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Your Expectation Matters When You Read Online Consumer Reviews: The Review Extremity and the Escalated Confirmation Effect

Jung Lee[a], Hong Joo Lee[b,*]

[a] *Associate Professor, Division of Global Business & Technology, Hankuk University of Foreign Studies, Korea*
[b] *Associate Professor, Department of Business Administration, Catholic University, Korea*

ABSTRACT

This study examines how an initially perceived product value affects consumer's purchase intention after reading online reviews with various tones. The study proposes that associations among initially perceived overall product value, degree of confirmation resulting from reading the reviews, and final purchase intention differ across review tones such that 1) when the tone is favorable, the effect of an initially perceived product value is stronger than when the tone is critical, and 2) when the tone is extreme, the effect of confirmation is stronger than when the tone is moderate. The survey was conducted with 276 online shopping mall users in Korea, and most of the hypotheses were supported. This study asserts that the effects of online reviews should be considered together with customer's level of expectation formed prior to reading online reviews, which resulted from extensive search and screening processes that the customer went through before reading online reviews.

Keywords: Electronic Word-of-mouth, Expectation-confirmation Theory, Product Value, Review Tone

Ⅰ. Introduction

Online consumer reviews are among the most important and critical information sources for online shopping mall users[1-3]. Consumer reviews are considered more informative, objective, and reliable than seller-provided information because they show frank and unbiased opinions from diversified consumers who have already experienced the product[4,5]. The reviews illustrate various details of the product, often with hints of criticism, whereas information from a seller is generally less dimensional and more biased. Online shoppers thus tend to trust consumer reviews more than seller-provided information and occasionally change their attitudes based on these online reviews[6].

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*Corresponding Author. E-mail: hongjoo@catholic.ac.kr Tel: 82221644009

However, reading consumer reviews is not the first step in online shopping. Online shopping usually begins with browsing through various products within the category of the consumer's interest, without cautiously reading online reviews[7]. Nowadays, almost everything is sold online. Consumers have to first narrow down their selection based on certain preference points, such as price and brand, because investigating all products on offer in detail and reading all related reviews are technically unfeasible for a consumer[8]. Once products are reduced to a manageable number, consumers then read consumer reviews and product specifications to determine which products would indeed best fit their needs.

An increasing numbers of products have become available online, such that the process that a consumer has to go through prior to reading the reviews (i.e., screening and narrowing down candidate products) has also become more complex and time consuming[9]. For example, selecting a hundred products among a thousand is significantly more difficult than selecting five among fifty. The more products are displayed, the more complex the decision-making process that customers have to go through. Although online shopping malls often provide various sorting options, such as date and rating, to assist consumers in narrowing down their candidate products more efficiently, the process remains an intricate one because the options and criteria for screening remain complex.

The extended and extensive screening and selection process involved in online shopping make consumers likely to build expectations about a particular product *prior to* reading online reviews. As consumers browse and narrow down their selection, they form judgments and specific preconceived perceptions of the products. For instance, screening products based on price will result in positive expectations about the price of selected items. Screening based on release date will result in positive expectations about product advancement. Such expectations that are formed prior to reading online reviews are strategically important because these expectations result in varying purchase behavior by customers even when they have read the same reviews. According to the expectation-confirmation theory (ECT)[10], different expectations result in various levels of confirmation, thereby generating different attitudes among consumers.

Interestingly, the customers' expectations formed *prior to* reading online reviews are not often discussed in literature. The numerous studies on consumer reviews have focused mostly on consumers' actions after reading reviews[11]. For instance, researchers have investigated the relationships of various characteristics of online reviews with other business factors, such as sales and prices[12,13], and they have identified factors that increase the effectiveness of online reviews[14]. Other studies have focused on the quantification aspect of consumer reviews[15] to identify their impact on consumer behaviors. Few studies have included the prior expectations of consumers in the research scope.

The current study hence suggests that the effect of online reviews should be discussed along with consumer expectations formed before reading the reviews. A research of online review effects should include consumer expectations in the analysis scope. This study investigates the effects of online reviews having different tones and hypothesizes that the total review effect is determined by the combined effects of the consumer expectations formed prior to reading the reviews, and the confirmations made based on the reviews. ECT is employed as the theoretical lens by which to explain the relationship between customers' initial expectations and subsequent behaviors, with the mediation of confirmation.

This paper is organized as follows. First, we describe existing works regarding online reviews and ECT. We then propose a research model that hypothesizes the associations among initial perceived value, review confirmation, purchase intention, and review tone. Based on the survey of 276 respondents, most of the hypotheses were supported. We then presented post-hoc analysis results to make a case for theory application. Finally, we discuss the new findings to highlight the academic contributions and practical implications of this study.

Ⅱ. Literature Review

2.1. Studies on Online Consumer Reviews

Given the critical influence of reviews on consumers' decision-making process[14], studies on online reviews have been conducted with various scopes and approaches. For example, a group of studies have focused on how helpful the reviews are for customers[16-18] and on the influential factors of their helpfulness[14]. Also, how much they can be manipulated[19], or what are the hidden motivations in writing and reading such reviews[1,20] were studied. These studies employed various validation techniques including fuzzy analytic hierarchy process[21] and text mining techniques[15,17] since these approaches are effective for observing how content is produced and for exploring the hidden rules and patterns in reviews.

Another stream of online review studies analyzed the relationships between the reviews and other business factors, such as sales[22,13] and price[12]. These studies aimed to determine the impact of review content and revealed that products and consumer types have moderating impacts[23]. Moreover, these studies demonstrated how reviews can be used for understanding consumers' preferences for different product features and to create predictive models of future sales[12]. These studies first made a significant effort to quantify the reviews and then examined their influences on various business factors.

The third approach made by online review studies is to analyze social effects via economic models. These studies hypothetically controlled social factors such as price, profit, and consumer surplus[11] and showed when and how sellers should adjust their marketing communication strategies in response to consumer reviews[24]. They also suggested that firms could benefit from altering their marketing strategies, such as pricing or advertising, to encourage positive reviews from consumers[11]. For repeat-purchase products, online reviews are known to intensify price competition and lead to lower profits[25].

2.2. Expectation-Confirmation Theory (ECT)

In 1980, Oliver[10] proposed expectation–confirmation theory (ETC) and verified that post-purchase attitude is a complex function of various previous experiences, including expectation, confirmation, and satisfaction. By analyzing the fully recursive path, Oliver[10] showed that post-purchase satisfaction is determined by the combined effect of pre-purchase expectation and the confirmation of that expectation and that post-purchase attitude is formed on the basis of post-purchase satisfaction. Oliver's study has been widely recognized and has provided insights to other researchers because it considered the attitude of the customer before purchase. Oliver highlighted that the final attitude is formed on the basis of a cognitive comparison between the anticipated satisfaction (i.e., expectation) and the received satisfaction.

ECT has often been applied in IS studies to explain the continuous usage of IS. This theory is highly effective in explaining the repeated use of IS because it takes into account previous experiences when observing current actions[26]. Other studies have extended ECT by applying different contexts, such as e-learning[27], or developed with new concepts such as playfulness[28], enjoyment[29], and online question answering communities[30]. On the other hand, Tesch et al.[31] methodologically extended this concept by measuring the gap between two parties' perceptions of the same project. Constructs that imply continuous usage, such as loyalty, were also investigated with this theory[32].

