The effects of consumer knowledge on message processing of electronic word-of-mouth via online consumer reviews

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Abstract

This paper investigates one type of electronic word-of-mouth (eWOM), the online consumer review. The study considers two components of review structure: the type and the number of reviews. Using the cognitive fit theory, we show that the type of reviews can be a key moderating variable to explain the inconsistent relationship between consumer expertise and WOM in previous research. This study examines which type of reviews cognitively fits consumers with a high (low) level of expertise. Using the elaboration likelihood model (ELM), we also investigate that the effects of the type of reviews and the number of reviews. The hypotheses were tested using a 2 (levels of expertise) $\times$ 2 (types of reviews) $\times$ 2 (number of reviews) mixed design including two control conditions. The results show that the effect of cognitive fit (the type of reviews) on purchase intention is stronger for experts than for novices while the effect of the number of reviews on purchase intention is stronger for novices than experts. This paper delivers managerial implications for online sellers providing consumer created reviews along with advertisements.
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1. Introduction

A product progresses through a sequence of stages from introduction to growth, maturity, and decline [1]. This sequence is known as the product life cycle. However, not all products go through each stage. In fact, many products fail even in the introduction phase, and the failure rate is as high as 50% [2,3]. To avert failure at various stages of the life cycle, marketers' marketing mix strategies should change as their products go through each stage because consumers at various stages desire different types of information. Consumers in the early stage want to be provided with information on attributes because they are innovators who are seeking technical information. Meanwhile, consumers in the mainstream are relatively less knowledgeable,

so they want to get information on benefits to evaluate a product. However, it is not easy for managers to recognize when and how they should change their method of providing product information because the stages are not definitely discrete. Then, do marketers have to provide information on both attributes and benefits in their advertisements? First, providing both attributes and benefits information in the same advertisement can be costly. Moreover, previous research shows that presenting both attributes and benefits messages may not be as effective as providing messages focused on either attributes or benefits information [4].

Word-of-mouth (WOM) is an effective way to help marketers overcome these limitations [5] because WOM provides product information from the user perspective in each stage. Since review posters are usually former users at any given stage, they can write about a product in a way that potential consumers in a particular stage can

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effectively process. Therefore, WOM communication is effective in providing the right type of information to each customer segment. However, traditionally marketers cannot effectively set strategic plans centered on WOM because the effects of WOM are very difficult to trace. Recently, the Internet has emerged as a new channel of WOM [6]. Different from traditional WOM, WOM on the Internet, called electronic word-of-mouth (eWOM), is measurable since comments on a product are written and available in the websites [7]. Also, some types of eWOM messages such as online consumer reviews in Amazon.com are also controllable because marketers can decide whether to allow consumer reviews to be shown or not, and if they are shown marketers can offer a specific review format in order to guide consumers to post their opinions in the way they want. Thus, marketers can apply marketing strategies for eWOM more strategically than traditional WOM.

The eWOM information providing both product information and recommendations can satisfy various consumer segments. Consumers in the early market called early adopters want product attribute information to figure out the importance of a product with their own criteria. On the other hand, consumers in the mainstream market are relatively less knowledgeable so they prefer product benefit information [8]. They also consider peripheral cues, such as product popularity or trends, as being important. Through eWOM activity, consumers in the early market can obtain supplement product information, while consumers in the mainstream market can get user-oriented information or a signal of product popularity. Therefore, eWOM has great potential for helping a product transition from the early market to the mainstream market if it can be managed well. Because of such importance and popularity of eWOM communication, studies in the last few years are actively examining the effect of eWOM on consumer behavior.

Previous research on WOM communication shows an inconsistent relationship between expertise and WOM behavior. Some studies show a positive relationship between the level of expertise and WOM [9,10], while other studies suggest that there is a negative relationship [11,12]. Our study attempts to explain these contradictory results by considering the specific type of eWOM message as a moderator. Consumers use different message-processing strategies depending on their level of expertise. According to the cognitive fit theory [13], when the information type matches the consumer information-processing strategy, cognitive fit occurs. Thus, the type of message is an important factor for analyzing the relationship between consumer expertise and eWOM. The study investigates which type of consumer review cognitively fits the processing strategies depending on the level of consumer expertise. In addition, with the elaboration likelihood model (ELM), the study examines for which consumers the cognitive fit is more important for decision making.

The number of reviews is another important factor of review structure. The number of reviews representing the number of previous consumers can be a signal of product popularity. In addition, an increase in the number of reviews relates to an increase in the amount of information. Thus, the number of reviews also influences review message processing. ELM can also explain the effect of the number of reviews depending on the level of expertise. According to ELM, consumers with low expertise are more likely to focus on a peripheral cue such as the number of arguments, while consumers with high expertise are more likely to engage in effortful cognitive activity through the central route, and they focus on the argument quality [14].

This study proposes several hypotheses and conducts an experiment to explore how consumers process online consumer reviews depending on the level of expertise. Specifically, focusing on the positive online consumer reviews, this study examines the effect of review structure – the type and the number of reviews – on consumer decision making. The key research questions are as follows:

(1) What is the relationship between the level of expertise and the impact of eWOM? That is, for which consumer (experts vs. novices) is the effect of online consumer reviews stronger?
(2) Which type of online consumer reviews (attribute-centric vs. benefit-centric reviews) fit consumers with a low (high) level of expertise?
(3) Which consumer is the effect of the review fit on the purchase intention stronger for?
(4) Which consumer is the effect of the number of reviews on the purchase intention stronger for?

