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The Influence of Shoppable Content Readability on Consumer Engagement in Brand Pages

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A B S T R A C T

Social media platforms have become prominent channels for e-commerce, and the role of social network sites' (SNS) content marketing is expanding as a strategic marketing communication approach to attract and retain consumers and increase sales. In this study, we focused on South Korea market and explored the influence of linguistic complexity and informality on consumer engagement. In particular, we identified the importance of complexity, focusing on its negative effects, as well as the moderating effect of commerce features to minimize these effects. Specifically, content length, hashtags, long words, and average sentence length significantly and negatively impacted consumer engagement. The influence of emojis, an informality variable, was not statistically significant. Shoppable tags, a commerce feature that provides both advertising explicitness and shopping convenience, were a moderating factor in the influence of complexity. Our findings provide new insights for content marketing researchers, and have practical implications for social media managers and content developers.

Keywords: Content Marketing, Content readability, Consumer engagement, Shoppable Tags

Ⅰ. Introduction

Social network sites (SNSs) have increasingly been integrated into their users' daily lives, and these platforms have become prominent channels for online shopping activities as well. Hund and McGuigan (2019) call this phenomenon "shoppable life" because social media significantly links brands to individuals' daily lives with shopping convenience. Companies widely use social media as a marketing communication tool, there remains a need for research about content engineering—the practice of organizing the shape, structure, and application of content such as written matter or photographs—to help marketers plan marketing and content strategies (De Vries et al., 2012; Mariani et al., 2016; Sabate et al., 2014; Seo, 2017).

According to Rohm et al. (2013), consumers inter-

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act and participate with a brand through content—they obtain product information, and their perceived enjoyment generates engagement and increases intent to purchase. Hence, consumers' response to business' social media content is critical to consumer retention (Kim and Lee, 2017). This is because consumers' positive response to content leads to brand interest but their negative response leads to consumer churn (Zeithaml et al., 1985). Content writing methods are especially important because text readability drives consumer engagement. For example, researchers have found that consumers prefer information that is accurate, instructive, and well-organized (Cvijikj and Michahelles, 2013; Kunz and Jahn, 2012). Conversely, consumers may become fatigued by content that is unrelated to brand or product information. (Pancer et al., 2019). As a result, content engineering has become increasingly important because of the effect of efficient content (Lee et al., 2018).

Prior research about content engineering has focused on the impact of content type on consumer engagement and classified content as interesting, informative, and participation-inducing (Arguello et al., 2006; Deng et al., 2020). However, despite their focus on the categorization of content, researchers have failed to emphasize the importance of content complexity and its negative effects on brand memory and brand attitudes (Deng et al., 2020; Pancer et al., 2019; Yeun Chun et al., 2014). Furthermore, scant research has been conducted about the moderating variables that can minimize this negative influence (Davis et al., 2019; Drago et al., 2018).

In this study, we focused on South Korea market and explored the moderating effect of commerce features (i.e., shopping functions in SNSs) on the influence of content complexity on consumer engagement. Our approach identifies relationships between variables and verifies the role of shoppable tags—allows to go to the purchase page by clicking on the tag above the picture in Instagram—for businesses and consumers on SNSs. We provide important information on content engineering tailored to the introduction of various shoppable features on social media platforms. First, each effect on consumer engagement was identified and compared by considering complexity and informality (François and Miltsakaki, 2012; Venturi et al., 2015). We endeavored to confirm existing research findings that complexity is an important factor in content marketing despite the wider range of textual acceptance of content such as informality (Deng et al., 2020). Second, we defined whether or not to use shoppable tags on Instagram product posts as a "commerce feature" and moderating variable. This commerce feature highlights advertising explicitness—accurately stating that content is intended for advertising—and shopping convenience and creates consumer confidence, reliability and positive response (Jackson, 2020). Shopping convenience and realiability created by commerce feature is the same factor which is degraded by complexity's negative effects. Therefore, in this study, we noted the potential for commerce features as a moderator. Finally, a strategy was formulated to minimize the negative effects of complexity, which helped derive and meaningful implications.