Another noteworthy application of ECT is SERVQUAL, a scale proposed by Parasuraman, Zeithaml and Berry[33]. SERVQUAL was initially designed to overcome the difficulties in measuring the quality of subjective services, such as call-center experiences. This scale was later adopted in numerous IS studies because of its high contextual applicability in the IT industry[34,35]. For example, Kettinger and Lee[36] refined the SERVQUAL measures and proposed the concept of the zone of tolerance, which represents the gap between the desired and adequate service.

Ⅲ. Hypothesis Development

3.1. Effect of Perceived Initial Product Value on Review Confirmation

When shopping online, the first action of consumers is selecting a pool of products to consider for purchasing[8], instead of immediately reading all of the consumer reviews. Although consumer review is a significant information source, reading all of the reviews prior to purchasing is nearly impossible. For example, as of October 2015, Amazon.com is displaying 30,758 types of digital cameras on their websites. Even if a consumer narrows down the category to DSLR cameras, 2,907 types remain available for purchase. Most customers spend time and effort to search and browse products first[37], and limit their product selection according to their needs and preferences. After this stage, customers would start examining product details by reading consumer reviews.

Such a screening process prior to reading online reviews builds certain expectations toward products. For example, if a consumer had screened products based on camera focusing function, he or she would have a specific expectation on a camera, such as "this camera will especially mitigate blurry photos even when my hands are not steady," before reading the reviews of the camera. If he or she has narrowed down the products based on camera resolution, his or her special expectations on this camera would be picture quality.

Such expectations are formed based on key product information, such as price, popularity (i.e., bestseller lists), consumer rating, and seller-provided descriptions, which are acquired before reading consumer reviews in detail[2]. While reading reviews, this expectation could be revised and modified based on the matching of product specifications to specific consumer needs. If the review does not match, then the consumer would stop reading reviews, leave the page, and search for an alternative[9]. Searching for an alternative product will end when he or she finds a product that has reviews satisfactorily describing the expected features.

These overall shopping processes verify that consumers read consumer reviews to find new product information and to confirm whether their expectations could be fulfilled. For example, a consumer who expects that a camera is water resistant can verify whether the water resistance feature of the camera works well by carefully reading various online reviews. Similarly, a consumer who expects that a camera will work well at night will read consumer reviews to confirm whether this camera will satisfy his need. This confirmation process creates perceived discrepancy of expectations from the initial reference point[10]. Confirmation is made according to the estimation whether his or her expectation would be realized based on online consumer reviews that the consumer had read.

However, the association sign (i.e., whether positive or negative) between expectation and confirmation cannot be easily projected because the evidence is inconsistent in the literature. On one hand, a positive association between expectation and confirmation is expected because a positive relationship exists both between expectation and satisfaction as well as between confirmation and satisfaction[28,29]. If A and B as well as B and C are positively associated, a positive association between A and C is also expected. Furthermore, review confirmation behavior based on the written description of the product is highly personal and subjective. Thus, high consumer expectations may result in additional positive consumer impressions when reading various reviews.

On the other hand, the original ECT[10] stated that confirmation is the "difference" between anticipated satisfaction (i.e., expectation) and received satisfaction. Although in the original study, the negative relationship between these factors was not statistically supported, the word "difference" implies the possibility of negative association. Additionally, in most ECT studies, the relationship between expectation and confirmation was not empirically tested; only the relationship between confirmation and attitude was examined[26,28,29]. Exceptionally, Kim et al.[32] did measure both expectation and confirmation, and they hypothesized that confirmation is "related to" expectation. The result shows a marginally negative (-0.098) relationship between expectation and confirmation.

From these, we operationalize this specific expectation on the product as an *initially perceived overall product value that is also largely influenced by the individual's personal preferences and past experiences* such as advertisement and product design. Specifically, this *initially perceived product value* refers to a set of desired product specifications that are rationally and systematically formed on the basis of combined information acquired prior to reading consumer reviews[38]. For example, if a consumer has watched TV advertisements for the product before the product evaluation, a perceptional difference will occur between the person who watched the advertisement and the one who did not watch it, based on the effectiveness of the advertisement[39]. This initial value (i.e., combined expectations on the product) is confirmed when the consumer reads the reviews of a specific product that satisfies the consumer requirements in the expectations. Finally, we developed the following hypothesis based on the discussion:

H1 : A consumer's confirmation of product value, which is made based on online consumer reviews, is related to his or her initial perception of the product's value.

3.2. Effect of Review Confirmation on Purchase Intention

The process of confirmation starts when a consumer reads online reviews to estimate the degree to which his/her expectations would be met by the product after the purchase. A review that presents product information helps the customer manage his/her expectations. For instance, if a consumer seeking a low-noise vacuum cleaner finds one with numerous reviews verifying the low-noise feature, then the said consumer's expectation of the product will be strongly confirmed[2]. By contrast, if a consumer reads reviews differing from his/her expectations, the disappointment would cause customer expectation to be disconfirmed.

Such confirmation plays a significant role in forming a customers' attitudes including purchase intention because it is directly associated with the expected gain in purchasing the product[27]. When a customer can gain increased confidence that the purchase will satisfy his/her needs (i.e., strong confirmation), purchase intention would naturally increase. In numerous studies about the antecedents of purchase intention, one consistently supported assumption is that purchase intention increases when a customer's expectation is confirmed. For example, brand reputation and website credibility significantly influences purchase intention because they increase the possibilities that the customer's needs and desires will be satisfied[40,41]. The attitudes affected by the confirmation would vary from satisfaction to trust[42] but purchase intention would be of the most significance that finalizes the customers' behavior. Thus, we developed the following hypothesis based on the causal relationship between confirmation and purchase intention:

H2 : A stronger confirmation a customer makes on perceived product value forms a stronger purchase intention.

3.3. Effect of Initial Value on Purchase Intention

According to ECT, expectations also directly affect satisfaction but not necessarily with the mediation of confirmation; high expectations directly correspond to high satisfaction[10]. In online shopping malls, an initial impression on a product prior to reading consumer reviews is built as a form of expectation, and such a first impression of the product becomes increasingly crucial as the competition among products intensifies. A negative first impression of a product causes consumers to hardly consider it further for purchase. Consumers are unlikely to read reviews of products at all if they deem the product unattractive.

This significance of the initially perceived overall product value explains why online websites use attractive colors and catch phrases to make good first impressions[43]. First impressions are built in seconds[43] but last possibly for a lifetime[44]. Recovering from a negative first impression is challenging, and changing the minds of customers once negatively formed is extremely difficult in consumer businesses[45].

Based on these studies, it is easily expected that the perceived initial value (i.e., first impression) in online shopping malls not only affects confirmation processes but also directly influences the customer's attitudes including satisfaction, trust and purchase intention. If the first impression is negative at a certain degree, purchase intention will not easily increase despite the information in consumer reviews complimenting the product. In this study, we focus on the customers' behavioral aspect and thus we develop the following hypothesis:

H3 : A higher perceived initial product value forms a stronger purchase intention.

3.3.1. Effect of the Review Tone

The tone of the review is different from the ratings in that it verbally integrates the overall opinions from the group of people. The tone of the reviews is perceived very subjectively—that is, customers form the overall impression on the reviews in terms of being warm and kind or being harsh and critical. Similar with other important subjective constructs, such as satisfaction and motivation, the tone of the reviews can be determined by the rule of majority and/or using widely known proxies, such as presence of specific words or average ratings[46].

