online customer reviews and increase the value of product ratings.

Keywords Online consumer reviews, Social media in marketing, Product involvement, Product experience, Congruity theory

Paper type Research paper

Introduction

Online consumer reviews (OCRs) have become critical determinants in informing customers about the strengths and weaknesses of different products and help them find the products that best suit their individual needs. It has been shown that OCRs with high perceived credibility play an important role in purchase decision-making; and credibility drives reliance on OCRs through consumer attitude (Mumuni *et al.*, 2019). From a consumer's perspective, while product descriptions are vendor-generated, OCRs are more user-oriented and can provide readers with a variety of scenarios (Chen and Xie, 2008). Therefore, OCRs exert a strong influence on sales, the information conveyed and purchase intention (Cheung *et al.*, 2014; Karimi and Wang, 2017; Park *et al.*, 2007).

As a consequence of the increasing significance of customer reviews in the consumer decision-making process, most e-commerce websites enable consumers to post OCRs for both the product and services they provide. However, not all OCRs are helpful. To help customers obtain information relevant for evaluating the quality and performance of products sold

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online, e-tailers attempt to use signals to highlight helpful reviews, for example, Amazon.com uses a "helpfulness" metric. It has been shown that helpful OCRs increase the sales of e-tailers (Banerjee *et al.*, 2017).

Recent research in the field of interactive marketing identified several perceptions of reviews. In terms of review outcomes, reviews have been shown to affect aggregate consumer behavior and product evaluations (Forman *et al.*, 2008; Sun, 2012; Ullah *et al.*, 2016). Another stream of research examined the characteristics and motivations of reviews (Guo *et al.*, 2020; You *et al.*, 2015). For example, consumer reviews vary by product type, such as search versus experience product types (Mudambi and Schuff, 2010). Online retailers aim to provide consumers with valuable online content. However, differences have been found in the effects of the length of reviews, product types and the degree of congruity (Luan *et al.*, 2016). A recent synthesis concluded a promising direction on the impact of culture on online customer reviews motivation by reviewing related articles (Chan and Yang, 2021). Therefore, the dimensions of OCRs need to be identified to determine whether reviews are valuable sources that indeed help consumers. To distinguish between high- and low-quality OCRs, the quality of a review can be evaluated through different variables, for example, length, readability, accuracy and understandability (Mikalef *et al.*, 2017). Moreover, the helpfulness of OCRs is influenced by the category and characteristics of products (Park *et al.*, 2007). However, how consumers ultimately decide whether they can rely on a specific review has been examined rarely. Despite research on a number of review dimensions, a better understanding of the factors that enhance review helpfulness is needed for both scholars and practitioners.

In this paper, three questions are investigated. First, the effects of the two product-type dimensions of involvement versus experience on online consumer reviews' characteristics are explored. Second, the relationships between review content and evaluations are studied (e.g. number of reviews, length of reviews, length of product descriptions, product rating and helpfulness). Third, this study analyzes whether the perceived helpfulness of reviews is related to the congruity between the reviewer's opinion and the overall product rating. The findings provide valuable product information for online vendors and e-commerce researchers who aim to promote online marketing.

Literature review

Online consumer reviews

OCRs are communicated via an online forum in which consumers can share their thoughts and attitudes toward a product or service after they have experienced it. As a functional feature of online platforms, many e-commerce websites display OCRs together with their product or service descriptions.

Scholars generally agree that OCRs play an important role in increasing sales (Sridhar and Srinivasan, 2012). Research on OCRs has been conducted in a wide range of product and service categories such as travel businesses (Gretzel and Yoo, 2008), books (Chen *et al.*, 2008) and electronics (Ho-Dac *et al.*, 2013). Research on OCRs has employed laboratory experiments to understand the influence OCRs exert on purchase intention. This research identified the following factors as most influential on purchase intention: the quality of online reviews (Lee *et al.*, 2008; Park *et al.*, 2007; Shin *et al.*, 2017), the number of reviews (Park *et al.*, 2007), product involvement (Lee *et al.*, 2008; Park *et al.*, 2007), negative online reviews (Chatterjee, 2001; Eslami and Ghasemaghaei, 2018), consumer knowledge (Park and Kim, 2008), Internet shopping experience (Park and Lee, 2009), agreement with reviews (Jiménez and Mendoza, 2013) and total average rating (Ye *et al.*, 2009). Many studies focused on Amazon reviews as this particular company is a leading online retailer worldwide and information can be readily retrieved.

