Investigating usefulness configurations of online consumer reviews:
A Fuzzy-Set Qualitative Comparative Analysis

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Abstract

Online reviews have a significant impact on consumers' purchasing decisions. Many researchers have studied the relationship between review usefulness based on various factors related to online review, but existing studies have focused only on the linear relationship between variables methodologically. Therefore, this study examines the usefulness of online reviews from a configurational perspective derived from the complex interactions between elements, and aims to identify how these configurations differ according to product types. This study developed a conceptual model by combining HSM and ELM based on the theoretical discussion on the information processing and analyzed 7,316 cases collected from Amazon.com using fsQCA. As a result, three configurations affecting online usefulness were derived from search goods and four from experience goods. In short, consumers consume reviews through the complex interaction of various factors related to reviews, and the factors affecting the usefulness of search goods and experience goods are different.

Keywords: Online review, Review usefulness, Fuzzy-set qualitative comparative analysis (fsQCA), Heuristic-Systematic Model (HSM), Elaboration Likelihood Model (ELM)

1. Introduction

Online reviews have a considerable impact on online purchase decisions. Before purchasing products and services, consumers seek information about potential purchases through online reviews written by other consumers, and more than 82% of consumers say they read reviews before making a purchase decision (Murphy, 2019). Several studies have already been conducted on the profound impact of online consumer reviews on not only consumer behavior but also on e-commerce companies (Mudambi & Schuff, 2010; Paul, 2003) and these companies are trying to effectively provide useful reviews to consumers in the midst of a large number of reviews. Specifically, the platform allows consumers to rate the value of a review by voting "useful" if it is helpful. Since useful and reliable

information contributes to building a trusting relationship between the platform and consumers, and serves as a basis for understanding consumer behavior (Lee & Choeh, 2018), a number of recent studies in information system, computer science and marketing seek to provide insight into this by identifying factors that influence review usefulness (Karimi & Wang, 2017; Qazi et al., 2016).

Researchers have reviewed various factors including review contents, reviewer, and context-specific that affect usefulness based on multiple theories such as dual processing theory and credibility theory (Hlee et al., 2018; Hong et al., 2017). Nevertheless, in the methodological aspect, previous studies focused on the linear relationship between variables to examine the effect of specific latent factors (e.g., review depth, extremity) on review usefulness (Ham et al., 2019). This means that existing studies have focused on simple causal relationships between dependent and individual independent variables, using symmetric analysis methods such as structural equation models or multiple regression analysis (Pappas & Woodside, 2021; Park & Mithas, 2020). However, if the complexity theory that a specific phenomenon occurs due to the interaction between various causes rather than one cause is applied, online reviews are also perceived by consumers through the complex interaction of various information(factors) from huge amounts of information. However, previous studies have only focused on the main effects of specific factors on usefulness, failing to consider how review readers perceive and consume reviews as a result of the interaction of various factors.

Therefore, this study seeks to discover various patterns in which consumers perceive the usefulness of online reviews based on the complexity theory. Additionally, we examine whether there is a difference in patterns according to the classification of search and experience products, which are important product characteristics. To this end, this study uses fuzzy-set qualitative comparative analysis (fsQCA), a set theory construction method suitable for complex causal relationships and multiple interaction studies, on the premise that core elements are interdependent, and the results are better explained by simultaneous combinations rather than individual elements (Woodside, 2013). By conducting an empirical test

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based on 7,316 reviews collected on Amazon, this study theoretically identifies the usefulness perception patterns of readers about the usefulness of online reviews and contributes to expanding the literature on online reviews and dual-processing models. In addition, this has significant implications for review platform operators and companies seeking successful marketing.

2. Literature review

2.1. Online reviews and review usefulness

Online reviews reduce consumers' purchasing uncertainty (Kim & Hollingshead, 2015) and influence sales of products and services (Hong et al., 2017; Ratchford et al., 2003). With the development of Internet technology, a huge number of online reviews are being generated at a tremendous rate, and each product and service has a huge number of reviews. With hundreds or thousands of online reviews, it can be difficult to find useful online reviews for consumers. Many online platforms have adopted helpful voting systems to help shoppers find useful reviews effectively (Lee et al., 2021). Review usefulness based on this system refers to the degree to which the reader perceives that the review is useful and helpful (Mudambi & Schuff, 2010), and consumers perceive the review as useful as it has a greater influence on their purchasing decision (Chevalier & Mayzlin, 2006; Constantinides & Holleschovsky, 2016).