The above questions will be highly covered throughout the paper. With the analysis of previous research, the predicted answers of the questions will be hypothesized in the experiment. The contributions of this research are twofold. From the theoretical perspective, the study integrates principles from different domains, which help us broaden the understanding of the effects of online consumer reviews. From the managerial perspective, our findings have implications for both marketers and designers of e-commerce web sites in terms of how to manage online consumer reviews.

2. Theoretical background and hypotheses

2.1. The relationship between eWOM and consumer expertise

Prior to the Internet era, consumers shared each others' product-related experiences through traditional WOM (e.g. discussions with friends and family) [15]. Today, the Internet makes it possible for consumers to share experiences and opinions about a product via eWOM activity. Godes and Mayzlin [7] show that eWOM can overcome the limitation of traditional WOM. In traditional WOM communication, the information is exchanged in private conversations, so direct observation has been difficult. However, online conversations may offer an easy and

cost-effective opportunity to measure WOM. In addition to overcome the limitations of traditional WOM communication, eWOM activity has allowed consumers to overcome most information asymmetries that characterize traditional consumer markets [16]. Thus, throughout the eWOM activity, consumers can obtain high levels of market transparency. In addition, they can take on a more active role in the value chain and influence products and prices according to individual preferences. Because of such importance and popularity of eWOM communication, studies in the last few years are actively examining factors which influence the effect of eWOM on consumer behavior.

The recent studies on eWOM focus on the motives for posting and reading reviews and the consumers' responses to the eWOM messages. Hennig-Thurau et al. [17] have developed a typology for motives of consumer online articulation based on findings from research on virtual communities and traditional WOM literature. Using an online sample of some 2000 consumers, information on the structure and relevance of the motives of consumers' online articulations is generated. The resulting analysis suggests that consumers' desire for social interaction and economic incentives, their concern for other consumers, and the potential to enhance their own self-worth are the primary factors leading to eWOM behavior. Hennig-Thurau and Walsh [18] derive several motives that explain why customers retrieve other customers' on-line articulations from Web-based consumer opinion platforms. The relevance of these motives and their impact on consumer buying and communication behavior are tested in a large-scale empirical study. These studies, however, did not examine how the characteristics of eWOM messages affect consumer purchasing behavior. This study extends prior research on eWOM by examining the characteristics of reviews, in particular the types of reviews (Table 1).

This study focuses on the online consumer review as one type of eWOM communication. The online consumer review is defined as any positive or negative statement about a product made by potential, actual, or former customers, which is available to a multitude of people and institutions via the Internet [19]. Chevalier and Mayzlin [20] examine the effect of consumer reviews on relative sales of books at Amazon.com and Barnesandnoble.com. The authors find that an improvement in a book's reviews leads to an increase in relative sales at that site. In addition, evidence from review-length data suggests that customers read review text rather than relying only on summary statistics. Clemons et al. [21] analyze how online reviews are used to evaluate the effectiveness of product differentiation. When consumers become more informed, firms that provide highly differentiated products should experience higher growth rates than firms with less differentiated offerings. In particular, the study finds that the variance of ratings and the strength of the most positive quartile of reviews play a significant role in determining which new products grow faster in the marketplace. Huang and Chen [22] discuss how sales volume and customer reviews influence consumer on-line product choices, and examine the relative effectiveness of two recommendation sources (expert reviews vs. consumer reviews). The results reveal that subjects use the choices and evaluations of others as cues for making their own choices. Additionally, the recommendations of other consumers influence the choices of subjects more effectively than recommendations from experts. However, these current studies on the online consumer review have not considered the characteristics of review readers such as their experience or knowledge. This study investigates the level of expertise moderating the effect of eWOM messages on consumer buying behavior (Table 2).

Wangenheim and Bayón [23] pointed out that the interaction of consumer expertise and WOM remains widely under-researched. In addition, we found that the study of Bansal and Voyer [24] discussed this inconsistent relationship between the level of expertise and WOM. Also, Gilly et al. [12] mentioned that some empirical evidence supports either a positive or curvilinear relationship between product knowledge and WOM. These previous studies were based on the study of Brucks [25]. Brucks reported that a number of studies suggested that there is a negative relationship between the amount of experience (used as a proxy for expertise) of an information seeker and the degree to which he or she conducts an external search for information. This is because consumers with high expertise think they already have enough information to make an accurate

Table 1
Previous studies on eWOM

Authors (year)	Theory and findings	Additional comments
Hennig-Thurau et al. (2004)	The motives for posting reviews are investigated	These studies do not investigate the effect of characteristics of eWOM messages
Hennig-Thurau and Walsh (2004)	The motives for reading reviews are investigated	
Chevalier and Mayzlin (2006)	Both the number of reviews and average star-rating scores are positively related to the product sales	These studies focus on review statistics not on review contents. They analyze the effects of reviews from aggregate-level approaches not from individual-level approaches
Clemons et al. (2006)	Both mean and variance of review ratings are positively related to the product sales	
Huang and Chen (2006)	The effect of review sources is examined	This study does not consider consumer characteristics. Also, this study focuses on credibility of review messages not on review contents