This paper is organized as follows. Section 2 describes the theoretical background regarding content readability, consumer engagement, and shoppable tags, and we describe the relationship between variables for hypothesis testing. Section 3 discusses the research methodology used in this study. Section 4 presents the results of analysis. In Section 5, we conclude and discuss the implications, limitations, and future research directions of our study.

Ⅱ. Conceptual Background and Hypothesis Development

2.1. Readability : Complexity and Informality

According to Klare (1963), readability can be defined as “the ease of understanding or comprehension due to writing style.”. An article is considered readable if it consists of words or sentences that can be easily and quickly understood without prior knowledge (Alter and Oppenheimer, 2009). Conversely, words and sentences that are excessively long or poorly organized cause reader fatigue (Pancer et al., 2019).

In the context of social media, complexity and informality can be included in readability (Deng et al., 2020). Complexity is divided into word or sentence complexity (DuBay, 2004). Word complexity is calculated by the length of a word or by the average length of entire words (Flesch, 1948; Gunning, 1952; Mc Laughlin, 1969). Sentence complexity is calculated by the length of a sentence or by the average number of words per sentence (Chall and Dale, 1995). Based on prior research, the detailed factors of the complexity considering social media’s attributes are shown in <Table 1> (Arguello et al., 2006; Jones et al., 2004; Lee et al., 2018; Venturi et al., 2015). As hashtags (#) and at (i.e., the symbol @) signs are utilized in social media, they can included in complexity factors (Ansary et al., 2013).

Informality refers to the colloquial characteristics of casual as opposed to formal expression (Delin and Oberlander, 2005; McArthur, 2003). Formality and informality can be distinguished in both written and conversational communication (Rueckert and Walker, 1987). Specific informality factors that reflect the context of social media based on prior research (Gretry et al., 2017; Mosquera and Moreda, 2012) are shown in <Table 2>. Emoji is any of various small images or icons used in text fields in electronic communication to express the emotional attitude of the writer (e.g., 😀). Contraction is a shortened expression of a word or words (e.g., “It’s”, “I’m” and

<Table 1> Description of Complexity Factors

Detailed factors	Description	Type
Content length	Total number of words in the content	Integer
Hashtag (#) ratio	Percentage of hashtags to total number of words	Float
Long word ratio	Percentage of “some words longer than average length of words in content” compared to the total number of words	Float
Average length of sentences	The average number of words in a single sentence	Integer
At sign (@) ratio	Percentage of the number of times tagged another (someone referred to another person's account using @) compared to the total number of words	Float

<Table 2> Description of Informality Factors

Detailed factors	Description	Type
Emojis ratio	Percentage of emojis to total number of words	Float
Contraction ratio	Percentage of contractions to total number of words	Float
Punctuation ratio	Percentage of punctuations to total number of words	Float
Personal pronoun ratio	Percentage of personal pronouns to total number of words	Float

<Table 3> Description for All Variables

Variables		Detailed factors	Description	Role
Readability	Complexity	Content length	Total length of content	Independent
		Hashtags	Hashtags' rate in content	
		Long words	Long words' rate in content	
		Average sentence length	Average length of sentence in content	
	Informality	Emojis	Emojis' rate in content	
Commerce Feature		Shoppable tags	Whether to use shoppable tags in content	Moderator
Consumer Engagement		Polarity	Average score of sensitivity for comments	Dependent

"We're") and Puntuation is symbols such as full stops or periods, commas, or question marks to divide written words into sentences and clauses (e.g., ".", "," and "?"). Personal pronoun is a pronoun such as "I", "you", or "They" which is used to refer to the speaker or the personal spoken to, or to a person or thing, usually because they have already been mentioned.