Review usefulness is considered very important since it shows how much a review influences consumer decision-making, and has been widely investigated for its importance (Racherla & Friske, 2012). Past studies have examined potential determinants of review usefulness based on various theories such as dual processing theory, credibility theory. As factors affecting the usefulness of a review, the characteristics of the review, the reviewer, the review context, and the product were considered (Choi & Leon, 2020; Hong et al., 2017). However, most previous studies have identified potential determinants based on only a single model (HSM or ELM). In addition, they focused only on the main effects of latent factors (e.g. review depth, extremity) on review usefulness and did not examine the combined effects between latent factors. Therefore, this study aims to detect combinations that explain consumers' perception of review usefulness.

2.2. Dual Processing Theory: Heuristic-Systematic Model and Elaboration likelihood Model

Online reviews not only convey information, but also function as a persuasive message as a means of expressing an individual's opinion. The dual processing model has been used in numerous studies on online reviews to try to understand how consumers process information about persuasive messages (Filieri, 2015; Zhang et al., 2014). Two typical models from the dual processing model theories—the heuristic-systematic model (HSM) and the elaboration likelihood model (ELM) — have been applied to explain consumer's online review behavior (Cheung & Thadani, 2012).

First, the HSM is an approach that assumes that messages can be processed in heuristic or systematic manner (Chaiken, 1980; Chaiken & Trope, 1999). Systematic cues are hints that entail careful scrutiny to grasp the merits of the message, whereas heuristic cues refer to applying heuristics, or short-cut cues, to evaluate the message (Tan et al., 2021). In a previous study, information such as ratings, photos, and videos as well as the reviewer's identity disclosure and reputation were considered in the heuristic message processing, and the length of the review message, readability and emotional tone were mainly considered in systematic message processing (Korfiatis et al., 2012; Mudambi & Schuff, 2010).

Next, the elaboration likelihood model (ELM), divides the information processing process into central path processing and peripheral path processing, unlike the heuristic-systematic model (HSM) discussed above (Cacioppo et al., 1983). Central cues indicate that it is directly related to the message, while peripheral cues rely on the environmental signal of the message ultimately decide whether to accept a message or not (Cheung et al., 2012). In previous studies, information directly related to the message was considered as the central cue, and review rating, reviewer's ranking, and reviewer's real name exposure were included as peripheral cues (Baek et al., 2012; Zhu et al., 2014).

By choosing one of the two models, prior studies have identified customer review behavior. As a result, depending on the model, even the same elements were categorized as cues of different information processing. For instance, the HSM assessed review length as a systematic cue, whereas the ELM model classified it as a central cue. Additionally, the reviewer's self-disclosure was categorized as a peripheral cue in the ELM model but as a heuristic cue in the HSM. HSM and ELM are closely related among the dual processing theories, however prior research has limitations in that they did not take both models into account. Therefore, by referencing how each review element was categorized in the HSM and ELM models in the previous validated studies, this study creates a unified framework of the two models. As a result, this study aims to comprehend the online review behavior in a

complicated dimension (Central-Heuristic, Central-Systematic, Peripheral-Heuristic, Peripheral-Systematic), which could only be explained by one information processing model. Considering that information processing cues interact with one another in a complicated manner, this study also looks at how these cues are combined and perceived as useful by consumers. This aids in clarifying up until now unclear mechanisms for consumer information processing. Therefore, this study proposes the following proposition.

Proposition 1. There is a combination of different causal conditions that influence perceptions of online review usefulness.

2.3. Product type: search and experience goods

Nelson (1974) classified search goods and experience goods based on whether consumers can check the quality before and after purchase. Search goods refer to products that can easily obtain information about product quality before purchase, and experience goods are defined as products with properties that are difficult to understand before purchase. Search goods can be easily evaluated and compared in an objective way without sampling or purchasing products, whereas experience goods are more subjective and more difficult to evaluate or compare (Huang et al., 2009). Cameras (Nelson, 1970), cell phones (Bei et al., 2004), laser printers, computers (Weathers et al., 2007), and USB (Baek et al., 2012) are typical examples of search goods, while Movies and TV, Video Games (Nelson, 1970), Music (Bhattacharjee et al., 2006; Weathers et al., 2007), Baby Books (Baek et al., 2012), and wine (Klein, 1998) are classified as experience goods.