Previous research also corroborated the importance of online customer reviews for consumer decision-making. It is important to understand how consumers acquire information through OCRs, especially in the current Internet-driven consumption environment. For example, Lee *et al.* (2008) found that negative online consumer reviews affect consumers' attitudes toward products, especially low-involvement products. In 2011, Lee *et al.* conducted another experiment and found that OCRs with higher perceived credibility increase purchase intention (Lee *et al.*, 2011). Moreover, Wu *et al.* (2020) found that consumers rely more on OCRs with pictures, as they view pictures as an alternative explanation of reviews and tend to have a more favorable attitude toward these reviews.

Moreover, relevant studies on OCRs have clarified the relationships among product rating, helpfulness, involvement and product type. For example, Chua and Banerjee (2015) found that review helpfulness is related to the reviewer's reputation, review rating and review depth. Filieri *et al.* (2018) recently confirmed that reviews with extreme ratings are correlated to review helpfulness and the length of a review moderates the relationship between extreme rating and review helpfulness. The relationship between review relevancy and perceived information diagnosticity has also been examined (Filieri *et al.*, 2018). Likewise, gender differences and age differences have been assessed in OCR research (Kwok and Xie, 2016).

Research themes related to Amazon's OCRs can be classified into three relationship groups: between OCRs and consumer behavior, among OCR dimensions and between products and OCRs. So far, scholars have only focused on the effects OCRs exert on consumers' purchase rates, intentions and attitudes. However, as OCR dimensions often interact with each other, the relationships among these dimensions are also important for a complete understanding of OCR effectiveness. Therefore, this study investigated the relationships among OCR dimensions.

Product type

The Foote, Cone and Belding (FCB) model, developed by the company Foote, Cone and Belding Communications Inc., categorizes products based on two dimensions: product involvement (high vs low) and product experience (think vs feel) (Ratchford, 1987). Within this system, products can be classified into four different types. The first is the type of high-involvement/think products for which purchasing decisions require deep involvement and the application of rational decision-making criteria by customers. An example of this class is the purchase of a television set. Second, high-involvement/feel products require deep involvement of purchasers and the application of emotional decision-making criteria (e.g. the purchase of a luxury watch). Third, low-involvement/think products only require cursory involvement of purchasers and the application of rational decision-making criteria (e.g. the purchase of a laundry detergent). Fourth, low-involvement/feel products require little involvement of purchasers and the application of emotional decision criteria (e.g. the purchase of beverages or take-away food).

Product experience

The "think/feel" distinction is often identified as one of the basic dimensions spanning consumer behavior and consumption experiences. Prior research showed that think and feel are two modules of experiential marketing. For example, feel results in affective experiences while think results in cognition experiences (Schmitt, 1999). From the perspective of experiential marketing, the think/feel distinction is increasingly utilized by marketers to build experiential product connections with consumers (Homburg *et al.*, 2017). "Think" marketing attracts the intellect and includes both problem-solving and cognitive experiences. During the "think" experience, consumers are creatively engaged. In contrast, "feel" marketing enhances consumers' emotions and inner feelings by involving affective experiences. These product experiences range from positive moods to feelings of joy (Rather, 2020).

Part research confirmed that the think/feel distinction can be categorized into three aspects: (1) motives for purchase, (2) modes for processing and (3) focus of concern (Gutman, 1982). For example, customers mainly purchase "think" products for utilitarian and cognitive reasons (Ratchford, 1987). When purchasing a think product, the left hemisphere of the brain is processing logically and analytically. In contrast, "feel" products are purchased to satisfy emotional needs using a more synthetic and intuitive approach, which is processed in the right hemisphere of the brain (Ratchford, 1987). Because of the differences in the motives for purchasing these two product types, consumers are more likely to make rational decisions based on evaluations of utilitarian factors when purchasing "think" products, whereas they are more willing to make emotional decisions based on evaluations of hedonic-affective factors when purchasing "feel" products (Cheong and Cheong, 2021).

The FCB grid, which is widely used in marketing and advertising studies, is commonly accepted as one of the "classics." It provides a clear framework with which products can be classified into the abovementioned four different types based on the level of customer involvement and their think/feel influence. These classes aid investigations on the relationship between product involvement and OCR characteristics. For this study, three of the most popular product categories from each of the four product types were chosen and a total of 12 product categories was assessed.

Research hypotheses and conceptual model

Product type and review helpfulness. The helpfulness of OCRs is a multifaceted concept that can be influenced by several different types of qualitative and quantitative factors. Text-based information can be evaluated using the number of words or pages. Therefore, the word count has been adopted as a measure of the insights offered by online reviews as such reviews are typically delivered in text format (Huang *et al.*, 2015). According to previous research, the understandability of a review text (e.g. a product review) is directly related to its qualitative characteristics, such as readability and length (Korfiatis *et al.*, 2012).