Table 2
The relationship between WOM and expertise

Authors (year)	Theory and findings	Additional comments
Johnson and Russco (1984) Punj and Staelin (1983) Johnson and Sathi (1984)	The effects of WOM are stronger when consumers have high expertise than low expertise (positive relationship between WOM and expertise)	These studies do not consider message characteristics such as message type. Also, they focus on consumers' ability to process WOM messages rather than consumers' motivation to process WOM messages
Bloch et al. (1986) Gilly et al. (1998)	The effects of WOM are stronger when consumers have low expertise than high expertise (negative relationship between WOM and expertise)	These studies do not consider message characteristics such as message type. These studies focus on consumers' motivation to process WOM messages rather than consumers' ability to process WOM messages

purchase decision so they devote little effort to obtaining additional product information or evaluations about a product from others [11,12]. Also, Brucks discussed other studies [9,10,26] that postulate that prior knowledge encourages an information search by enabling the receiver to process information in a faster and easier way than if he or she possesses little expertise. In sum, traditional WOM studies have shown contradictory results about the effects of prior knowledge on WOM behavior.

This study suggests that the type of WOM message is a key to resolving this inconsistent relationship. The studies on traditional WOM have not considered the message type because it was neither measurable nor traceable. However, the type of WOM messages on the Internet is both measurable and traceable because the comments about a product are posted on the website and they accumulate as time goes by. With cognitive fit theory, this paper integrates prior contradictory results by considering the type of review message as a moderator.

Cognitive fit theory indicates that individuals' information processing would be more efficient and effective when they are able to use appropriate cognitive processes from given information [13]. Performance of a decision-making task will be enhanced when the information is given in a form that an individual is likely to process because the match between the information-processing strategy and the information type minimizes cognitive effort [27]. The cognitive fit theory has been empirically validated by other studies in several industries [28–30].

Individuals with different levels of expertise seek different types of information. Experts prefer specific attribute data, while novices seek data that are interpreted and reproduced to be easily understandable. Previous research in accounting shows that experts want attributes to be shown in tables with specific numbers when evaluating alternatives, while novices like the same data to be shown in the graphs. In terms of product information, experts are likely to infer product benefits by themselves from technical attribute information, whereas novices are likely to

process literally expressed benefit information [31]. That is, experts consider attribute statements as being informative, while novices find benefit statements informative [4]. For example, experts make judgments about food items on the basis of technical attributes (e.g. nutritional information), but novices tend to use benefit information about the items (e.g. good for you) [31].

The same review contents can be framed into two types: the attribute-centric type and the benefit-centric type. Reviews contain both evaluations and recommendations. This study assumes that recommendation parts of the reviews are the same in both types of reviews. More specifically, this study focuses on positive recommendations that are based on favorable evaluations of a product. In addition, review positiveness is also controlled as the same strength in both types of reviews. The difference between the two types of reviews is the way of evaluating a product to support recommendations. In attribute-centric reviews, arguments supporting reviewer's evaluations are based on technical attributes such as numbers representing attribute levels. Thus, their subjective evaluations are supported by objective data and descriptions. By contrast, in benefit-centric reviews, supporting arguments convey subjective interpretations about such technical attributes. Reviewers subjectively interpreted benefits of each attribute in their own way to evaluate a product. One example of an attribute-centric review is, "I want to recommend this product. It has 10 GB memory capacity, so I can store seven AVI files, which are 1.4 GB video contents compressed with a wide variety of codecs." Meanwhile, an example of a benefit-centric review is, "I want to recommend this product. One of the most attractive aspects of this PMP is that it has a large memory capacity so I can store seven movies with good video quality."

Therefore, holding that a review delivers information about the same aspect of a product, the information-processing strategy of experts fits reviews framed as attribute-centric, while the information-processing strategy of novices fits reviews framed as benefit-centric. When

individuals are able to process online consumer reviews represented in a way that is cognitively fit, they can efficiently process given reviews, thereby those reviews positively affect purchase intention.

> Hypothesis 1 (Cognitive review fit hypothesis on experts): For consumers with high expertise, reviews framed as attribute-centric have a better fit than reviews framed as benefit-centric.
> Hypothesis 2 (Cognitive review fit hypothesis on novices): For consumers with low expertise, reviews framed as benefit-centric have a better fit than reviews framed as attribute-centric.
> Hypothesis 3 (Review fit hypothesis on experts' purchase intention): For consumers with high expertise, reviews framed as attribute-centric have a stronger effect on the purchase intention than reviews framed as benefit-centric.
> Hypothesis 4 (Review fit hypothesis on novices' purchase intention): For consumers with low expertise, reviews framed as benefit-centric have a stronger effect on the purchase intention than reviews framed as attribute-centric.

2.2. The effect of cognitive fit (review type) and the number of reviews

The cognitive fit theory explains which type of reviews is effective for consumers depending on the level of expertise. Then, for which consumers is the cognitive fit more important? This question can be answered from ELM. ELM, a dual route theory, explains that attitude changes are based on different degrees of effortful information processing [32]. A message is transmitted and received through one of two routes of persuasion depending on the elaboration continuum: the central route and the peripheral route. In this model, the elaboration continuum refers to how motivated and able people are to assess the central merits of a stimulus. If a person has high motivation and the ability to process a message, individuals can engage in effortful cognitive activity through the central route. However, when individuals lack either the motivation or ability to process detailed information, persuasion comes from the peripheral route so they tend to rely on peripheral cues or mental heuristics rather than focal messages. Therefore, a message with many arguments can be accepted if a person thinks that "more is better," without the need to carefully evaluate those arguments [33].