Among the characteristics of various products, the classification of search and experience goods continues to be widely accepted (Huang et al., 2009), and many researchers have noted that, in terms of information processing, consumers depend on different information sources when purchasing search or experiential goods (Nelson, 1970). Peterson et al. (1997) argued that the purchase decision of experience goods is based on subjective judgment, whereas the purchase decision of search goods is determined based on external information that can be objective, and this argument has also been confirmed in the context of online reviews. Compared to purchasing search products, consumers who want to purchase experience products value the reviews of other consumers more important (Bei et al., 2004) and are more likely to choose products recommended by others (Senecal & Nantel, 2004). In addition, the type of product has been considered as

important in understanding the consumption behavior of online reviews. Mudambi and Schuff (2010) found that product type mitigates the effects of review extremes and review depth on review usefulness, and Baek et al. (2012) argued that central cues for search goods and peripheral cues for experience goods have a positive effect on review usefulness. As such, previous studies confirmed that the purpose of reading online reviews can vary depending on which product a consumer intends to purchase, but they are focusing on the net effect of an individual factor rather than the complex interaction between factors. Therefore, this study intends to examine the difference between search goods and experience goods in the usefulness of online reviews from a configurational perspective derived from the complex interaction between elements. Therefore, this study proposes the following proposition.

Proposition 2. Combination of different causal conditions affecting perception of online review usefulness depends on product characteristics (Search or Experience goods).

3. Research methodology

3.1. Research design and measure

The conceptual model of this study is developed based on the theoretical background of information processing related to the consumption of online information. The study constructs a framework based on the cues of the HSM and the ELM based on existing studies and based on this, factors including review rating, review length, review negativity, cognition, review photo, self-disclosure, review impact, and number of reviews are divided. Furthermore, we apply the fsQCA methodology to the conceptual model to check whether their configurations differ between useful reviews of search and experience goods. Figure 1 depicts our conceptual model, focusing on the configurational perspective, and explains how the elements related review combine to produce clear and powerful results through parsimonious configurations. The definitions of the variables in this study are listed in Table 1. For the measurement of variables and classification of factors, the existing literature was referred to. First, the central-heuristic factor includes review rating and review length, and the central-systematic factor includes review negativity and cognition. The central - cue focuses on the content of the review, and the review length, review negativity, and cognition extract the results of content analysis using the LIWC-22 software, which is actively applied to studies based on language analysis. Second, the peripheral-heuristic factor includes information about the review
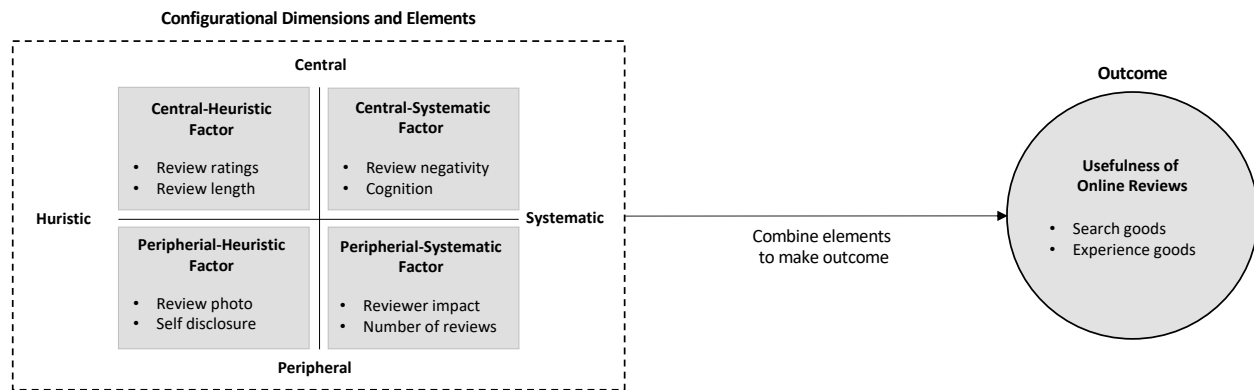
Configurational Dimensions and Elements

Figure 1. Conceptual model

photo and the reviewer's self-disclosure, and in case of the peripheral-systematic factor, the study extracts review impact and the number of reviews written by reviewers from the page that Amazon provides information on individual reviewers. Finally, values of "useful" votes are used to measure the review usefulness.