This paper assumes that product types might affect both the length and the number of reviews. According to the heuristic-systematic model (HSM), customers use two modes of information processing when establishing their purchase process (Chen and Chaiken, 1999). Emotional content in reviews is particularly associated with heuristic information processing, whereas nonemotional content is indicative of systematic information processing. Based on the think/feel distinction, products are classified into cognitive (think) versus affective (feel) information processes. Korfiatis *et al.* (2012) found that lengthier reviews are more informative for readers and often have qualitative characteristics that differ from those of shorter reviewers. This is because the level of cognitive effort is proportional to the review length. Moreover, Mudambi and Schuff (2010) found a high correlation between review helpfulness and the number of words a review contains. These findings seem to support that the product experience moderates the relationship between the length of a review and the helpfulness a reader perceives. Thus, Hypothesis 1 is formalized:

H1. The relationship between the length of reviews and their helpfulness as perceived by customers is moderated by product type. In particular, for think products, longer reviews increase perceived helpfulness.

Product popularity is the first element of review effectiveness and represents the ability of a review to attract consumer attention (Wu, 2017). For experience products, product popularity, measured by the number of reviews, plays a powerful role (Cui *et al.*, 2012). Products with high popularity are likely perceived as highly credible, and as a result, their reviews are likely perceived as more useful and helpful for experience products. This is because of the nature of experience/emotion products. Therefore, Hypothesis 2 is proposed:

H2. The relationship between the number of reviews and their perceived helpfulness is moderated by product type. In particular, for feel products, a higher number of reviews increases their perceived helpfulness.

Product involvement and ratings. Product involvement is associated with the motivation to process information (Celsi and Olson, 1988). It has been confirmed that issue-relevant arguments and product-relevant attributes are more influential in high-involvement products, while information sources and the number of arguments are more influential in low-involvement products (Chaiken, 1980; Petty *et al.*, 1983). Park and Lee (2008) argued that different product involvements affected different patterns of participants in reviews.

The length of a product description influences OCRs based on product type, and this influence can be explained by the elaboration-likelihood model (ELM). For high-involvement products, consumers carefully process the information provided by the product description. Assuming that the quality of the product description is sufficiently high, this can result in consumers changing their attitudes toward the product. For low-involvement products, the length of a product description may not be as influential because consumers do not feel compelled to process such information. A previous study showed that consumers tend to rely more on consumer reviews when purchasing high-involvement products (Park *et al.*, 2007). Such consumers likely expect to extensively use reviews for decision-making. For example, more than 50% of travel purchasers visited a message board, forum or online community prior to their online travel purchase, and one in three of these buyers reported that online consumer reviews helped them making decisions. Therefore, the length of a product description is predicted to influence the product ratings of high-involvement products.

This study assumes that product involvement is likely a key moderator for determining the consequences of behavior. According to the ELM, individuals are more likely to engage in the thoughtful and effortful processing of persuasive arguments and evidence if they are highly involved with a product (Pettey and Cacioppo, 1986). However, individuals who are less involved with a product are likely affected by noncontent elements (i.e. peripheral cues) rather than argument contents. Zhang *et al.* (2016) found that information length, information forms (e.g. narratives) and the proportion of positive/negative reviews influence the effectiveness of the persuasive argument. Thus, the helpfulness of long consumer reviews depends on involvement; a high-involvement product requires more information and consumers are more likely to leave detailed after-use information. This suggests Hypothesis 3:

H3. The relationship between the length of a product description and product rating is moderated by the involvement level associated with the product. In particular, for high-involvement products, a longer product description increases product rating.

Product rating consistency and review helpfulness. Congruity theory was originally introduced to explain how opinions change according to the congruity of presented information (Osgood and Tannenbaum, 1955). This theory explains why readers' attitudes toward a review (i.e. the helpfulness of the review) are driven by the consistency between a particular review and the overall opinion collected from all reviews. This model suggests that the object of interest (i.e. the reader of a review) evaluates both the source and the statements when forming an opinion (Shaver *et al.*, 1987). That is, congruity theory proposes that whether someone recommends or does not recommend an object, a receiver's attitude toward that object changes depending on the thoughts of the receiver on the source of the opinion.