Compared to other quantitative measures, such as rating or the length of the reviews, the tone of the review is more difficult to capture and measure for its subjectivity. However, there have been numerous studies that attempted to capture this subjective aspect of the reviews with various methodologies. For example, a group of researchers used text mining approaches to capture the various subjective aspects of consumer reviews, such as stylistic and semantic characteristics[15] and readability of the reviews[16]. Such studies decomposed textual reviews into segments to analyze the content of the reviews[12]. Another group of studies used ontological approaches based on the hierarchies among specific words. For example, Willemsen, Neijens, Bronner, and de Ridder[47] analyzed review content from the argumentation aspect by NET method (i.e., a relational content analysis). Schindler and Bickart[46] also used the similar typology-based approach to test the influence of tone of the product evaluative statements.

Studies on the review tones were always based on the robust assumption that the arguments or statements (i.e., tone) of the reviews are different from the quantitative measures such as ratings. Schlosser[48] showed that the rating and arguments interact with and influence each other. Zhang, Craciun, and Shin[49] also conducted an experiment to show that the reviews are perceived separately and differently from ratings. Sparks, Perkins, and Buckley[50] tested the influence of specific content during the survey. They tested the contents by controlling the ‘tone’ of the review comments. Alternatively, Li, Hitt and Zhang[25] used parameter Θ for their modelling to define the informativeness of the reviews as the probability of receiving a correct signal about the value of the other product. These studies indirectly supported the existence of tones, which must be treated and captured separately from previous quantitative measures, such as rating and length.

For this study, we adopted the *tone of reviews* as a construct to operationalize. The *tone of reviews* more naturally and interactively reflect the overall impressions and feelings of reviewers than other parameters, such as rating or length of reviews[48]. Generally, the associations between rating and review tone are considered linear and positive, such that if the rating were high, the review tone would be favorable, and vice versa. However, the implication of the tone as a research construct compared with rating is clear, as the former contains richer and more comprehensive product information than the latter[22].

Given this conceptualization of tone, we further argue that the tone of reviews significantly influences confirmation as a moderator. As previously mentioned, prior to reading online reviews, customers already went through product searching and browsing processes[47]. During navigation, customers have built their own expectations on products that they are searching. Considering that their primary goal is to identify the best among many, consumers click and read reviews only when the product seems to be the one they need. If the product is unattractive and apparently different from consumer expectation, consumers skip the product and seek alternatives. Consequently, by the time customers read the reviews of the product of interest, most of them have certain expectations, that is, most of times, positive and favorable.

When a customer confirms his or her expectations based on the review, the tone of reviews interacts with personal expectations built from the preceding activities and comprehensively determines the level of confirmation. If the positive initial perception of the consumer meets favorable reviews, review confirmation is strengthened. By contrast, if the tone is negative, confirmation is made but will not be as strong as when the tone is favorable or moderate.

This condition is similar to the reinforcement effect of expectation. When a customer expects the product to be good and if the review tone exactly confirms this expectation, the influence of confirmation is reinforced as the review tone becomes increasingly positive. Consumers tend to analyze situations based on their expectations[51]. In addition, such a perspective can be considered an example of consumer vulnerabilities that are sensitive to external premises[52].

Although consumer review is regarded as one of the most significant product information sources in online shopping environment[2], reviews do not imply that initially perceived value is dismissed immediately when the tone of the reviews is critical. Customers do not solely rely on information in the reviews, but they make decisions based on the entire information acquired during the shopping processes[11]. If after reading critical reviews, the expectation built prior to reading the reviews remains, then the review has influenced the confirmation. Influence is only diminished because of the moderating effect of review tones. Therefore, following hypothesis is proposed based on this discussion.

H4 : A more favorable review tone results in the perceived initial product value having a stronger effect on review confirmation.

H4a : The effect of perceived initial product value on review confirmation is stronger when the review tone is favorable than when the tone is moderate.

H4b : The effect of perceived initial product value on review confirmation is stronger when the review tone is moderate than when the tone is critical.

H4c : The effect of perceived initial product value on review confirmation is stronger when the review tone is favorable than when the tone is critical.

Extremity is another important aspect of the review tone[53]. The extremity of a review is technically defined as the distance of the review from the neutral opinion. This concept represents the strength or density of opinions in the reviews, which is usually indicated by their containing words such as “very,” “quite,” or “really.” As a construct indicating the expressiveness of reviews, the extremity of a review has often been discussed in literatures[14]. Forman, Ghose and Wiesenfeld[22] found that extreme reviews are more helpful than moderate reviews when buying books. In another study, Pavlou and Dimoka[54] reported that extreme ratings are more influential than moderate ratings in eBay.

The extremity of the review tone is important in the expectation–confirmation circumstance because extremity moderates the effect of confirmation on purchase intention. If the review tone is stronger, either positively or negatively, then the impression a consumer receives from the review (i.e. confirmation) is stronger, which in turn increases the effect of confirmation on purchase intention. Positive confirmations significantly increase a consumer's purchase intention when reviews are favorable compared to when reviews are neutral. Likewise, a more critical tone increases disconfirmation, which in turn decreases the consumer's purchase intention. We develop the following hypothesis on the basis of these discussions:

H5 : The effect of review confirmation on final purchase intention is stronger when the review tone is extreme than when the tone is moderate.

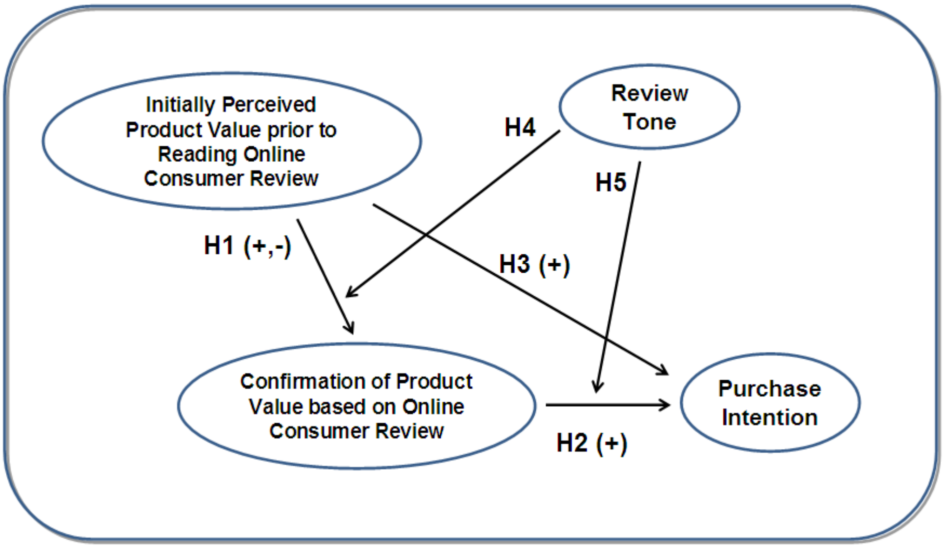
H5a : The effect of review confirmation on final purchase intention is stronger when the review tone is favorable than when the tone is moderate.

H5b : The effect of review confirmation on final purchase intention is stronger when the review tone is critical than when the tone is moderate.