Table 1. Measurements

Elements (Variables)		Measurements
Causal conditions	Central-Heuristic factor	Review ratings	Score given by reviewer to a review (1-5)
		Review length	Number of words in a review (log)
	Central-Systematic factor	Review negativity	The extent of negativity of a review (0-100)
		Cognition	The extent of cognitive thinking in a review (0-100)
	Peripheral-Heuristic factor	Review photo	Number of photos in a review
		Self-disclosure	Whether a reviewer reveals reviewer face in reviewer profile photo (0-1)
	Peripheral-Systematic factor	Reviewer impact	The extent of influence of a reviewer (log)
		Number of reviews	Number of reviews written by a reviewer (log)
Outcome conditions	Usefulness		Number of "useful" votes obtained by a review

3.2. Sample and data collection

Data crawling (scraping) was performed using python 3.8 to obtain data for analysis. This data for this study were selected from reviews on the Amazon.com, a representative e-commerce platform, and reviews were collected from April 18 to 22, 2022. In this study, to reduce the bias in the analysis, data without any "useful" votes after data collection was excluded. The collected data includes information on product codes, values of "useful" votes, review content, star ratings, reviewer impact, and the number of reviews written by reviewers. Based on previous research, cell phones, laser printers, computers, and USB categories were included in the search goods, and movies and TV, video game, and music were included in the experience goods. According to the characteristics of the product, each 22 products were selected, and the overall review was collected. Finally, 7,316 reviews (3,658 reviews per product type) of 44 products were collected.

3.3. fsQCA

By using fsQCA, this study moves beyond simply identifying correlations between independent and dependent variables and patterns of factors influencing outcomes. FsQCA provides two types of configurations with necessary and sufficient conditions (Park et al., 2020). These configurations can be marked as present, absent, or "don't care" status. Necessary and sufficient conditions make it possible to distinguish between a core element and a peripheral element. The core element is a factor with a strong causal condition in the outcome, and the peripheral element is a weak factor (Fiss, 2011). FsQCA 3.0 software is used to analyze the data. The first step of fsQCA involves a calibration process, which converts data about causal conditions and the outcome into fuzzy scores. The second step identifies the configurations of causal conditions that sufficiently

produce the outcome of interest using a truth-table algorithm. Each case is assigned to one of several possible combinations based on the calibration results, each of which corresponds to a row in the truth table. The consistency score, which is determined by the truth-table algorithm and is comparable to the significance level in regression analysis, is then calculated. It describes how consistently a combination produces the outcome.

4. Data analysis and results

4.1. Descriptive statistics

Table 2 shows the descriptive characteristics of the datasets.

Table 2. Descriptive statistics

Elements (Variables)		N	Mean	SD	Min	Max
Central-Heuristic factor	Review ratings	7,316	3.90	1.55	1	5
	Review length	7,316	56.13	85.52	1	2,480
Central-Systematic factor	Review negativity	7,316	1.24	3.89	0	100
	Cognition	7,316	11.12	8.96	0	100
Peripheral-Heuristic factor	Review photo	7,316	0.07	0.54	0	18
	Self-disclosure	7,316	0.20	0.40	0	1
Peripheral-Systematic factor	Reviewer impact	7,316	190.10	1,401.22	0	60,620
	Number of reviews	7,316	107.07	446.69	0	16,036
Usefulness		7,316	3.15	24.97	0	963

First, looking at the collected 7,316 data, the average of each review rating is 3.09, and one review contains an average of 56.13 words. Also, each review has an average of 1.24 points for negativity, and these reviews were cognitively written (11.12 points). Second, each review contains an average of 0.07 photos and the number of reviewers who exposed their faces in their profile photos reached 20%. The influence of reviewers was 190.10 on average, and the average number of reviews written by reviewers was 107.07. Finally, each review has an average of 3.15 usefulness.