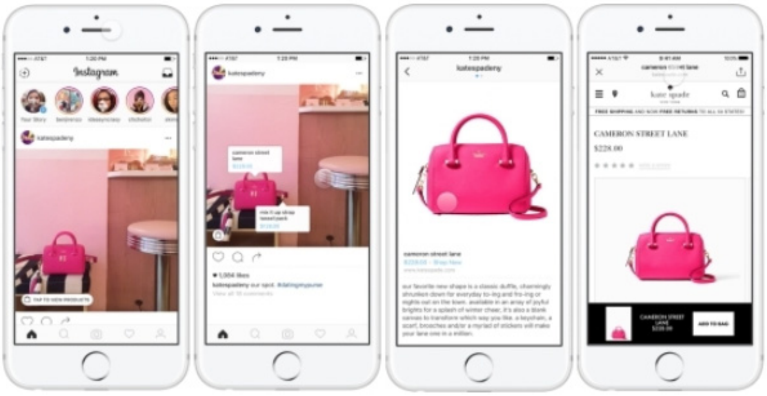
The variables used in this study are shown in <Table 3>. Based on existing studies, at-sign ratio, contraction ratio, punctuation ratio and personal pronoun ratio are excluded. Sun et al. (2014) found that at-sign behaviour (At-mention behaviour) is not significant with social network users' answering passion and willingness. Also, Deng et al. (2020) said At-sign ratio, Contraction ratio, Punctuation ratio and Personal pronoun ratio have no statistically significant effects on likes, shares and comments.

2.2. Consumer Engagement

Consumer engagement refers to consumers' interactive experience within online brand communities —both in terms of engagement with the brand and with other members of the online brand community (Brodie et al., 2013). Positive Electronic word-of-mouth (eWOM) on consumer attitude toward a brand or a product is formed by consumers' positive attitude toward content's messages and it leads to purchase intention (Cvijikj and Michahelles, 2013). Hence, consumer engagement is an indicator of consumers' satisfaction, trust, and loyalty toward a brand (Bowden, 2009). In the context of social media, representative indicators of consumer engagement can be defined by consumers' expressions to others through likes, shares, and comments (Cvijikj and Michahelles, 2013; De Vries et al., 2012; Kwok and Yu, 2013; Mariani et al., 2016; Sabate et al., 2014; Statista, 2015). These expressions create positive eWOM that attracts potential consumers' attention (Lipsman et al., 2012).

2.3. Shoppable Tags

Shoppable Instagram posts and product tags (i.e., Shoppable tags) were introduced in 2018. This commerce feature provides shopping experiences to Instagram consumers utilizing the keywords "simple" and "personalized" (Animalz, 2018; Hund and McGuigan, 2019). Once a consumer hovers over a content, the product tag will appear, displaying the product label and price. Consumers can click on the tag to access further product information and then click directly to the product's landing page to purchase the product. The process of using shoppable Instagram product tags is presented in <Figure 1>.



<Figure 1> Example of Shoppable Instagram Product Tags (Geyser, 2018)

With the introduction of shoppable tags directly into its posts, Instagram created a commerce feature for businesses looking to drive traffic from Instagram to their landing pages (Fylan, 2018). Thus, shoppable Instagram posts have streamlined the purchasing process, reduced the consumer churn rate, and increased the purchase conversion rate (Kang, 2019). Commerce feature also achieved one of the six Instagram marketing tactics—including features of story, profile, hashtag, video advertising, product catalog—that helped foster e-commerce industry (Lee, 2020). Hence, Instagram's shoppable tags are that lowers purchasing barriers—they facilitate both businesses' and consumers' use of Instagram as a shopping platform (Dod, 2018). Consumers can seamlessly browse on social media without directly visiting a brand's website and companies can organize content and induce purchase without directly listing the purchase link in the content, enabling businesses to retain existing consumers and convert potential consumers to new buyers (Animalz, 2018).

2.4. The Effects of Content Readability on Consumers' Sentiment

Researchers have found that consumers' positive sentiment toward brand content builds positive brand attitude, creates loyalty and, as suggested by Lee et al. (2011), exerts a positive influence on online eWOM (Bowlby, 1979; Kim et al., 2019a; Labrecque, 2014; Lee et al., 2011; Rubin and Step, 2000). Kim et al. (2019a) also found that consumers' positive comments led to increased brand loyalty when they indicated they liked product promotions and survey content posted by companies' social media brand pages. Researchers noted that consumers believe they have a quasi-social relationship with the brand when they acquire product information through content and freely submit their comments on the online brand pages (Labrecque, 2014; Rubin and Step, 2000). Bowden (2009) posited that this positive consumer engagement and brand loyalty reflects consumer satisfaction and trust.