Ⅳ. Methodology

4.1. Item Development and Review Tone Control

Survey items for this study were developed as follows. Perceived initial product value was measured by asking respondents about their perceptions of product value before showing them the consumer reviews. To develop items for product value, first, we drew keywords from the relevant literature, including valuable (value for money), good product (to buy), well made, useful, and worthy (offers value for money) were drawn[55,56]. Then, we constructed questionnaires based on these keywords. For confirmation, we carefully modified the approach of Bhattacherjee[26] for online consumer review contexts. For example, "My experience with using online banking division (OBD) was better than what I expected" was modified to "The product quality seen in the review seems better than what I expected about the product." For purchase intention, major prior studies



<Figure 1> Research Model

were used as reference[2,57]. Appendix A displays the entire list of items.

To operationalize the review tones for H4 and H5 tests, reviews with different tones were prepared as follows. First, 10 to 12 reviews were each selected for critical, moderate, and favorable review tones from Amazon.com's bestselling smartphone reviews. Given that Amazon.com sorts voluminous reviews based on their helpfulness as assessed by other customers, Amazon.com buyers are guided to read more helpful reviews first than unhelpful ones. This helpfulness voting system assists customers in reading reviews with rich and unbiased information, thereby saving time and effort[14]. To ensure the relevance and usefulness of the review contents, we also selected Amazon.com reviews based on these helpfulness rankings, which are displayed on the first few pages.

To control the review tones, critical reviews were selected from the "most helpful critical reviews" with a one-star rating, favorable reviews were selected from the "most helpful favorable reviews" with a five-star rating, and moderate reviews were selected from "helpful reviews" with three- or four-star ratings. The review contents were carefully checked after the selection to assure the consistency between the rating and the review tones. If the review tone was different from the rating (e.g., the tone is moderate while the rating is one-star), the review was discarded. Reviews that were too long or short were also removed.

Eight reviews for each group are prepared for several reasons. First, more than half of the consumers make a purchase decision before they finish reading the first page of the reviews[37]. Although abundant reviews are created online, the actual number of reviews that are read by customers and affect their purchase decision is less than most people thought. For customers, reading five helpful reviews is more efficient than reading 20 ordinary reviews[15]. Furthermore, most major shopping malls display 10 consumer reviews on their first product page; thus a similar number of reviews is displayed to simulate the actual online shopping malls.

4.2. Survey Procedure

First, we selected smartphones for the survey item because of popularity, online availability, and model diversity. More than 100 types of smartphones are currently available in online shopping malls. When people purchase smartphones online, the acquisition of rich and accurate information about the product is important because of the high involvement level of the process. Hence, online consumer reviews are sources that aid in information acquisition[58]. Moreover, the number of smartphone users is rapidly increasing, particularly in Korea, where the penetration rate of smartphones is 59% and is currently the second highest in the world [1)]. To examine the confirmation effect of online consumer reviews, smartphones provide the most adequate conditions among various products in terms of customer reliance level on consumer reviews[7].

Then we constructed a smartphone shopping mall website that was shown to the respondents in the following sequences. First, three types of smartphones (i.e., A, B, and C) with similar price levels and specifications (e.g., color, size, and functionality) were shown to the respondents without consumer reviews. Any information that could imply a specific brand or product was hidden. Respondents were then asked to indicate their perceived initial product values of the three smartphones.

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1) http://www.korea.net/NewsFocus/Sci-Tech/view?articleId=102433

Instead of testing with the existing online shopping mall website, new online shopping mall webpages were created for this research to avoid any possible biases of the respondents such as brand effect. Instead, simulating a real shopping mall situation, the researchers explained to the respondents that these products were the bestselling items in major shopping malls; this was done to control for the positive first impression of the products before reading the reviews.

After measuring the perceived initial product values of the three smartphones, the participants were shown the consumer reviews for each product. They were then asked to report the confirmation levels and purchase intentions they experienced for each product. We first showed product A with moderate reviews, and then asked about their confirmation level and purchase intention of A. We repeated this process for product B with critical reviews and product C with favorable reviews. Before the experiment, detailed explanation was provided to ensure that the respondents clearly understood the different tones of reviews of the products. All scales used were 10-point scales.

Ⅴ. Results

5.1. Data Collection

Data collection was outsourced to Embrain Co. (www.embrain.com), a large market research company in Korea with more than 1.8 million panels in various Asian countries. They recruit survey respondents based on specific requests from clients. For this study, the target respondents we requested were people over 20 years old who currently use cellular phones because they are the most immediate potential customers of the smartphones. Given these requirements, the company first sent e-mail invitations to the targeted respondents; if they accepted the offer to participate in the survey, they were guided to the websites we built. The invitation continued until 300 people accepted the offer. Four days, including weekends, were needed for 300 respondents to complete answering the questionnaires.

For data authenticity, Embrain has established a solid reputation for managing panels. The company carefully selects participants from a pool of panels based on the clients' specific requests. The company also keeps a track record of respondents to control the panel integrity. If inconsistency is detected during a panel's responses, the data from that panel is discarded and he/she is excluded from the panel pool (i.e., company policy on spurious panels).

To ensure that respondents fully understood the survey context, we asked an initial screening question, specifically, whether they were currently using a smartphone or considering purchasing one in the near future. If a respondent responded negatively to both questions (i.e., not using a smartphone and not considering purchasing one in the near future), they were not allowed to participate in the survey. In total, 276 panels out of 300 participated. Selected respondents were then given the following instructions: (1) They will pretend they are buying a new smartphone. (2) They should not recall any previous experience about smartphones and make decisions based solely on the information provided from our Web site.

After the instruction page, the respondents were asked to browse the Web sites of three smartphones for at least three minutes. If any respondent clicks the next page to proceed before the three given minutes are over, a small screen pops up and reminds the respondent to examine the products carefully. Next, they were allowed to click the next page and

<Table 1> Respondent Demographics

Age	Frequency (%)	Currently using a smart phone (%)	Considering buying a smart phone soon (%)	Gender	Frequency (%)
20-29	**71 (25.7)**	70 (98.6)	1 (0.4)	Male	141 (51.1)
30-39	**70 (25.4)**	66 (94.3)	4 (5.7)	Female	135 (48.9)
40-49	**68 (24.6)**	64 (94.1)	4 (5.9)	Total	276
50-59	**67 (24.3)**	55 (82.1)	12 (17.9)		
Total	276	255	21		

to start answering questions on initial value. For the consumer review page, respondents were asked to read the reviews carefully for at least three minutes. To avoid any outliers, the respondents were not allowed to proceed to another question page if they had answered too quickly.

5.2. Demographic Analysis

A total of 300 respondents initially participated in our survey. However, 24 respondents were screened out prior to the actual survey because their answers to the initial screening question were negative (i.e., not using a smartphone and not interested in purchasing one in the near future). Among the 276 remaining participants (<Table 1>), 92% (255) reported currently using smart phones. With regard to age range, 98% of the respondents (70 out of 71) in their 20s and 82% of those (55 out of 67) in their 50s were currently using smartphones. This high overall penetration rate of the smartphone can be explained by the initial screening conducted prior to the survey and by the information in the e-mail invitation that the survey was about smartphones. The panels who were not interested in smartphones may have rejected the e-mail invitation from the beginning.

To avoid any bias from demographic factors, data were controlled with almost equal distributions of gender and age. Furthermore, we conduct ANOVA tests at the construct level and confirmed that no significant difference existed in answering the questions across gender or age. The significance levels of ANOVA tests ranged from 0.14 to 0.91, thus showing no significant difference across groups (<Table 1>).