4.2. Calibration

In the calibration phase, data on causal and outcome conditions were transformed into membership scores ranging from complete non-members such as 0 to full members equal to 1 (Pappas & Woodside, 2021). The outcome condition, "Review usefulness", was converted into a membership score using the 95th, 50th, and 5th percentiles of the total number of "useful" votes (Pappas & Woodside, 2021). Causal conditions were transformed according to the following criteria. First, review length, review negativity, cognition, review impact, and number of reviews with numeric values were converted into membership scores using quartiles (0.95, 0.50, and 0.05). In addition, review photo was converted into a membership score based on the values of 2, 1, 0 for full membership, cross-over point, and full non-membership considering the overall distribution, and self-disclosure was calibrated depend on the values of 1, 0, 0 for full membership, cross-over point, and full non-membership. Finally, the review rating, which is divided into 1 to 5 points, was converted into membership score based on the values of 5, 3, 1 for full membership, cross-over point, and full non-membership (Pappas et al., 2016). Table 3 provides a summary of the membership score applied to each causal and outcome conditions. After transforming the membership scores, fsQCA 3.0 statistical software was used to analyze combinations of causal conditions affecting the usefulness of online reviews.

4.3. Necessary condition tests

Through the necessary condition tests on all elements, the elements necessary for review usefulness of experience goods and search goods were identified. The necessary condition test analyzes the presence or absence of a single element according to the usefulness of the review in search good and experience goods. If the consistency value for the causal factor is 0.9 or higher, it indicates that it is almost always a necessary condition (Schneider & Wagemann, 2012). Regardless of product characteristics, the consistency values of review length and self-disclosure are 0.9 or higher, which is a necessary condition for review usefulness. Reviewer impact is a necessary condition for experience goods, but they are different in that they are not necessary conditions for search goods. The results of the necessary condition test are shown in Table 3.

4.4. Sufficient configurations

FsQCA 3.0 software was used to analyze the data. To examine configurations that affect review usefulness,

Table 3. Calibration and necessary condition test

Elements (Variables)		Calibration values			Usefulness in Search Goods		Usefulness in Experience goods	
		Full membership	Cross-over point	Not full membership	Consistency	Coverage	Consistency	Coverage
Central-Heuristic factor	Review ratings	5	3	1	0.74	0.19	0.84	0.11
	Review length	5.204	3.466	0.693	0.94	0.25	0.92	0.22
Central-Systematic factor	Review negativity	5	1	0	0.63	0.31	0.76	0.26
	Cognition	25	10.980	0	0.84	0.25	0.85	0.23
Peripheral-Heuristic factor	Review photo	2	1	0	0.41	0.68	0.52	0.89
	Self-disclosure	1	0	0	0.90	0.25	0.95	0.17
Peripheral-Systematic factor	Reviewer impact	6.246	2.996	0	0.87	0.33	0.94	0.19
	Number of reviews	5.714	3.611	0.693	0.70	0.27	0.86	0.16
Usefulness		8	1	0	-	-	-	-

fsQCA was performed based on 10 causal conditions: review rating, review length, review negativity, cognition, review photo, self-disclosure, reviewer impact, and number of reviews. Based on previous studies and knowledge of context, more than 80% of cases were included, and cutoff values were determined (Pappas & Woodside, 2021). The analysis results are depicted in Figure 2 using the symbols by Ragin and Fiss (2008). In the figure, the black circles (●) indicate the presence of elements, while circles with X indicate no elements. Also, large circles indicate core elements, and small circles indicate peripheral elements. The blanks represent a "don't care" situation in which the element may or may not be present (Park et al., 2020; Ragin, 2006). In Figure 2, consistency indicates the degree to which the membership scores of the elements covered in outcome condition "review usefulness" are a subset of the results, meaning reliability (Ragin & Fiss, 2008). If the consistency value is 0.75 or more, it is judged appropriate. Coverage can be interpreted as a concept similar to R^2 in traditional quantitative analysis. In other words, it indicates how much the configuration of causal elements explains the review usefulness, which is an outcome condition. Unique coverage refers to the extent to which the configuration of causal elements that explain the review usefulness overlaps with other configurations (Ragin & Fiss, 2008). As a result of the analysis, the overall solution consistency, indicating the degree to which the derived configurations are a subset of review usefulness, was 0.774 for the search goods and 0.748 for the experience goods. In addition, the overall solution coverage, which means overall explanatory power, is 0.388 for search goods and 0.576 for experience goods.