According to congruity theory, people seek harmony when making decisions. Wang and Chou (2019) indicated that, when using advertising strategies to increase usage frequency, the use of highly game-product congruity information in the advertising process yields heavily positive attitudes toward the advertisement. The present study uses congruity theory to understand how the characteristics of reviews and reviewers might affect the perceived helpfulness of reviews. If an agreement exists between a review and the overall rating of the product, readers are more likely to trust the review and perceive it as helpful. Based on the assumption of agreement or disagreement between online reviewers' product rating and the overall rating of the product, the following congruity prediction can be derived. Assuming that a reader's attitude toward a product is initially neutral, if a review recommends the product and offers a high rating, and if this rating is consistent with the overall product rating, the review changes the reader's attitude toward the product from neutral to positive. However, if a review does not recommend the product and offers a low rating, while the overall product rating is high, the reader's attitude toward the product does not change, but rather, the reader's attitude toward the review itself becomes negative. This suggests that reviews expressing views that are extremely inconsistent with the opinion of the majority would lead to a negative attitude toward those reviews, resulting in lower trust.

H4. High consistency between an individual product rating and total product ratings increases perceived review helpfulness.

In summary, this study aims to identify the relationship among products, online consumer reviews and customer perceptions of reviews as well as products. The length of a review is important as it affects consumer decision-making. Assuming that longer reviews provide more information, they might help to increase consumer confidence regarding a purchase decision (Mudambi and Schuff, 2010). While the direct relationship between the length of a review and review helpfulness has been extensively quantified in OCRs literature, the moderating effect in the relationship between the review length and helpfulness remains unexplored. Most research in OCRs recognizes the importance of source and user characteristics in analyzing factors influencing a review as helpful (Huang *et al.*, 2015). However, the related findings imply that the product type might also be an important factor to consider when investigating the moderators of review helpfulness.

Based on the hypotheses presented above, the assumed relationships among variables are shown in Figure 1.

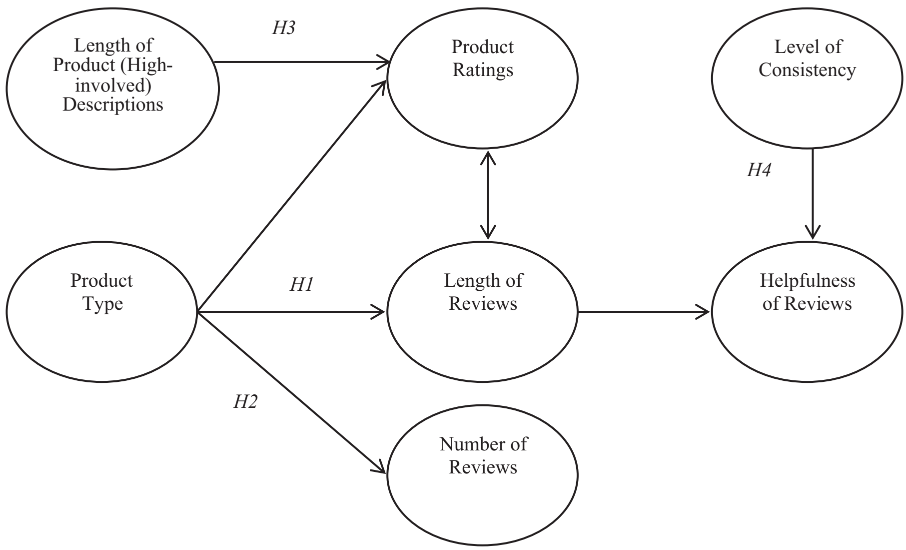

Figure 1.
Proposed relationships among variables

Methods

Sample selection

Retailers such as Amazon.com played a critical role in the ability of US customers to purchase groceries and other household essentials. Amazon.com provides a variety of OCR information (e.g. comments, stars and review helpfulness) and users leave their opinions about products and services through the information platform. To test the proposed research hypotheses, the OCRs of Amazon.com were investigated.

By applying the FCB grid, products can be categorized into four different types: high-involvement/thinking, high-involvement/feeling, low-involvement/thinking and low-involvement/feeling. The unit of analysis was one OCR. Three products, representing each of four FCB product types, were selected (i.e. high-involvement/thinking: digital camera, washing machine, instant film camera; high-involvement/feeling: hair colorant, wall sticker, perfume; low-involvement/thinking: insect repellent, laundry detergent, paper tower; and low-involvement/feeling: peanut butter, regular soft drink, snack). One hundred reviews on each selected product were gathered according to the post dates. In total, 1,200 consumer reviews were collected for analysis (i.e. 4 product types $\times$ 3 products $\times$ 100 reviews).