In ELM, expertise is associated with the ability to process information. Consumers with high expertise can draw upon prior experience and knowledge to scrutinize and evaluate carefully all of the information. It is clear that such message processing demands a considerable amount of cognitive resources, but consumers with high expertise have enough cognitive resources to perform this kind of information processing. Reviews framed as attribute-cen-

tric meet their information-processing strategy. On the other hand, reviews framed as benefit-centric do not meet their information processing needs because benefit-centric reviews have already been processed and interpreted by previous unknown consumers. On the other hand, consumers with low expertise lack the ability to understand and assess a product from attribute-centric product information, so they prefer the reviews framed as benefit-centric. Even though they do not understand the reviews framed as attribute-centric well, they will try to get a signal implying whether the reviews are positive or negative. According to ELM, novices form purchase intention through peripheral cues when they cannot process information through the central route, so the signal of review positiveness itself (positive nuance of consumer reviews) can provide useful information for novices even when they cannot fully understand the reviews. Therefore, the impact of cognitive fit (review type) on purchase intention is stronger for consumers with high expertise than for consumers with low expertise.

The number of reviews is another important factor of review structure. The role of the number of reviews is to provide a signal of product popularity and to increase the total amount of review information. Both roles are crucial for consumers with low expertise because they tend to rely on a peripheral cue such as the signal of product popularity, and because they are persuaded by a simple decision rule, "lots of messages are good." Consumers with high expertise, however, are not likely to be persuaded via heuristic processing. Since the information strategy of experts focuses on acquiring informative and useful information for them, an increase in information quantity is welcomed only when the information fits their needs. Thus, the effect of the number of reviews on purchase intention is stronger for consumers with low expertise than consumers with high expertise (Table 3).

> Hypothesis 5 (ELM hypothesis on review type): The type of online consumer review has a stronger effect on the purchase intention of consumers with high expertise than on consumers with low expertise.
> Hypothesis 6 (ELM hypothesis on review number): The number of online consumer reviews has a stronger effect on the purchase intention of consumers with low expertise than on consumers with high expertise.

3. Research method and design

3.1. Subjects and experimental design

Two hundred and twenty two undergraduate and graduate students participated in the experiment. All of the subjects received a gift worth $5 for their participation. The hypotheses were tested using a mixed design of 2 (levels of expertise) × 2 (types of reviews) × 2 (number of reviews) including two control conditions. The experimental

Table 3
Summarized hypotheses

No.	Name	Statement of hypothesis	Predicted effect
1.	Cognitive review fit hypothesis on experts	For consumers with high expertise, reviews framed as attribute-centric have a better fit than reviews framed as benefit-centric	(cognitive fit of experts) Attribute-centric reviews > benefit-centric reviews
2.	Cognitive review fit hypothesis on novices	For consumers with low expertise, reviews framed as benefit-centric have a better fit than reviews framed as attribute-centric	(cognitive fit of novices) Benefit-centric reviews > attribute-centric reviews
3.	Review fit hypothesis on experts' purchase intention	For consumers with high expertise, reviews framed as attribute-centric have a stronger effect on the purchase intention than reviews framed as benefit-centric	(experts' purchase intention) Attribute-centric reviews > benefit-centric reviews
4.	Review fit hypothesis on novices' purchase intention	For consumers with low expertise, reviews framed as benefit-centric have a stronger effect on the purchase intention than reviews framed as attribute-centric	(novices' purchase intention) Benefit-centric reviews > attribute-centric reviews
5.	ELM hypothesis on review type	The type of online consumer review has a stronger effect on the purchase intention of consumers with high expertise than on consumers with low expertise	(purchase intention) Experts > novices
6.	ELM hypothesis on review number	The number of online consumer reviews has a stronger effect on the purchase intention of consumers with low expertise than on consumers with high expertise	(purchase intention) Novices > experts

procedure was the same for each group, and participants within each of the 10 cells were randomly assigned.

3.2. Experimental product

We chose a relatively new product, the portable multimedia player (PMP). The new product ensures that consumers process the suggested information with no stereotypes about the brand and its category. In addition, consumers tend to rely on the opinions from previous users due to the fact that electronic products are generally complicated. The brand name of the product was not presented in order to prevent any brand effects.

3.3. Experimental procedure

Subjects read the first page of the booklet, which was a statement about the study's purpose. The statement was same for all groups. Then, respondents read the product information page consisting of a product advertisement and online consumer reviews. The advertisement provided a picture of the product and a brief description of the features. Online consumer reviews were located under the advertisement. Five different sets of online consumer reviews were developed for each condition. Each participant was exposed to one of the five review sets. First in the attribute-centric condition, attribute-centric reviews were presented with two overall evaluation reviews. More specifically, in the condition involving the small number of reviews, two overall evaluation reviews and two attribute-centric reviews were presented. In the condition involving the large number of reviews, two overall evaluation reviews and six attribute-centric reviews were presented. On the other hand, in the benefit-centric condition, two overall evaluation reviews and two (or six) benefit-centric reviews were given depending on the number of reviews. Finally, in the control condition reviews,

only two overall evaluation reviews were presented without the addition of either type of review. An example of review sets – 4 attribute-centric vs. 4 benefit-centric conditions – is shown in Appendix A. The number of reviews for each condition was determined after we interviewed 22 undergraduate students in order to find out how many reviews were evaluated as being a small or large number. The four-review condition was chosen as the small number and the eight-review condition was chosen as the large number of reviews. Each review had three lines.