4.4.1. Sufficient configurations in search goods. The left section of Figure 2 shows three configurations as fsQCA results indicating review usefulness of search goods. The three configurations derived from the analysis have review negativity as a core element for review usefulness in common. Specifically, it can be divided into U-S1a and U-S1b with review negative and review photo as core elements, and U-S2 patterns with review negativity, review length, and reviewer impact as core elements. First, in U-S1a and U-S1b, review negativity and review photo are core elements affecting review usefulness. These two configurations commonly include review rating, review length, and self-disclosure as peripheral elements. On the other hand, U-S1a includes review impact as a peripheral element, whereas U-S1b includes the presence of cognition and the absence of number of reviews as a peripheral element. These two configurations represent substituting or competing effect of the elements. Cognition and self-disclosure were determined to be unrelated factors in U-S1a, and reviewer impact was not thought to be significant in U-S1b. In addition, the inherent coverage of U-S1a among the two configurations is relatively high, which means that empirically, it is more related to review usefulness.

In the third configuration, U-S2, as in the previous two configurations, review negativity was included as a core element, and additionally, the absence of review length and the presence of reviewer impact appeared as core elements. Through this configuration, this study can confirm the importance of influential reviewers in

review usefulness. In addition to the three core elements, the existence of review rating, recognition, and self-disclosure elements and the absence of review photo and number of reviews were included as peripheral elements. By showing different results from other configurations in which review photo is included as a core element, it can be confirmed that pathways with different core elements exist.

4.4.2. Sufficient configurations in experience goods. The right section of Figure 2 shows four configurations as fsQCA results indicating review usefulness of experience goods. The four configurations derived from the analysis have a minimum of 1 and a maximum of 3 different elements as core elements for useful reviews. More specific characteristics for each configuration are as follows. In the first pattern, U-E1, only review photo appeared as a core influencing elements of review usefulness, and review negativity, reviewer impact and other heuristic factors appeared as peripheral elements. This means that in experience goods, consumers consider photos in reviews as important. However, it is a notable difference that the absence of review photo is included as a peripheral element in the other three configurations. Additionally, regardless of cognition and the number of reviews, usefulness perception is present. The second pattern, U-E2, has the absence of review rating, cognition, and reviewer impact as a core element. This type shows that the influence of reviewers is not high, and even a review with low ratings and few

cognitive words can be recognized as a useful review. This configuration is distinctive in that only the absence of the elements is core elements.

The third configuration, U-E3, has the same elements as U-E2, but has a different role. In U-E3, review negativity and number of reviews included as peripheral elements in U-E2, are included as core elements, whereas cognition is a core element U-E2 but appears as a peripheral element. Also, in this configuration, systematic factors such as review negativity and number of reviews are emphasized. Finally, U-E4 has reviewer impact, review rating, and number of reviews as core elements. The review rating is a core element in common with U-E2 and U-E3, but there is a difference in the status of peripheral-systematic factor and the elements that play the role of peripheral factors. As raw coverage is the highest, the fourth configuration appears to explain the usefulness of the review relatively well.

5. Discussion and Implications

5.1. Discussion

This study examines the configurations of consumers' perceptions of the usefulness of online reviews. In addition, this study divided product types into search and experience goods and analyzed the combination of factors that consumers mainly consider when recognizing reviews as useful. This study

Configuration Elements		Configuration for Search goods			Configuration for Experience good			
		U-S1a	U-S1b	U-S2	U-E1	U-E2	U-E3	U-E4
Central-Heuristic factor	Review ratings	●	●	●	●	⊗	⊗	⊗
	Review length	●	●	⊗	●	⊗	⊗	●
Central-Systematic factor	Review negativity	⬤	⬤	⬤	●	●	⬤	●
	Cognition		●	●		⊗	⊗	●
Peripheral-Heuristic factor	Review photo	⬤	⬤	⊗	⬤	⊗	⊗	⊗
	Self-disclosure	●	●	●	●	●	●	●
Peripheral-Systematic factor	Reviewer impact	●		⬤	●	⊗	⊗	⬤
	Number of reviews		⊗	⊗		●	⬤	⊗
Raw coverage		0.357	0.332	0.329	0.490	0.455	0.455	0.498
Unique coverage		0.025	0.001	0.031	0.051	0.020	0.020	0.041
Consistency		0.927	0.937	0.817	0.946	0.825	0.825	0796
Overall solution consistency			0.774			0.748		
Overall solution coverage			0.388			0.576		