To create advertising effects of a certain level, content engineering aims to achieve positive consumer feedback to content. Researchers have found that content readability—a leading variable in consumer engagement—includes complexity and informality (Deng et al., 2020). In particular, consumers are sensitive to content complexity (Deng et al., 2020; Pancer, 2019; Yeun Chun, 2014). For example, the higher the complexity of a word or sentence is, the more negative a consumers' attitude toward the content, leading to negative consumer engagement (Archak et al., 2011; Liu and Park, 2015). Excessively long words or sentences or a high proportion of long words or sentences cause consumer fatigue and disinterest in the content (Arguello et al., 2006; Jones et al., 2004; Lee et al., 2018; Venturi et al., 2015). Owing to so-called social media overload, consumers prefer easily read or understood content (Ashley and Tuten, 2015; Jepsen and Jensen, 2007). Therefore, positive consumer engagement requires shorter words and sentences (Arguello et al., 2006; Jones et al., 2004). In this study, we establish the importance of complexity based on this relationship and explore the effects of specific complexity factors on consumer engagement.

Scholars have defined informality—along with complexity—as an element of readability, and in our study, we expected to confirm the influence of each element on consumer engagement. Informality reduces consumer psychological distance from online brands and creates familiarity (Dwyer, 2007). Scholars have identified and compared the effect of informality with the effect of complexity on consumer engagement (Delin and Oberlander, 2005; Ruekert and Walker, 1987). By aggregating the results of these processes, content engineering strategies can generate advertising effects. We propose the following hypotheses:

H1: Complexity of content will have negative effects on consumer engagement.

H2: Informality of content will have positive effects on consumer engagement.

Researchers have measured consumer engagement according to the number of likes, shares, and comments on a brand. However, these findings are limited in expressing consumers' negative or neutral sensitivity toward content as they focus only on positive feelings, and scant research exists that utilizes an indicator that fully reflects consumers' sentiments (Deng et al., 2020). In this study, we define consumer engagement as the average score of sentiment toward comments, as the specific sentiment contained in comments includes content engineering measures that companies should pursue in the future (De Vries and Carlson, 2014). Our approach utilizes the consumer's positive, neutral, and negative emotions toward content as a measurement of consumers' engagement.

2.5. The Moderating Effects of Commerce Features on the Effects of Complexity

Several researchers have explored the direct negative effects of complexity on consumer engagement (Deng et al., 2020; Liu and Park, 2015) and indicated the need for measures to minimize these negative effects (Davis et al., 2019; Drago et al., 2018; Pancer et al., 2019). Following Drago et al. (2018), because complexity plays an important role in achieving performance goals, it is essential to identify the variables that moderate the relationship between complexity and the achievement of these performance goals. Davis et al. (2019) identified the moderating effect of brand hedonism between complexity and consumer engagement and noted that various moderating variables should be further explored for a deeper understanding of these relationships. However, despite the recent interest, existing research remains insufficient.