After reading the product advertisement and reviews, subjects indicated their purchase intentions using two items: willing to buy/not willing to buy, willing to recommend/not willing to recommend [34,35]. On the following page, three measurement items were administered to check the treatment effects of the review type. Subjects responded to three 7-point items: the reviews were informative/not informative, useful/not useful, and helpful/not helpful [4]. For the manipulation of the number of reviews, two items were measured to check if subjects perceived the number of reviews as we intended. Then, product knowledge about PMPs was assessed using 12 multiple-choice questions. These questions were about the video data format, the speed of data transport, and so on. Subjective knowledge about PMPs was also measured to classify subjects as experts and novices.

Finally, subjects completed measures used to control the effects of possible confounding variables in order to improve the internal validity of this study. If there is a statistically significant difference among treatment groups, these variables should be used as the covariate variables. First, the perception of review positiveness was measured. This control was measured using two items ("Reviews were positive," "Most of the reviews recommended buying the product"). The final variable was measured to control each subject's general attitude toward reviews through four 7-point items ("When I buy a product online, I always read

reviews that are presented on the website," "When I buy a product online, the reviews presented on the website are helpful for my decision making," "When I buy a product online, the reviews presented on the website make me confident in purchasing the product," and "If I don't read the reviews presented on the website when I buy a product online, I worry about my decision").

4. Research results

Two hundred and fifty undergraduate and graduate students participated voluntarily. Their average age was 26.58 years, and 51.2% were male. The average frequency of online purchases per month was 0.89 times. There are no significant differences in gender ($F(9, 240) = 0.766$, $p < 0.648$), age ($F(9, 240) = 0.862$, $p < 0.560$), and frequencies of online purchase ($F(9, 240) = 0.896$, $p < 0.530$), indicating that the random assignment was successful.

Subjects were classified as either experts or novices according to their prior knowledge dichotomized into high and low levels. We sorted the participants based on the number of correct responses to the 12 questions. For the participants with the same score, we sorted them again ordered by the subjective knowledge score. Afterwards, we performed the median-split to divide the participants into two groups – expert and novice. For each group, there are significant differences for both the objective knowledge score ($M_{expert} = 8.68$ vs. $M_{novice} = 3.77$, $F(1, 248) = 257.656$, $p < 0.001$) and the subjective knowledge score ($M_{expert} = 5.69$ vs. $M_{novice} = 2.32$, $F(1, 248) = 720.492$, $p < 0.001$). Our focus is to classify the participants as either being the group with a relatively higher level of expertise or the group with a relatively lower level of expertise. The method used in this experiment is common for manipulating consumer knowledge in marketing literature [4,36]. In this experiment, 125 subjects were experts and 125 were novices.

Since two items to measure the perceived number of reviews were loaded on a single factor (Cronbach's $\alpha = 0.952$), the average of the items was used to check whether the number of reviews was manipulated as we intended. An ANOVA analysis indicated the presence of the main effect of the number of reviews ($M_{2\text{-review(control)}} = 2.85$, $M_{4\text{-review}} = 3.89$, vs. $M_{8\text{-review}} = 4.89$, $F(2, 247) = 198.334$, $p < 0.001$), indicating that the number of reviews was manipulated as we intended.

Control variables including the perception of review positiveness, and the general attitude toward reviews were analyzed to see if there were significant differences among groups. No significant difference was shown in the perception of review positiveness ($F(9, 240) = 0.205$, $p < 0.993$) and the general attitude toward reviews ($F(9, 240) = 0.036$, $p < 0.999$). Thus, these control variables were excluded in the following analysis.

To test hypotheses 1 (Cognitive review fit hypothesis on experts) and 2 (Cognitive review fit hypothesis on novices), subjects' responses relevant to the type of review informa-

tion were examined. MANOVA was performed to check the effects of the types of review information and the levels of expertise on the three dependent variables: informativeness, usefulness, and helpfulness. The results showed that there were significant main effects of the type of review information (Wilk's $\lambda = 0.384$, $p < 0.001$) and expertise (Wilk's $\lambda = 0.954$, $p < 0.001$). In addition, there was a significant interaction effect between the type of review information and expertise (Wilk's $\lambda = 0.527$, $p < 0.001$). This interaction was significant for all the dependent variables including informativeness ($F(2, 244) = 57.708$, $p < 0.001$), usefulness ($F(2, 244) = 59.682$, $p < 0.001$), and helpfulness ($F(2, 244) = 63.027$, $p < 0.001$). Planned contrasts showed significant differences between experts and novices. For experts, reviews framed as being attribute-centric were viewed as being more informative ($M_{attribute-centric} = 5.24$ vs. $M_{benefit-centric} = 3.24$, $F(1, 244) = 179.31$, $p < 0.001$), useful ($M_{attribute-centric} = 4.96$ vs. $M_{benefit-centric} = 2.94$, $F(1, 244) = 127.23$, $p < 0.001$), and helpful ($M_{attribute-centric} = 5.06$ vs. $M_{benefit-centric} = 2.90$, $F(1, 244) = 167.12$, $p < 0.001$) than reviews framed as being benefit-centric. By contrast, novices stated reviews framed as being benefit-centric were more informative ($M_{benefit-centric} = 5.24$ vs. $M_{attribute-centric} = 3.24$, $F(1, 244) = 44.83$, $p < 0.001$), useful ($M_{benefit-centric} = 4.96$ vs. $M_{attribute-centric} = 3.90$, $F(1, 244) = 35.03$, $p < 0.001$), and helpful ($M_{benefit-centric} = 5.00$ vs. $M_{attribute-centric} = 4.02$, $F(1, 244) = 34.40$, $p < 0.001$) than reviews framed as being attribute-centric. For overall evaluation reviews, the level of expertise has no significant effect on the perceived informativeness ($F(1, 244) = 0.04$, $p < 0.85$), usefulness ($F(1, 244) = 0.62$, $p < 0.43$), and helpfulness ($F(1, 244) = 0.01$, $p < 0.99$). The results show that experts seek attribute information because they want to use their prior knowledge to infer product benefits from the stated attributes. Benefit information does not permit such inference. By contrast, novices prefer the benefits only messages because the specification of product benefits facilitates understanding of the given reviews. Interestingly, we found that the difference between attribute-centric and benefit-centric messages in terms of message preference was greater for experts than for novices. It is consistent with a previous study saying that experts have a clear preference structure rather than novices [36]. Hence, hypotheses 1 (Cognitive review fit hypothesis on experts) and 2 (Cognitive review fit hypothesis on novices) are accepted.