In estimating the minimum required data size, the commonly used rules include a rule of 10. However, the study of Westland[59] provided an articulated formula for calculating the sample size. His calculation tool shows that with 3 latent variables and 9 indicators, the calculated minimum required sample size is 200. Our sample size is 276; thus, we believe that our study does not have problems in terms of sample size and statistical validities. We revised section 5.2 and specified how we calculated the sample size by presenting information about the calculation tool.[2)]

5.3. Measurement Model

The measurement model test analyses results are summarized in <Table 2>, <Table 3> and <Table 4>.

2) The calculator downloadable at http://www.indigo.lib.uic.edu/bitstream/handle/10027/7655/SEM%20Sample%20Size%20Calculator.iso?sequence=2

<Table 2> EFA Results

Items	Favorable Review			Moderate Review			Critical Review		
	C1	C2	C3	C1	C2	C3	C1	C2	C3
IV1	.161	**.916**	.211	.162	.166	**.920**	-.011	.105	**.918**
IV2	.138	**.899**	.268	.165	.155	**.920**	.088	.062	**.944**
IV3	.244	**.823**	.265	.145	.170	**.894**	.069	.080	**.947**
CF1	.334	.334	**.846**	**.930**	.211	.168	.327	**.898**	.096
CF2	.307	.305	**.872**	**.938**	.198	.181	.344	**.903**	.123
CF3	.350	.248	**.872**	**.928**	.232	.152	.371	**.891**	.084
PI1	**.897**	.201	.290	.203	**.924**	.187	**.902**	.372	.065
PI2	**.905**	.200	.300	.216	**.930**	.176	**.929**	.322	.058
PI3	**.911**	.170	.295	.222	**.926**	.159	**.918**	.345	.043
Cronbach's Alpha	**.969**	**.922**	**.969**	**.969**	**.964**	**.930**	**.981**	**.965**	**.933**

Note: IV: Initial product value; CF: Confirmation on review; PI: Purchase intention;
Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization

We performed exploratory factor analysis (EFA) and confirmatory factor analysis (CFA) to test the validity of the constructs. Through an exploratory factor analysis using PASW 17, convergent and discriminant validities were tested. As shown in <Table 2>, the cut-off value for cross-factor loading was 0.82, which satisfied the normally used minimum loading value[60]. For the internal consistency of the items, we conducted a Cronbach's alpha test. All the scales were acceptable; with the lowest being 0.922.

All statistics from CFA results in the three groups with favorable, moderate, and critical review tones also show high levels of model fit (GFI = 0.96, 0.98, 0.97; RMR = 0.037, 0.011, 0.017; RMSEA = 0.070, 0.020, 0.056; AGFI = 0.92, 0.96, 0.93; NFI = 0.99, 0.99, 0.99). We tested the internal consistency and convergent validity of the constructs by examining the items, including construct loading, composite reliability, and average variance extracted (AVE). All items exhibit loading values higher than the recommended levels (0.7) (<Table 3>). The values of composite reliabilities are sufficiently higher than 0.7[61], and the values of AVE are above 0.5[62]. Discriminant validity was examined by comparing the square root of the AVE and off-diagonal construct correlations. All square roots of the AVE are greater than the off-diagonal construct correlations in the corresponding rows and columns[62], thus indicating convergent consistency.

In addition, to verify the absence of multicollinearity in the dataset, we conducted four tests, as shown in appendix B. The range of variance inflation factors of all models are less than 10, as suggested by[63]. Tolerance limit, which must be larger than 0.1, has high values ranging from 0.66 to 0.96. Eigen values in three models also met criteria that all must be above 0.01. Condition indexes are also at the adequate level of less than 20[64].

Then, we checked for possible common method variance (CMV) through Harman's single-factor

<Table 3> CFA Results

Review Tone	Construct	Indicator	Standardized Loading	Measurement Error	Composite Reliability	AVE (Average Variance Extracted)
Favorable	IV	FIV1	0.94	0.12	0.93	0.81
		FIV2	0.94	0.12		
		FIV3	0.82	0.33		
	CF	FCF1	0.95	0.09	0.97	0.91
		FCF2	0.96	0.08		
		FCF3	0.95	0.09		
	PI	FPI1	0.94	0.12	0.97	0.91
		FPI2	0.97	0.06		
		FPI3	0.96	0.08		
Moderate	IV	MIV1	0.94	0.12	0.93	0.83
		MIV2	0.93	0.14		
		MIV3	0.86	0.26		
	CF	MCF1	0.95	0.10	0.97	0.91
		MCF2	0.97	0.06		
		MCF3	0.95	0.10		
	PI	MPI1	0.94	0.11	0.97	0.90
		MPI2	0.96	0.07		
		MPI3	0.94	0.11		
Critical	IV	CIV1	0.94	0.11	0.94	0.83
		CIV2	0.93	0.13		
		CIV3	0.86	0.27		
	CF	CCF1	0.93	0.14	0.97	0.91
		CCF2	0.97	0.06		
		CCF3	0.96	0.08		
	PI	CPI1	0.96	0.07	0.98	0.95
		CPI2	0.98	0.04		
		CPI3	0.97	0.05		

Note: IV: Initial product value; CF: Confirmation on review; PI: Purchase intention.

test[65]. CMV refers to the amount of spurious co-variance shared among variables because of the common method (e.g., ambiguous wording) used to collect data. This issue can be a problem in research because the actual phenomenon under investigation may be difficult to differentiate from measurement artifacts[66,67]. Although multi-trait multi-method (MTMM) is a reliable *ex-ante* CMV remedy, Harman's single factor analysis is a widely used *ex-post* CMV treatment[68]. This test shows that CMV exists if a

<Table 4> Correlation Analysis Results

	Favorable Review Tone				Moderate Review Tone				Critical Review Tone			
	M(SD)	IV	CF	PI	M(SD)	IV	CF	PI	M(SD)	IV	CF	PI
IV	6.42 (1.67)	**0.90**			6.41 (1.69)	**0.91**			6.41 (1.67)	**0.91**		
CF	6.39 (1.68)	0.59**	**0.96**		5.68 (1.81)	0.37**	**0.96**		3.81 (1.82)	0.20**	**0.95**	
PI	7.14 (1.59)	0.44**	0.65**	**0.96**	5.69 (1.69)	0.38**	0.45**	**0.95**	2.68 (1.76)	0.14**	0.67**	**0.97**

Note: ** Correlation is significant at the 0.01 level (2-tailed).
The bold numbers in the diagonal row are square roots of the average variance extracted.

single factor accounts for most of the covariance in the variables. Harman's single factor analysis has a methodological limitation in that it is less sensitive in detecting moderate or small levels of CMV effects[69]. However, it is widely used by researchers because of its applicability and methodological simplicity[69].

The Kaiser criterion was used to examine the significance of the major factors and to check for common method bias. All three factors explained 92% to 93% of the variance in the constructs (91.9% in the favorable review group, 92.0% in the moderate review group, and 92.9% in the critical review group). The first factor explained 54.9% to 65.2%, whereas the last one explained 9.8% to 17.1%. Considering that there are three factors for each group, arguing that a single dominant factor exists is difficult. These results indicate that our data are not compromised by common method bias(<Table 4>).