Coding scheme

Based on the proposed hypotheses, information was collected on the length of reviews, the number of reviews a given product received, product ratings, the length of each product description, the helpfulness of reviews, the overall degree of congruity, the congruity of the product review and the publication date.

The total number of reviewers who rated a review and the number of customers who found the review helpful are shown at the top and bottom of each product review, respectively. Additionally, the percentage of people who voted the review as helpful was coded.

The *length of reviews* represents the number of words the review contains. The *number of reviews* represents the total number of individual reviews a product received. The variable *product rating* corresponds to the star rating of the review on a product. This star rating ranges from 1 (low) to 5 (high). The *length of a product description* refers to the textual description providing important information about a product or service (e.g. available colors, weights or protection plans). OCRs and product descriptions are differentiated in terms of their sources: The manufacturer or seller usually provides the product description. The length of a product description is defined as the number of words it contains. The *helpfulness of reviews* refers to other users' evaluations of OCRs. When consumers read a review, they can rate it according to its helpfulness. The *degree of congruity* is measured by the consistency of the review according to these three designations: consistent (high fit), moderately consistent (moderate fit) and inconsistent (low fit). These designations are compared to other reviews of the same product. To measure congruity in terms of consistency, the absolute value of the difference between a product's overall score and the review's rating was calculated, yielding a value from 0 to 4. For example, if the product's overall score is 5 and the reviewer's rating is 1, the absolute value of inconsistency is 4. Therefore, consistency was categorized into three levels: an absolute value from 0 to 1 represents a high fit (low inconsistency), from 1 to 3 represents a moderate fit (moderate inconsistency) and from 3 to 4 represents a low fit (high inconsistency). The *release date* represents the number of months since the product was launched on the online shopping site. This variable might be a confounding factor and was therefore used as a control variable. For example, assuming that Product A was released one year ago and received 500 reviews, while Product B was released one week ago and received 100 reviews, it cannot be concluded that Product A is far more popular than Product B, as the release date also needs to be considered.

Administration

In accordance with the FCB grid, products are classified into four types. Three product categories from each of four product types were chosen based on the high popularity of the product on Amazon.com. The 12 products have been presented in Section 4.1. In each product category, the most popular seller was used as the target sample. The most popular product was identified by choosing the option to rank the products by the newest and most popular. The popularity ranking was created by an Amazon.com internal mechanism. However, if the most popular product had fewer than 100 customer reviews, the second most popular product was chosen (and so on), until a product was found that met all criteria.

Customer-review comments were retrieved for each product. In detail, the first review was retrieved and then, every third review thereafter was also retrieved. Each review was copied and pasted into a word document. The entry of each date was separated into records (the review) and fields (the data in each review). Fields were extracted from the coding sheet.

Coding procedure

Two authors conducted the coding. All anecdotes were numbered, formatted and pasted into a Word document. Each coder was responsible for coding two product types, containing six products and 600 reviews in total. The authors counted the words in each customer review and the product description by using the "Word Count" function under the "Review" menu of Microsoft Word. Also, the star rating (from 1 to 5) of the review, the total number of reviews a specific product received, the total number of people who voted on the question "Was this review helpful to you (yes/no)?", the total number of people who voted "yes," and the level of consistency of the review were recorded. By using the release date, the length of time the product has been available for sale was calculated and a relevant figure was lotted in Microsoft Excel, 8E. The results of the above coding were also obtained via Excel. The percentage of people who voted a review as helpful was calculated using the "Formula" function in Excel.

To test the reliability of the procedure, the two researchers randomly exchanged 100 reviews (i.e. 16.7% of the total reviews were exchanged) and re-evaluated them (Riffe *et al.*, 2005). Intercoder reliability was calculated using Cohen's Kappa. The overall result was 0.94. In detail, Cohen's Kappa for the release date was 0.95, for the length of review, it was 0.92, for the product star rating, it was 0.92, for the total number of people who voted "yes," it was 0.87 and for the total number of people who voted it as helpful, it was 0.83. The level of reliability for each coding category was well above the acceptable threshold of 0.80 as suggested by Riffe *et al.* (2005).

Results

H1 predicts that product type mediates the relationship between the length of a review and its helpfulness. The helpfulness of a review was initially measured by dividing the number of consumers who answered "yes" to the question "was this review helpful" by the total number of consumers who answered the question. To test H1, a simple linear regression was conducted, and a significant relationship was found, as shown in Table 1.