Since factor analysis indicated that the two items measuring purchase intention were loaded on a single factor (eigen-value = 1.936, Cronbach's $\alpha = 0.966$), the two items were averaged to compose a purchase intention score. The mean and standard deviation are in Table 4.

To test hypotheses 3 (Review fit hypothesis on experts' purchase intention) and 4 (Review fit hypothesis on novices' purchase intention), an ANOVA was performed. The two-way interaction effect between review type and expertise was significant as shown in Table 5. The relationship is shown in Fig. 1. For experts, purchase intention was significantly higher in the benefit-centric condition than in

Table 4
Descriptive statistics of purchase intention (mean, standard deviation, and cell size)

	Experts		Novices	
	Attribute-centric	Benefit-centric	Attribute-centric	Benefit-centric
Control (overall evaluation only)	1.86 (0.69), $n = 25$		1.85 (0.55), $n = 25$	
Small number of reviews	3.90 (0.68), $n = 25$	2.90 (0.58), $n = 25$	2.88 (0.58), $n = 25$	3.90 (0.71), $n = 25$
Large number of reviews	4.92 (0.61), $n = 25$	3.10 (0.52), $n = 25$	3.80 (0.60), $n = 25$	4.88 (0.62), $n = 25$

Table 5
ANOVA results

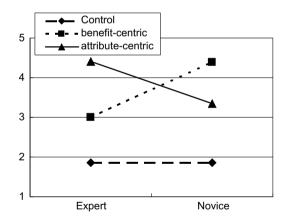|	Purchase intention	
	F	p
Number of reviews	80.985	0.01
Type of reviews	4.313	0.04
Expertise	3.408	0.07
Number of reviews × type of reviews	4.805	0.03
Number of reviews × expertise	3.847	0.05
Type of reviews × expertise	201.384	0.01
Number of reviews × type of reviews × expertise	6.443	0.01

Fig. 1. The interaction effect of the review type × the level of expertise.

the overall evaluation only condition ($F(1, 244) = 41.70$, $p < 0.001$). Therefore, experts are also affected by benefit-centric reviews. They had higher purchase intention when there was additional benefit information in the reviews. However, an increase in purchase intention was greater in the attribute-centric condition than in the benefit-centric condition ($F(1, 244) = 95.69$, $p < 0.001$). Since experts have better fit with attribute-centric reviews, they have higher purchase intention when they process attribute-centric reviews than when they process benefit-centric reviews. Thus, hypotheses 3 (Review fit hypothesis on experts' purchase intention) is supported.

Novices showed higher purchase intention when they were given additional attribute-centric reviews than when they were given overall evaluations only ($F(1, 244) = 70.29$, $p < 0.001$). Therefore, even though they might not understand the benefits of a product by reading attribute-centric reviews, a simple increase in the number of reviews from two overall evaluation reviews to two overall evaluation reviews and two additional attribute-centric reviews affected their purchase intention. However, when they were provided with benefit-centric reviews, which have a better fit, their purchase intention was higher than when they were provided with attribute-centric reviews ($F(1, 244) = 53.07$, $p < 0.001$). Therefore, hypotheses 4 (Review fit hypothesis on novices' purchase intention) is also accepted. In sum, the results are consistent with the expectation based on the cognitive fit theory that experts have higher purchase intention when they read attribute-centric reviews, while novices have higher purchase intention when they are exposed to benefit-centric reviews.

To test hypotheses 5 (ELM hypothesis on review type) and 6 (ELM hypothesis on review number), an ANOVA of the $2 \times 2 \times 2$ factorial design (not included control conditions) was performed. The significant interaction between review type and expertise ($F(1, 192) = 201.384$, $p < 0.001$) revealed that the review type had a stronger impact on purchasing intention under high-expertise conditions than under low-expertise conditions (see Fig. 1). This result was the same as the prediction from ELM. Thus, hypotheses 5 (ELM hypothesis on review type) is accepted. The two-way interaction effect between the number of reviews and expertise was significant ($F(1, 192) = 3.847$, $p < 0.001$). The relationship is shown in Fig. 2. The increase in purchase intention of novices when shifting from the small number of reviews to the large number of reviews is greater than the increase in purchase intention of experts. Thus, hypothesis 6 (ELM hypothesis on review number) is also accepted.