Finally, we checked the initially perceived values of the three smartphones to confirm the lack of difference among the products. <Table 4> shows that the average values and standard deviations of initially perceived overall values of the three smartphones are equitable (mean: 6.41 to 6.42; SD: 1.67 to 1.69). These results assure the lack of difference across products. Furthermore, independent sample t-tests on the three groups support that no statistical differences exist among the initial values of the products. Detailed results on the t-tests are available upon request.

5.4. Testing H1, H2, and H3 through Structural Model Path Analysis

We conducted a structural model analysis to test H1, H2, and H3. Structural equation modeling (SEM) was adopted for testing the hypotheses because the relationship between the latent variables and observed ones and the association of the latent variables with the overall fit indexes needed to be tested. The normality of the data was satisfactory as shown in Q-Q plots in Appendix B; thus, no problems in applying SEM approach were identified[70].

A summary of the analysis can be found in <Table 5>. The statistics in the three groups with favorable, moderate, and critical review tones indicated high levels of model fit, thereby supporting the adequacy of the models. The *p-values* for the χ^2 tests in the favorable and critical review groups were less than 0.1. However, the results of the χ^2 test statistics are widely known to be sensitive to

<Table 5> Fit-index of Structural Models

Fit Index	Recommended Level	Structural Model		
		Favorable	Moderate	Critical
Absolute Fit Measures				
Chi-square test statistic (χ^2); *df*		55.95:24	26.62:24	44.63:24
p-value	> 0.10	0.00023	0.32246	0.00644
Goodness-of fit index (GFI)	> 0.80	0.96	0.98	0.97
Root mean square error of app. (RMSEA)	< 0.08	0.070	0.020	0.056
Root mean squared residual (RMR)	< 0.05	0.037	0.011	0.017
Incremental Fit Measures				
Adjusted goodness-of-fit index (AGFI)	> 0.80	0.92	0.96	0.93
Normed fit index (NFI)	> 0.90	0.99	0.99	0.99
Parsimonious Fit Measure				
Normed chi-square	1.00 ~ 3.00	2.33	1.11	1.86

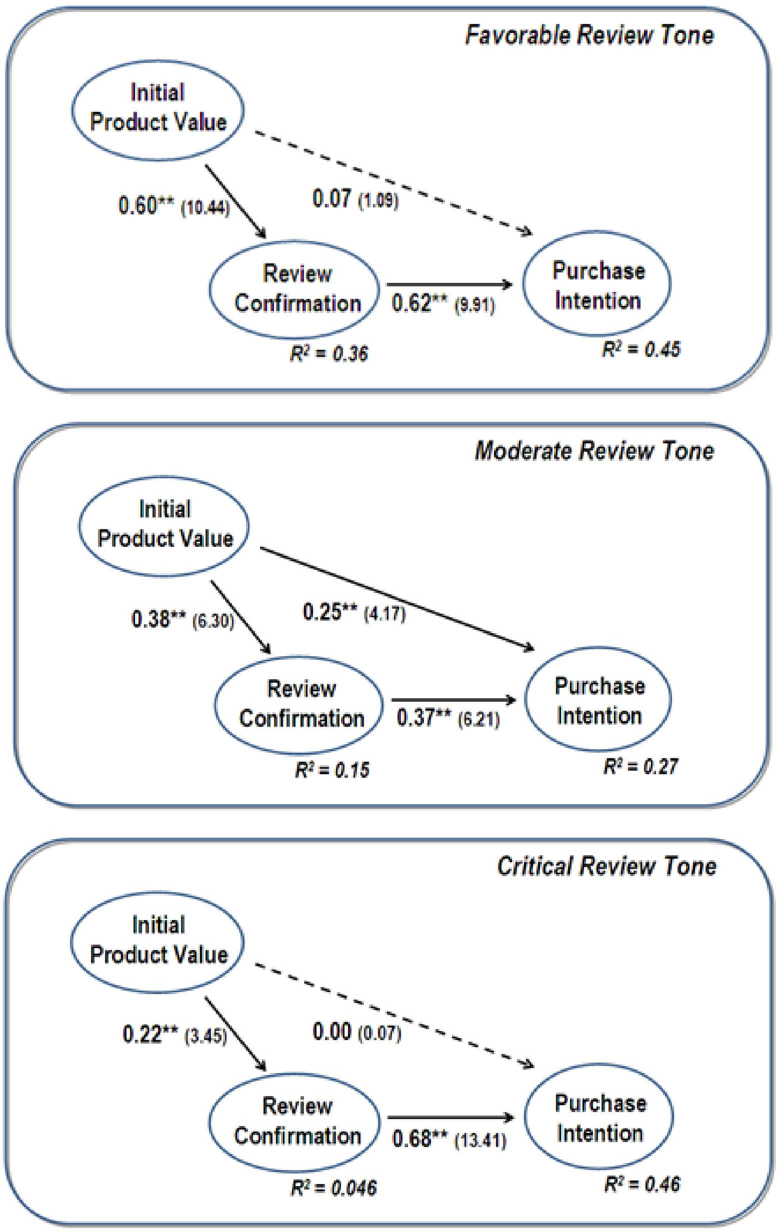
changes in sample size[71]. It has been recommended to not use the χ^2 test and its *p-value* alone to reach a definite decision but rather to consider all other indices together with the χ^2 value[72,73]. In the current study, all models were shown to be adequately proposed and formed because all other fit indices displayed excellent model fit.

The path coefficients in the three groups were then examined. As <Figure 2> shows, the paths from initial value to confirmation (H1) and from confirmation to purchase intention (H2) are significant in all groups; thus, H1 and H2 are supported. However, the path directly from initial value to purchase intention (H3) is significant only in the group of moderate review tone. The path from the initial value to purchase intention is not significant in the groups with critical and favorable review tone groups. Thus, H3 is partially supported. The significant paths are accepted at the significance level of 0.01. The R-squared values of purchase intention in the three groups are 0.45 (in favorable reviews), 0.27 (in moderate reviews), and 0.46 (in critical reviews). These results show that the explanatory power of initial value and review confirmation for purchase intention is stronger when the review tone is extreme.

5.5. Group Comparison: H4 and H5 Tests

For H4 and H5, we calculated the differences in chi-square value between the pooled model (i.e., the model using the entire data set) and the testing model (i.e., the model relaxing the assumption that target paths are the same among groups) by using Amos 17. This software is one of the most widely used SEM analysis tools in IS research and is especially convenient for path comparison. It provides a full result of the analysis process with user-friendly interface including *chi-squared* value differences as the constraints on the paths change. If the *chi-squared* values are significantly different between groups, the differences in path coefficients between groups are confirmed statistically.