To further confirm that product types exert a significant influence on the length of a review, ANOVA was conducted. The descriptive statistics of the length of reviews of product type sets are presented in Table 2. The results show a significant correlation between both product involvement and the length of reviews, $F(1, 1{,}196) = 28.35$, $p < 0.000$, as well as product experience and the length of reviews, $F(1, 1{,}196) = 13.90$, $p < 0.000$. Moreover, a significant interaction effect of involvement and product experience on length of reviews was found, $F(1, 1{,}196) = 3.97$, $p < 0.05$. Follow-up t-tests indicate that, in the think-product condition, longer customer reviews lead to higher helpfulness ($M = 4.00$ vs $M = 3.09$, $t = 2.34$,

$p < 0.02$). This pattern suggests that consumers who are purchasing think products tend to favor longer customer reviews and evaluate these as more helpful.

Figure 2 presents a visual representation of this interaction. The evidence supports H1.

H2 predicts that product type mediates the relationship between the number of reviews and review helpfulness. The hypothesis was tested via ANOVA. No significant effects or interaction effects of product type on the number of reviews were found; thus, H2 is not supported.

H3 predicts that a longer product description is associated with a higher product rating for high-involvement products. To test H3, two-way ANOVA was conducted, for which, the

	Beta	*t*-value	Sig
Constant		18.712	0.000
Length of review (word count)	0.286	10.326	0.000
ANOVA summary			
R^2	0.082		
F-value	106.633		
Sig	0.000		

Table 1. Results of linear regression analysis

Involvement	Think/feel	*N*	Mean	SD
High	Think	300	75.650	116.057
	Feel	300	49.050	83.112
	Total	600	62.350	101.728
Low	Think	300	41.633	62.587
	Feel	300	33.560	40.581
	Total	600	37.598	52.855
Total	Think	600	58.642	94.701
	Feel	600	41.305	65.804
	Total	1,200	49.973	81.969

Table 2. Descriptive statistics of the length of reviews

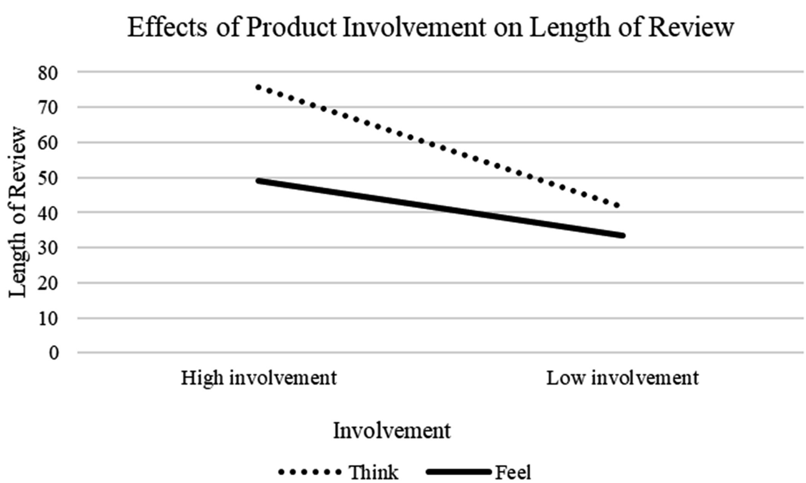

Figure 2. Effect of product involvement and think/feel products on the length of a review

length of product descriptions was converted from a continuous variable to a categorical variable. The median score was used to create two groups: long descriptions with a higher-than-median score and short descriptions with a lower-than-median score. The descriptive statistics are listed in Table 3. A significant interaction effect of product involvement and the length of the product description on product ratings was found, $F(1, 1{,}196) = 14.46, p < 0.000$. This interaction is presented in Figure 3.

To make multiple comparisons of the involvement and length of the product description with product ratings, post hoc tests were conducted using Bonferroni adjusted alpha levels of 0.00625 per test (0.05/8). The statistical outcomes (shown in Table 4) presented significant

Table 3. Descriptive statistics of the individual review rating score

Involvement	Product description	*N*	Mean	SD
High	Long	400	3.988	1.420
	Short	200	4.50	1.042
	Total	600	4.157	1.327
Low	Long	200	4.595	1.003
	Short	400	4.565	0.967
	Total	600	4.575	0.978
Total	Long	600	4.190	1.327
	Short	600	4.542	0.992
	Total	1,200	4.366	1.184