In this study, we explored moderating variables to determine the factors that mitigate the negative effects of complexity and creates advertising effects. For this reason, we considered factors that have a positive influence on maintaining the essence of advertising such as to inform, differentiate, persuade, and remind consumers about brand, product or service. Previous studies showed that the perceived reliability of the brand in online advertising is an important attribute that directly affects advertising effectiveness and sales (Cha and Lee, 2018; Son and Kang, 2017; Wojdynski and Evans, 2016; Wu et al., 2016). Kang (2017) noted that explicitness of advertising—in which the advertiser is transparently identified—is a key condition to obtain a low advertising evasion rate and high advertising recognition while reducing advertising deception. Wojdynski and Evans (2016) and Wu et al. (2016) examined that labeling advertising as "sponsored" or "advertising" increased advertising recognition. Kang (2017) found that sufficient explicitness of content is a measure of advertising quality—explicitness leads to trust in the brand, helping to maintain the essence of advertising purposes. The recent increased in deceptive or exaggerated advertisements on social media has increased consumers' desire for explicitness and has revealed the need for honesty in advertising. For example, the number of deceptive or exaggerated food-related advertisements on social media posts and blog posts has increased sharply from 617 (in 2014) to 10,492 (in 2017) in South Korea (Ministry of Food and Drug Safety, 2019). This is expected to lead more deceptive and exaggerated advertisements—including uncounted SNS transactions because of the actual situation without going through official registration and sales procedures on Facebook, Instagram, and Twitter; researchers have noted that consumers increasingly perceive these advertisement as deceptive (Um, 2020). Hence, it can be predicted that commerce features with explicitness can be used to secure consumers' trust of SNS brand pages.

In this study, we confirmed Instagram's commerce feature of shoppable post tags as a moderator. Shoppable tags work facilitate both businesses' and consumers' use of Instagram as a shopping platform (Rogers, 2018), providing shopping convenience for consumers as well as customer retention, new customer generation, and increased brand value for businesses (Fylan, 2018). Previous studies have shown that the reliability and convenience created by commerce features (i.e., shoppable tags) are the same factors that are degraded by content complexity. Therefore, we can assume that many content complexity factors will have different effects on consumer engagement in accordance with shoppable tags. To minimize the negative influence of complexity, we must identify its role as a moderator. We propose the following hypothesis:

H3: The Commerce feature will moderate between content complexity and consumer engagement.

Ⅲ. Research Methodology

3.1. Set of variables

In this study, we defined variables based on prior research findings (Arguello et al., 2006; Gretry et al., 2017; Jones et al., 2004; Lee et al., 2018; Mosquera and Moreda, 2012; Venturi et al., 2015). Detailed factors are described in <Table 3>. Independent variables reflect the characteristics of Instagram, which combines emojis and hashtags in content in both Korean and English.

"Content length" refers to the total number of words in content. The factor "Hashtags" was calculated as the number of hashtags compared with content length, considering one hashtag as a single word.

"Long words" were measured by the proportion of words that have a greater number of characters (i.e., alphabet letters) than the average among all words in the content. "Average sentence length" was measured by the number of words the sentence consisted of on average, based on the words used in one sentence. The factor "Emojis" was calculated as the number of emojis compared with content length by considering one emoji as a single word.

The factor "Shoppable tags" was configured in the form of a dummy variable. Content posted on Instagram shoppable posts can use shoppable tags regardless of the format of photos and videos. Therefore, it reflected a mix of content in an Instagram account.

"Polarity" was calculated the emotional score of comments written by consumers. Since a number of comments can written in a single content, 'the average emotional score of comments' was defined as polarity. In addition, comments are mixture of Korean, English and emojis in a content. So, the emotional score was calculated and averaged respectively. As a result, one emotional score was matched to one content. It was calculated as follows. First, each sentiment score is extracted by separating Korean, English, and emojis for one comment. Kim et al. (2014) found that Korean messages can be converted to English for sentiment analysis in the absence of official Korean sentimental dictionaries based on high quality of sentiment forecasting performance. Therefore, in this study, Korean was translated into English using Googletrans, a Google Translate API provided by Python library, and the sentiment score was extracted through TextBlob (a Python library for simplified text processing). TextBlob is a python library for Natural Language Processing (NLP) and it actively used Natural Language Toolkit (NLTK). NLTK is a library which gives an easy access to categorization, classification and many other tasks. TextBlob returns polarity and subjectivity of a sentence. Polarity lies between [-1,1]. For TextBlob, if the polarity is > 0, it is considered positive, < 0 is considered negative and = 0 is considered neutral. So, we used the function 'TextBlob (text).sentiment. polarity' in Python. In English, the sentiment score was extracted using TextBlob. Emojis' score was calculated by Emoji Sentiment Lexicon (Novak et al., 2015). Second, the sentiment scores of Korean, English, and emojis extracted from one comment were added together. Third, we repeated steps 1 and 2 to average each comment's sentiment score for one content. Through this process, one sentiment score was calculated per content.