Figure 2. Patterns of Usefulness review

develops a framework related to online review by combining HSM and ELM based on previous literature on the information processing that consumer go through when consuming reviews. This framework divided the factors related to online reviews mainly considered in previous studies into central-heuristic factor, central-systematic factor, peripheral-heuristic factor, peripheral-systematic factor.

To find configuration for review usefulness, 7,316 reviews collected on Amazon.com were analyzed through fsQCA. According to the results, review negativity exists as a core element in all solutions of search goods (U-S1a, U-S1b, U-S2). The absence of review ratings, however, is a core element in three of the four solutions (U-E2, U-E3, U-E4) for experience goods, and in this situation, the peripheral-systematic factors are present or absent. Finally, self-disclosure always exists as a peripheral element regardless of product characteristics.

5.2. Theoretical implications

This study provides theoretical contributions in the following three aspects. First, this study combines HSM and ELM to create a new framework based on the major factors considered in previous studies on review usefulness. This study combining the two models is significant in terms of extending earlier studies because HSM and ELM are representative models of dual processing theory, an information processing that is primarily mentioned when customers read online reviews. Analysis based on the framework helps to understand consumer by providing criteria for interpreting the behavior of consumers who consume online reviews.

Second, this study reflects the complex causal relationship by explicitly considering the necessary and sufficient conditions for the outcome through the constructive approach using fsQCA. This overcomes the limitations of previous studies that failed to examine the combined effects between latent factors by focusing on the main effects. The use of the fsQCA methodology can also be an alternative approach to other studies of information processing theory, which argue that cues within a model should be able to be explained together (Pappas et al., 2017). This study contributes to existing knowledge by applying fsQCA to identify various configurations affecting review usefulness. In each pattern, the existence and importance of elements affecting review usefulness are identified, and specific interpretations and implications of the results are provided.

Third, this study divided into search goods and experience goods according to the type of product, and separately looked at the combination of elements that lead to useful reviews. Supporting the existing research that factors influencing review usefulness differ according to product type and analyzing the difference between search and experiential goods from a configurational point of view, it is meaningful in that it supplements existing knowledge.

5.3. Practical Implication

This study provides practical implications in the following three aspects. First, review platform operators can utilize the practical guidelines provided by this study to obtain and manage useful reviews from consumers. The operator can provide better reviews to consumers by establishing an appropriate review system according to the characteristics of the product and managing reviews based on the pattern derived from the combination of elements. For instance, Amazon is developing the same review system regardless of the characteristics of the product. However, a different approach to developing a review system is required considering the characteristics of the product, which emphasizes the negative aspects in search goods and the review rating, reviewer impact, and number of reviews in experience goods.

Second, online reviews are an external source for businesses to hear their customers and a signal to understand what consumers think about their products. Therefore, companies can use the combination of reviews that many consumers find helpful to improve their products or market their products. For example, companies that sells search products may focus on improving the negative aspects of their products, while companies that sell experience products can manage low ratings and hold an event to post reviews with photos.

6. Limitation and further research

Further studies are needed to draw further implications from these findings. First, other methodologies such as SEM and ML may be used to compare research results or utilize them for further analysis to derive interesting insights. Using the combination derived from fsQCA as an input, it will be possible to develop a usefulness prediction model using several classification techniques such as SVM, NB, CART, and RF. If the combination derived based on the complex interaction of factors has a positive effect on the usefulness prediction, this could be a new and meaningful implication in the method of deriving the predictor variables.

Second, this study did not consider all factors frequently revealed in previous studies, such as videos of review, and extreme ratings. These factors are mainly dummy variables with a value of 1,0 and were excluded

because membership could not be precisely distinguished during the calibration process of the fsQCA methodology. However, if these variables are considered together, it is expected that existing studies will be enriched.

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