The path from initial value to confirmation (H4) is significantly different between the favorable and



<Figure 2> SEM Result

moderate review groups (β = 0.60 → β = 0.38, H4a is supported) and between the moderate and critical review groups (β = 0.38 → β = 0.22, H4b is supported) (<Table 6>). Differences between the favorable and critical groups are also significant (i.e., H4c is supported). The path from confirmation to purchase intention (H5) is significantly different between the favorable and moderate groups (i.e.,

<Table 6> Group Comparison – H4 and H5 Test Results

Comparison between	Chi-square/DF when paths are unconstrained	A → B	Chi-square/ DF after constraining a path A → B	p-value	Path A→B are different across groups	Testing H
Favorable and Moderate	82.0/48	IV → CF	129.2 / 49	0.00	**Yes**	H4a
		CF → PI	136.2 / 49	0.00	**Yes**	H5a
		IV → PI	267.3 / 49	0.00	Yes	NA
Moderate and Critical	71.4/48	IV → CF	152.5 / 49	0.00	**Yes**	H4b
		CF → PI	190.6 / 49	0.00	**Yes**	H5b
		IV → PI	213.7 / 49	0.00	Yes	NA
Favorable and Critical	99.5/48	IV → CF	146.7 / 49	0.00	**Yes**	H4c
		CF → PI	153.7 / 49	0.00	Yes	NA
		IV → PI	284.8 / 49	0.00	Yes	NA

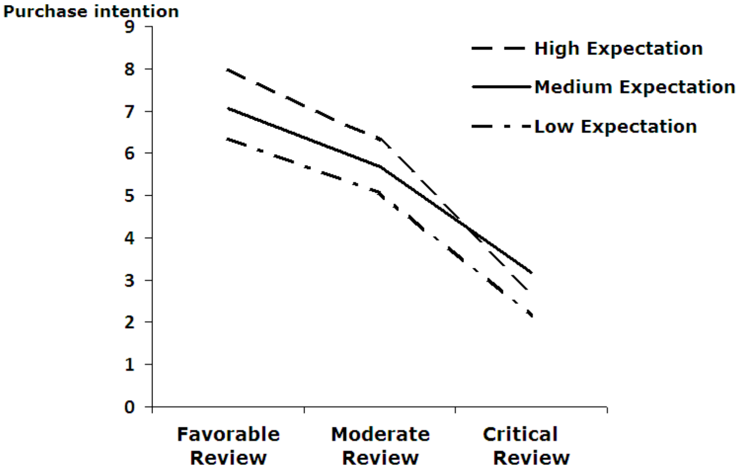
<Table 7> Summary of Hypotheses Test Results

	Tone of Review			Hypotheses Test Results
	Favorable	Moderate	Critical	
H1	Supported	Supported	Supported	Supported
H2	Supported	Supported	Supported	Supported
H3	Not supported	Supported	Not supported	Partially Supported
H4a	----------Supported------------			Supported
H4b		------------Supported--------------		
H4c	----------------------Supported----------------------			
H5a	------------Supported-------------			Supported
H5b		-------------Supported---------------		

β = 0.62 → β = 0.37, H5a is supported) and between the moderate and critical groups (i.e., β = 0.37 → β = 0.68, H5b is supported). A summary of the hypotheses test results is presented in <Table 7>.

5.6. A *Post-hoc* Analysis on Groups with Different Expectation Levels

A *post-hoc* analysis was conducted to exemplify ECT application in an online review context. An exploratory *post-hoc* analysis provides a snapshot of the case that is applied and interpreted by the theory, whereas the hypotheses tests in the previous sections verify the associations and/or dynamics among the constructs. Because ECT is often referenced in cases in which people who experience the same service experience different levels of satisfaction because of their different expectations, we explore the context of online reviews in which consumers with different expectations (i.e., initially perceived overall product values) form different levels of final purchase intention even if they read identical reviews.



<Figure 3> Impact of Review on Purchase Intention for Difference Levels of Expectation

<Table 8> Purchase Intention for Different Levels of Expectation

Expectation level of the group	Final purchase intention when the reviews are			F statistics (p value, Duncan's test)
	Favorable	Moderate	Critical	
High (> 7; n = 92)	7.99	6.31	2.71	225.547 (0.000, H > M > L)
Medium (Between 5.6 and 7; n = 92)	7.06	5.68	3.17	156.347 (0.000, H > M > L)
Low (5.6 >; n = 92)	6.37	5.08	2.15	219.214 (0.000, H > M > L)
F statistics (p value, Duncan's test)	30.855 (0.000, H > M > L)	14.108 (0.000, H > M > L)	8.418 (0.000, H, M > L)	

The consumer groups were divided into three groups based on their initially perceived product value levels. As shown in <Figure 3> and <Table 8>, the group with high expectation included consumers whose expectations scored more than 7 out of 10. The group with moderate expectation consisted of customers whose expectations ranged from 5.6 to 7. Consumers in the low expectation group had scores lower than 5.6. Each group had the same number of customers (n = 92). The average final purchase intention of each group (shown in <Table 8>) was then calculated. The plotted values are presented in <Figure 3>.

One interesting finding of the post-hoc analysis is that the high expectation of a customer can weaken the final purchase intention when the reviews are critical. <Table 8> and <Figure 3> show that the final purchase intention of the high-expectation group is significantly weaker than that of the medium-expectation group when the reviews are critical (2.71 < 3.17). An independent t-test revealed a significant difference between both groups at the 0.1

level (0.093 < 0.1), whereas the result of Duncan's test showed a significance level higher than 0.1 (< 0.15).

This interaction of high expectation and weak purchase intention with critical reviews shows a case that can be well explained by ECT. That is, the high expectations of a customer may lead to final purchase intentions that are weaker than usual if reviews (i.e., reported performance) are unfavorable. When reviews are favorable or moderate, high expectation generally strengthens purchase intention. However, the intersection (crossing) lines of high and medium expectations in <Figure 3> show that an unexpectedly poor review produces a significantly negative effect on the purchase intention of the consumer.

The results of the post-hoc analysis additionally strengthens the main idea of this study that, even if customers are exposed to the same review tones, their purchase intentions may differ according to their expectation levels. In the groups with moderate and favorable reviews, final purchase intention was generally formed based on initial product value, implying that higher expectations lead to higher purchase intention. Also, the purchase intentions of the same expectation groups became lower when the review tones changed from favorable to moderate or from moderate to critical. These results provide support that the manipulations of the review tones were done properly in the experiment.

Ⅵ. Discussion

6.1. Summary of Finding

In addition to the hypotheses supported, findings from the current study are as follows. First, the finding provides empirical support that a positive relationship exists between expectation and confirmation. Customers have a strong tendency to hold their initial belief when they have high expectations of a product. In other words, when customer expectations are high, favorable reviews are perceived as more favorable, and critical reviews are perceived as less critical. The results also indicate that confirmation is based on highly subjective judgments rather than objective evaluations. When Oliver[10] defined confirmation as a "difference" between the anticipated satisfaction (i.e., expectation) and the received satisfaction (i.e., actual performance), he assumed that such confirmation would be made by the consumers who judge the performance rationally and objectively. However, the results in this study suggest that consumers who read reviews in online shopping malls are not always as rationale and objective, but rather are subjective and emotional and have the tendency to believe as they wish.

Another interesting finding of the study is that, as shown in <Table 9>, the total impact of initial value on purchase intention is distinctively low when the review tone is critical. Considering that customers who are reading reviews usually have positive impressions of the product (i.e., relatively high initial values), it is understandable that such impressions would be suddenly rejected if the review is different from expectations. As shown in the table, there is a clear distinction among the total effects of initial value between the groups. When the review tone is critical, initial value does not have a direct impact and has a low indirect impact through confirmation.

6.2. Academic Contribution

The academic contribution of this study is multifaceted. First, it explains why two consumers who read the same review may respond to it differently through the application of ECT to the electronic commerce context. The current study specifically captures the subjective nature of consumer reviews readership and argues that the effects of reviews should be examined along with consumers' expectations that they built before reading the reviews. Most related prior studies have attempted to quantify and measure the influence of reviews rather objectively, without much consideration of the expectation that customers individually built before they read the reviews[74]. ECT application in this study accordingly enhances the understanding on the influence of online reviews because it provides logical support to the relationships between expectation, confirmation, and consequent behaviors[10]. The theory also supports the assumption of the study that reading consumer reviews is a highly subjective individual activity that can be interpreted differently by each consumer, thus strengthening the findings of the study.