3.2. Conceptual Model

The research model and hypothesis of this study are as follows.

Based on the model in <Figure 2>, we propose the following research questions and hypotheses:

RQ1: Complexity will be an important factor in determining consumer engagement.

H1: Complexity of content will have negative effects on consumer engagement.

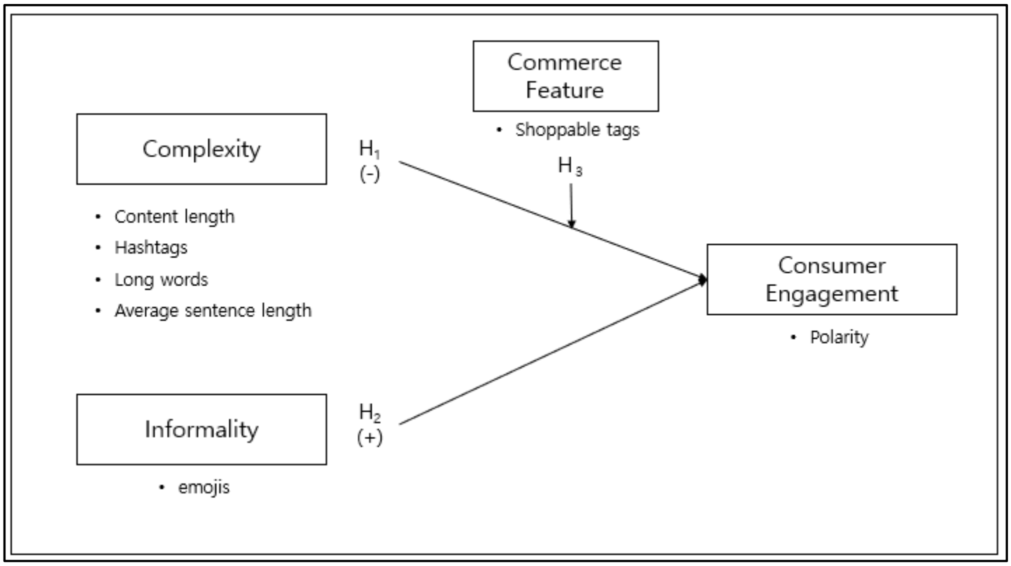
H2: Informality of content will have positive effects on consumer engagement.

RQ2: The commerce feature is a way to mitigate the negative effects of complexity.

H3: The commerce feature will moderate between content complexity and consumer engagement.

3.3. Data Collection

In this study, Instagram—the most actively used social marketing platform using shoppable tags



<Figure 2> The Research Model

Note: The hypotheses about detailed factors of each hypothesis is not marked separately.

(Animalz, 2018) — is the target of our analysis. In order to create variables, posts and comments posted on the official Instagram accounts of various companies in Korea were collected. The process of selecting specific industries and companies follows.

First, Socialbakers' Facebook Pages Stats in South Korea (2020) statistics were used to classify industries and list their brands. Through this, we listed the official accounts of brands categorized by industry in descending order by Facebook followers to identify the top brands in the market. Among them, the top 20 most popular brands were selected for consideration. Second, the top three brands within the selected industry that met the criteria set in this study were selected as final collection targets. The criteria for the final selection of brands are applied by steps shown in <Table 4>. In step 2, when converting a personal account into a business profile, shoppable tags can be used in the brand's Facebook page and Instagram personal account (Facebook for Business, 2020). Therefore, we determined that this step is a prerequisite for analysis.