For further explanation of the results, we explored the different effects of the number of reviews and review type under low- and high-expertise conditions. It was possible
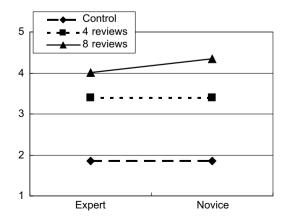

Fig. 2. The interaction effect of the number of reviews × the level of expertise.

Table 6
Hypotheses testing

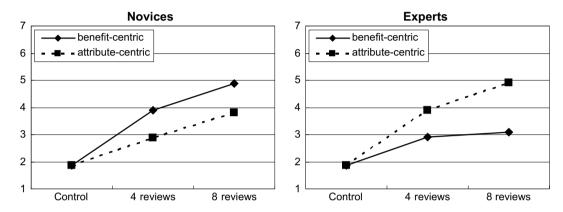| No.	Name	Predicted effect	Results
1.	Cognitive review fit hypothesis on experts	(cognitive fit of experts) Attribute-centric reviews > benefit-centric reviews	Accepted
2.	Cognitive review fit hypothesis on novices	(cognitive fit of novices) Benefit-centric reviews > attribute-centric reviews	Accepted
3.	Review fit hypothesis on experts' purchase intention	(experts' purchase intention) Attribute-centric reviews > benefit-centric reviews	Accepted
4.	Review fit hypothesis on novices' purchase intention	(novices' purchase intention) Benefit-centric reviews > attribute-centric reviews	Accepted
5.	ELM hypothesis on review type	(purchase intention) Experts > novices	Accepted
6.	ELM hypothesis on review number	(purchase intention) Novices > experts	Accepted

Fig. 3. The interaction effect of the review type × the number of reviews × the level of expertise.

to perform these analyses because the three-way interaction effect of the number of reviews × review type × expertise was significant ($F(1, 192) = 6.443$, $p < 0.05$). Experts did not have significantly higher purchase intention when they read a large number of benefit-centric reviews than when they read a small number of benefit-centric reviews ($F(1, 192) = 1.33$, $p < 0.25$). That is, the effect of an increase in the number of reviews on purchase intention was higher for the attribute-centric condition than for the benefit-centric condition ($F(1, 192) = 11.19$, $p < 0.001$). Since experts are likely to engage in the effortful process of reviews, a simple increase in benefit-centric reviews may not affect their purchase intention. By contrast, for novices, a simple increase in the number of reviews affects their purchase intention regardless of the types of reviews (benefit-centric reviews: $F(1, 192) = 31.96$, $p < 0.001$; attribute-centric reviews: $F(1, 192) = 28.17$, $p < 0.001$). Through further analysis on the three-way interaction, we could explain the acceptance of hypotheses 5 (ELM hypothesis on review type) and 6 (ELM hypothesis on review number) more clearly (Table 6, Fig. 3).

5. Conclusion

This study makes several theoretical contributions. First, this study resolves the previous inconsistent analyses on the relationship between WOM and expertise by considering the type of WOM message as a moderator. Studies on traditional WOM have not investigated the moderating role of message type because it was difficult to measure or trace the contents of WOM messages. This study, focusing on online consumer reviews as eWOM messages, explains this contradiction using the cognitive fit theory. The results show that cognitive fit occurs when experts (novices) process the reviews framed as attribute-centric (benefit-centric).

Second, this study applies ELM to investigate the effects of cognitive fit (review type) and the number of reviews. Previous research on ELM mainly focused on motivational factors (e.g. involvement and relevance) and its relationships with the qualitative aspect of messages. This study examined how an ability-related factor (the level of expertise) affects the processing of different types of messages. By integrating the cognitive fit theory and ELM, this study examines that consumers with different levels of expertise prefer different types of review messages (based on cognitive fit theory), and the effect of cognitive fit on purchase intention is stronger for experts than for novices (based on ELM). In addition to the effect of cognitive fit depending on consumer expertise, this study shows that the number of reviews is a more important factor for novices than for experts. It is because the number of reviews can be a peripheral cue to show product popularity and many advantages of a product for novices.

The findings of this study have several managerial implications. These findings help marketers develop strategic plans for each stage of the product life cycle. Marketers need to provide differently framed product information

for potential consumers with different levels of expertise. In the introduction stage of a product, target consumers are likely to be early-adopters with a relatively high level of expertise, so reviews should contain attribute information. On the other hand, consumers in the mainstream market (consumers in the maturity stage of the product life cycle) have a relatively low level of product knowledge, so they seek reviews framed as benefit-centric.

Online consumer reviews are presented on the Internet without any standard format [37]. That is, consumers freely write about the experience they had with a product. According to this study, though, online sellers need to deliver product information framed in a cognitively fitted way for both experts and novices. However, it is unrealistic and unnatural for online sellers to provide a standardized review format for previous buyers because "word-of-mouth" messages are supposed to be informal and, therefore, format-free. We suggest a different strategy reflecting the results of this study instead of a strategy providing different review formats. Marketers can sort reviews depending on the type of reviews (attribute-focused reviews and benefit-focused reviews) or the level of reviewer knowledge. Then, they can first show the reviews that match the level of expertise of potential consumers. In order to figure out which type of review should be given to which reader, marketers need to get information about the level of expertise of individual potential buyers as well as reviewers (previous buyers). This information can be acquired at the time that consumers become a member of the online shopping mall. The strategy to sort reviews depending on the level of reviewer expertise is even more efficient when there are plenty of reviews.