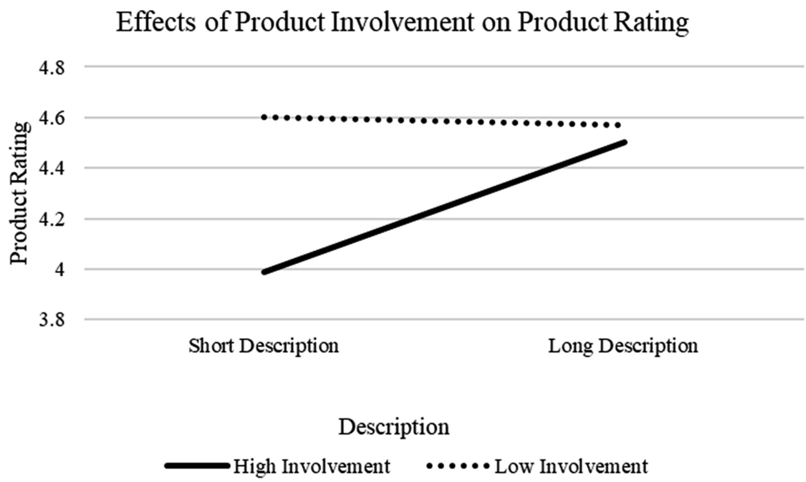

Figure 3. Effect of product involvement and product-description length on the product rating

Table 4. Results of linear regression analysis

	Beta	*t*-value	Sig
Constant		22.740	0.000
Difference between total and individual rating	−0.146	−5.111	0.000
ANOVA summary			
R^2	0.021		
F-value	26.126		
Sig	0.000		

differences between high-involvement products with long product descriptions, high-involvement products with short product descriptions and low-involvement products with short product descriptions. However, no significant difference was found in product ratings between short and long product descriptions for low-involvement products. The results of follow-up *t*-tests indicate that in the high-involvement product condition, products with a long description condition obtained higher product ratings than products with a short description ($M_{long} = 4.30$ vs $M_{short} = 2.19$, $t = 2.84$, $p < 0.02$). However, in the low-involvement product condition, the differences between long descriptions and short descriptions were not significant ($M_{long} = 3.01$ vs $M_{short} = 2.89$, $t = -0.30$, $p = 0.76$). This pattern enables two conclusions. First, the relationship between product description and product rating is partially moderated by the degree of product involvement. Second, if products are considered high-involvement products, consumers would like to obtain more information and user feedback related to the product and need to feel more secure than for low-involvement products. Overall, H3 is partially supported.

H4 predicts that a higher level of inconsistency between individual product ratings and total product ratings would decrease review helpfulness. To test H4, ANOVA was conducted. Inconsistency was calculated as discussed in Section 4. Thus, an inconsistent database was obtained with values between 0 and 4. The results show that significant differences exist in helpfulness among the levels of inconsistency (Table 4). Additionally, post hoc tests using Bonferroni adjusted alpha levels of 0.00833 per test (0.05/6) showed that all comparisons were significant. This evidence supports H4.

Discussion

The study generated meaningful findings on the relationships among product characteristics, consumer participation in online reviews and responses to the reviews of others. The findings showed different concepts of review helpfulness emerge for think and feel goods. The result for product type is consistent with the findings of Sen and Lerman (2007). In their study, utilitarian products yielded more active interactivity (e.g. consumer participation on helpfulness ratings) than hedonic products. The present study also shows that think (i.e. utilitarian) products are positively associated with consumer interactivity (e.g. length of reviews).

Moreover, the ELM (Pettey and Cacioppo, 1986) motivated the prediction of the effect of the length of product descriptions on product ratings for high-involvement products. More specifically, for high-involvement products, but not for low-involvement products, a difference in product ratings was expected between short and long descriptions. The test confirmed that only for high product involvement, a positive relationship exists between a long product description and product ratings.

Finally, this paper presents an exploration of the association between the length and perceived helpfulness of an online review moderated by product type. Most previous OCR studies set review length as a control variable, assuming that the length of reviews affects the quality and quantity of information provided (Lee *et al.*, 2008; Park *et al.*, 2007). Although both studies conceded the influence of review length, a specific focus on the influence of review length is still necessary. Interestingly, high inconsistency was negatively associated with review helpfulness. In other words, if total product ratings differ from the product rating of a particular review, consumers tend to perceive the review as not helpful and *vice versa*.

Theoretical contributions

This study makes several contributions to the literature. First, by using the developed comprehensive review model, the relationships among review characteristics can be better understood. For example, based on this study, product type (high/low involvement and think/feel) can be understood as an influential element of a review, which leads to differences in helpfulness and the rating of a review. The introduction of product experience also shed light on the moderating effect. This research further defined experience products (think/feel) from utilitarian/hedonic products and confirmed that this mode of information processing or category of motives influences the helpfulness of the review.