Second, this study empirically tests the association between expectation and confirmation. Although the original theory in 1980 states that confirmation is the "difference" between anticipation (i.e., expectation) and reception, it has not been clearly verified in prior studies whether the association between the expectation and confirmation is positive or negative[32]. Most prior ECT studies instead excluded measuring expectation but measured only the level of confirmation because of the methodological difficulty[28,29]; a longitudinal study is required to measure both expectation and confirmation in a single study scope. In this sense, this study contributes to this theoretical ambiguity by empirically verifying that the relationship between expectation and confirmation in the electronic commerce context is rather positive. This result also strengthens the main argument of the study that the interpretation process of an online consumer review is a more highly subjective activity than what was previously thought.

Lastly, this study suggests an alternative approach that the *tone* of a review can be an effective parameter in analyzing reviews, along with specific words or ratings. Most prior studies on online reviews have attempted to quantify online reviews at the micro level, that is, counting the frequency of a specific word or the length[16,14]. However, because of the complexity of the contents and analysis, drawing a generalizable implication has been complicated. Therefore, this study uses the tone of a review that shows the general tendency of all reviewers as a moderating factor and examines its marginal effect instead of capturing the details of a single reviewer's opinion. This study provides additional parsimonious, consistent, and generalizable results and makes readers easier to understand and manipulate.

6.3. Practical Implication

This study highlights the practical significance of the expectation that a customer has formed prior to reading online reviews, and provides practitioners with insights into the importance of attracting and leading customers seamlessly from the start to the end of an online shopping experience[9]. Most previous studies on online reviews have discussed the direct effect of the review contents, which are not controllable by the seller or manufacturer. By contrast, this study shows that the ultimate effect of online reviews is determined by the interaction of the expectation that a customer has built before reading the reviews and their nature. In this situation, attracting and guiding customers in purchasing a product are as crucial as acquiring their favorable reviews[75]. The current study includes the factor that is mostly manageable by the seller (i.e., a specific expectation of the product) within the scope of the review effect analysis, and emphasizes the importance of properly managing the expectation-building stage of customers to successfully complete their purchases.

This study also helps practitioners develop a moment of truth in the online shopping environment by demonstrating how and when the first impression of products, specifically the expectation consumers have before reading reviews, critically influence customer behaviors[76]. According to the results, a strong confirmation significantly weakens the effect of initial perception. When the tone of a review is highly negative or positive, the initial impression diminishes its direct effect on purchase intention. However, in reality, such a strong confirmation is not often realized, that is, most of the products lack extreme evaluations but exhibit mixtures of moderate reviews because of the natural diversity in people's preferences. Most bestsellers in major online shopping malls have rather moderately positive review tones. In this situation, the initial perception would still play an important role in consumer decision-making processes. If practitioners fail to attract customers and prompt them to read the reviews, then the favorable review would not have a chance to be read by customers and consequently influence their decision-making processes. The study shows practitioners the importance of maintaining positive first impressions, even if people now regard consumer reviews as more important information sources.

Another practical implication of this study comes from its treatment of the review tones as a moderator. Compared with ratings, such as 3.5 out of 5, the tone of the reviews is subjectively and individually perceived. For practitioners, the tone of the reviews is considered more difficult to capture, quantify, and examine its effects. However, this study captures the tone of the review as a moderating factor, instead of a mediating factor, to investigate its marginal influences when it is critical, moderate, or favorable, and verify its critical influence on consumer behavior. These results provide useful ideas for managers because they show the varying effects of a review tone, facilitating their understanding for practical applications.

6.4. Limitation and Future Study

One of the limitations this study bears is that it tests hypotheses for only one type of product, a smartphone. Even though it is a product with high involvement and widely sold in online, we hope to test the hypotheses for other types of products in the future, especially the products with low involvement such as a pen or a simple plate to contrast the results. Furthermore, since the data is collected from a single Asian country, Korea, it may raise a generalizability concerns. Cultural characteristic such as uncertainty avoidance and collectivism may have a significant effect on the processing of information while consumers read online reviews[77]. Also, inclusion of other attitudinal variables such as trust and satisfaction is highly recommended. Numerous prior studies have discussed the relationship between confirmation and attitudes other than purchase intention[27]. Extending the focus from purchase intention to other attitudinal variables will deepen the understanding of the impact of online consumer reviews. Lastly, interaction effects between review tone and other factors besides initial value should be investigated in future research. Other important factors that affect consumer decision making include brand and price. Considering these factors together with the impact of reviews will further in-depth understandings of researchers and practitioners of the online review context.

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<Appendix A> Items

Construct	Items	Questionnaires
Initially Perceived Product Value	PV1	This product seems to offer value for money.
	PV2	This product looks valuable for money.
	PV3	This product seems to be a good product to buy.
Confirmation of Product Value based on Consumer Reviews	CF1	The product quality indicated by the review seems better than what I expected of the product.
	CF2	According to the reviews, this product seems better than what I expected.
	CF3	Overall, most of my expectations would be confirmed if I purchase this product.
Purchase Intention	PI1	I am positive towards buying this product.
	PI2	I have the intention of buying this product.
	PI3	I think it is a good idea to buy this product.

<Appendix B> Various Multicollinearity Tests

	Variance Inflation Factor (must be < 10)			Tolerance Limit (must be > 0.1)				Eigen Value (must be > 0.01)			Condition index (must be < 20)		
	F	M	C	F	M	C		F	M	C	F	M	C
IV	1.526	1.155	1.043	0.656	0.866	0.958	1	2.945	2.920	2.855	1	1	1
CF	1.526	1.155	1.043	0.656	0.866	0.958	2	0.031	0.051	0.117	9.684	7.549	4.939
							3	0.023	0.029	0.028	11.248	10.106	10.080

Note: F: favorite tone, M: moderate tone, C: critical tone

◆ About the Authors ◆

Jung Lee

Jung Lee is an Associate Professor at Hankuk University of Foreign Studies. She was a post-doctoral research fellow in the Department of Information Systems at the National University of Singapore. She received Ph.D. degree in MIS from Korea University Business School, M.S. degree in Information Systems from the Graduate School of Information of Yonsei University, and B.S. degree in Biology from Korea Advanced Institute of Science and Technology (KAIST). Her research interests include electronic word-of-mouth, trust/distrust and social media. She has published papers in journals including Decision Support Systems, Information & Management, Information Systems Frontiers, International Journal of Electronic Commerce, and presented papers at conferences including ICIS, AMCIS, and PACIS.

Hong Joo Lee

Hong Joo Lee is an Associate Professor of Business Administration, the Catholic University of Korea. He has a Ph.D. from the KAIST Business School (2006) and was with the MIT Center for Collective Intelligence as a postdoctoral fellow in 2006 and a visiting scholar in 2011. His research areas are utilizing intelligent techniques and harnessing collective intelligence in business settings, and analyzing effects of intelligent aids in e-commerce and m-commerce. His papers have been published in International Journal of Electronic Commerce, Decision Support Systems, Expert Systems with Applications, Information Systems Frontiers, and other journals.

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