Using a star-rating system, we suggest another strategy for potential consumers to obtain better reviews easily. There can be two different types of star-rating systems. First, sellers can provide a summary of product evaluations with a star system. By showing the average star-rating score and the number of reviewers, review readers, especially those with a low level of expertise, simply can infer the value of the product. This star-system is widely used in online shopping malls. Second, review readers can evaluate posted reviews using a star system. In this case, the number of stars means the extent to which the reviews themselves are well written. These star scores can be a cue to provide information on the quality (usefulness or helpfulness) of reviews, resulting in potential consumers finding good reviews more easily. If online sellers have already acquired enough data on the level of consumer expertise, they can provide both "best reviews selected by novice consumers" and "best reviews selected by expert consumers." This will help potential review readers focus on reviews with a high cognitive fit.

There are some limitations to this study. First, we limit our investigation to positive reviews. The purpose of this study is to find that consumers with different levels of expertise fit different types of reviews. Furthermore, this study tries to find the differences in the effect of the number of reviews depending on whether consumers put more weight on the review fit or the number of reviews itself. This research, therefore, focuses on three main factors influencing the processing of reviews: (1) a characteristic of consumers (expertise), (2) a quantitative characteristic of reviews (the number of reviews), and (3) a qualitative characteristic of reviews (the type of reviews). However, in reality, consumers seek to read both positive and negative reviews simultaneously. In general, the number of positive reviews occupies a larger portion of total reviews. Resnick and Zeckhauser [38] reported that 99.1% of customer feedback on eBay in the late 1990s was positive, followed by negative (0.6%) and neutral (0.3%). Mulpuru [39] evaluated 4000 reviews in the Electronics and Home & Garden categories on the Amazon.com site. She found that more than 80% of the reviews were positive. Although the number of positive reviews overwhelms that of negative reviews, negative reviews are influential to consumers. Chevalier and Mayzlin [20] concluded that negative reviews have a greater effect than positive reviews in their study. Other references, such as and Pavlou and Dimoka [40] and Ba and Pavlou [41] found evidence on the stronger effect of negative comments compared to the positive ones. Mulpuru [39] also reported that the negative reviews occupying a smaller portion of total reviews were generally considered helpful to consumers.

If we consider only negative reviews, the effects of types of reviews and the number of reviews can be expected to be a mirror image of our current results. Novices will be more sensitive to benefit-focused negative reviews, while experts will be more sensitive to attribute-focused negative reviews in terms of cognitive fit with reviews. Consistent with our hypotheses, we can expect that consumers will be able to more effectively process reviews compatible with their processing strategy. Thus, reviews that fit them (either experts or novices) in terms of their type will amplify the effect of the valence of reviews. More specifically, consumers will have a more positive (negative) attitude toward the product when they processed positive (negative) reviews that fit them. However, it will still be worthwhile to see whether this mirror image can be generated in the context of negative reviews. Moreover, studies on mixed reviews (a combination of positive and negative reviews) can be another future research area. For example, investigating whether novices or experts are more sensitive to negative reviews will be an interesting future research area.

Second, this study focuses on reviews on product evaluations. Reviews or WOM communication can focus either on the seller or the product (or both). The reviews about a seller mainly mean the reviews on transactions such as product delivery or product payment. These reviews may be critical at the time when consumers make a final buying decision. The previous studies in the context of online auction sites like eBay mainly deal with the effect of seller reviews [42–45]. The common finding of these studies is that the seller's reputation can become an important factor in the bid, and this indicates that there is an strong impact of the seller's reputation on

the willingness of buyers to bid on items sold via Internet auctions. The seller reviews may be important for consumers in the context of online shopping malls as well as online auction sites, so further studies on this issue are necessary.

The final limitation is that, according to ELM, product involvement is also a critical factor that affects the perception of online consumer reviews because consumers rely more on them when they want to purchase high involvement products such as expensive products. However, in this study, involvement is controlled through random assignment of subjects. Finally, product category (for example, high-tech vs. low-tech) and product type (tangible vs. intangible) may also have an effect on the information processing of online consumer reviews. The effects of online consumer reviews can be generalized in further studies by considering these variables.

Appendix A

The example of reviews used in this experiment (four reviews in attribute-centric condition vs. benefit-centric condition)

Attribute-centric condition	Benefit-centric condition
"I would like to recommend this PMP. This product is just so good."	"I would like to recommend this PMP. This product is just so good."
"I am pretty satisfied with this product."	"I am pretty satisfied with this product."
"I want to recommend this product. It has 10 GB memory capacity, so I can store seven AVI files, which are 1.4 GB video contents compressed with a wide variety of codecs."	"I want to recommend this product. One of the most attractive aspects of this PMP is that it has a large memory capacity so I can store seven movies with good video quality."
"I like this PMP. First, it has a 3.8" TFT LCD weighing as little as 1 pound. Also, it is twice as bright as other LCDs with a broader gap in terms of contrasts."	"I like this PMP. It is light because it has a handheld-size screen and it has a display for showing photos and videos with satisfactorily high resolution."

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