Second, congruity theory applies in this study. Specifically, the range of individual and average star ratings was divided into three levels of high, moderate and low. The least consistent reviews were the least helpful. Therefore, reviews with lower consistency have the least power to affect customer's trust evaluation.

Third, customers are more likely to extend negative feelings toward a review if any inconsistency exists between the review and the overall rating. It has been posited that the likelihood to vote on a review may demonstrate a "bandwagon effect" (Mudambi and Schuff, 2010). Therefore, further research needs to be conducted, testing whether a conformity process, such as the bandwagon effect, exists when customers rate a review.

Practical implications

The CBR has changed from the traditional mode of visiting storefronts to shopping at home via e-commerce platforms. Therefore, OCRs can be interpreted as a basic method of online communications. OCRs play an essential role in interactive marketing. According to Wang (2021), interactive marketing can be defined as two-way value creation and mutually influencing the marketing process of active customer connection, engagement, participation and interaction. User-generated content marketing, where customers share their purchase and use experience, is increasingly used in content marketing (Wang, 2021). This new form of product evaluation process helps consumers to skip an inconvenient shopping procedure and reduce the risk of abandoning purchase actions.

Engaged consumers are more likely to advocate the company and its products, provide positive statements and feedback on products and share experiences with the brand within the brand community (Corrêa *et al.*, 2020). Consumers present their engagement with the company and brand by writing reviews on the product page and giving recommendations. In this context, the findings of this study are applicable to online stores in identifying the relationship between consumer engagement to the brand and intention of using the brand or product. For example, the level of consistency of reviews may influence a customer's attitude toward a product. Based on the findings of this study, customers are most likely to trust an individual review if it is consistent with other reviews. If reviews show a consistently positive opinion of a product, customers tend to believe those positive evaluations while ignoring negative evaluations. Therefore, online retailers should pay more attention to reviews with ratings that are close to the average product rating. If replying to all reviews is too time-consuming, it would be more useful to reply to reviews near the average since these reviews influence future customers. Moreover, for high-involvement products, the product description is positively associated with the star rating of the product. If this relationship is causal, online retailers who sell high-involvement products should try to describe a product comprehensively, providing as much detail in the overview of the product as possible. This will yield a higher star rating.

The results also show that longer reviews achieve a higher helpfulness ranking for thinking products. Longer reviews are perhaps more valuable to online retailers who sell thinking products, regardless of whether positive or negative attitudes about the product are communicated. To facilitate this, online retailers can implement promotion policies, for example, by providing coupons for OCRs with more than 100 words. Long positive online reviews exert a stronger impact on future consumers and can attract potential buyers. In contrast, long negative online reviews allow retailers to read carefully and resolve problems mentioned in the reviews. In this way, negative consumer reviews can help retailers as the suggestions originate directly from consumers.

Limitations and future research

The study is subject to some limitations that should be addressed in the future study. Firstly, only 12 products were considered. Although the sample size for each product is sufficient, claims for products outside of this sample cannot be made. Further research is needed to assess other products within these categories.

OCRs are receiving considerable interest and provide much scope for future research, as OCRs are considered as the second-most trusted source of purchase information, after family and friends (Salehan and Kim, 2016). For example, businesses have started to incentivize buyers with a variety of discounts and promotions for posting positive reviews. This phenomenon is popular among online influencers. Such influencers are highly engaged with their audience by posting after-use reviews and unboxing videos, which attract a large number of viewers. Studies have shown that incentivized reviews tend to have a higher rating than nonincentivized reviews. In future studies, the effect of incentivized reviews on consumer decision process or customer engagement relationship toward incentivized reviews would be investigated. Moreover, the relationship among review length, helpfulness of the review and product rating can be further examined based on the review type (i.e. incentivized vs nonincentivized). Also, further research could make a step forward toward the effect of product experience. For instance, an individual's purchase decision of a feel product is more discretionary and may require more justification compared to a think product. More clarification can be studied when looking into the effect of OCRs based on product experience type.

With the changing landscape of interactive marketing, a two-way interaction dominates the CBR. Today, marketing can be delightful, engaging and inviting, thus generating more customer participation and involvement. Future studies related to interactive marketing, especially content marketing, could switch their focus from online consumer reviews to word-of-click and shoppable posts. Similar research methods may be used to examine the effectiveness of shoppable content including articles, images, photos or videos. Moreover, a recent study assessed the potential negative effects of positive customer reviews on social networking sites (Feng *et al.*, 2021), which could provide insights into detailed dimensions of customer reviews on social networking sites for further investigation.

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