Finally, the content of 27 brands were collected for a total of nine industries. Since the amount of content posted by each brand is different, up to 300 of the postings from January 2020 to July 2020 were randomly collected based on the lowest number of 300 posts. For data collection, Selenium and BeautifulSoup in Python were used as a tool, and a dynamic Web Crawler was established. A total

<Table 4> Selection of Brands

Steps	Criteria of brand selection
1	Does this company have an official domestic account on Instagram?
2	Is this company using the account as a business profile and using shoppable tags?
3	After step 2, the top three brands are selected based on Instagram followers.

of 5,689 posts with more than one comment were used for analysis and 45,118 comments were used for analysis. The results of the data collection were compiled in <Appendix A>.

Ⅳ. Data Analysis and Results

4.1. Descriptive Statistics and Normalization

A total of 5,689 data and 11 variables are summarized in <Table 5>.

The results of descriptive statistics, which have been converted to the range of the minimum value of 0, the maximum value of 1 through normalization are as shown in <Table 6>.

4.2. Correlation Analysis

The results of the correlation analysis between all variables except interaction variables are shown in <Table 7>. The correlation coefficients between all variables and the polarity were statistically significant within the range of -0.36 to 0.37, except

<Table 5> Composition of All Variables

Variables	Non-Null Count	Type
1. Content length	5689	int64
2. Hashtags	5689	float64
3. Long words	5689	float64
4. Average sentence length	5689	float64
5. Emojis	5689	float64
6. Shoppable tags	5689	int64
7. Polarity	5689	float64
8. Content length x Shoppable tags	5689	int64
9. Hashtags x Shoppable tags	5689	float64
10. Long words x Shoppable tags	5689	float64
11. Average sentence length x Shoppable tags	5689	float64

<Table 6> Descriptive Statistics After Data Normalization

	1	2	3	4	5	6	7	8	9	10	11
count	5689	5689	5689	5689	5689	5689	5689	5689	5689	5689	5689
mean	0.139	0.535	0.478	0.317	0.381	0.851	0.289	0.117	0.459	0.417	0.280
std	0.101	0.218	0.132	0.066	0.183	0.357	0.041	0.106	0.280	0.213	0.133
min	0.000	0.000	0.000	0.000	0.101	0.000	0.000	0.000	0.000	0.000	0.000
25%	0.070	0.410	0.444	0.295	0.152	1.000	0.278	0.050	0.310	0.279	0.280
50%	0.113	0.600	0.519	0.327	0.443	1.000	0.297	0.092	0.570	0.514	0.331
75%	0.185	0.690	0.563	0.354	0.544	1.000	0.311	0.162	0.670	0.571	0.362
max	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000

Note: Specifications for variables 1 to 11 are based on <Table 5>.

<Table 7> The Results of Correlation Analysis

	1	2	3	4	5	6	7
1	1.000000						
2	0.192***	1.000000					
3	0.116***	-0.056***	1.000000				
4	0.231***	0.048***	0.367***	1.000000			
5	-0.095***	-0.060***	0.034***	0.076***	1.000000		
6	-0.099***	0.047***	-0.128***	-0.080***	0.038***	1.000000	
7	-0.107***	-0.045***	-0.359***	-0.261***	0.014	0.153***	1.000000

***$p < .001$, **$p < .01$, *$p < .05$
Note: Specifications for variables 1 to 7 are based on <Table 5>.

<Table 8> Confirmation of Multicollinearity

	VIF	Variables
0	45.232730	Intercept
1	1.107931	Content length
2	1.207843	Hashtags
3	1.024180	Long words
4	1.193584	Average sentence length
5	1.050219	Emojis
6	1.035012	Shoppable tags

for emojis (r = 0.014, p = 0.3021). Although this is lower than the level of 0.8 at which multicollinearity occurs, Variance Inflation Factor (VIF) additionally confirmed among independent variables. The results are shown in <Table 8>. All of VIF were derived from approximately 1 and revealed no distortion in the correlation results.

4.3. Hypothesis Test

For Hypothesis testing, multiple regression was used. Leagerwood and Shrout (2011) said MRA (Manifest regression anlaysis) which is a multiple regression with latent variables, is more efficient than SEM in that latent variables approach causes larger standard errors. Prior to hypothesis testing, the assumptions of multiple regression were verified. First, linearity and homoscedasticity were satisfied. Next, normality was satisfied by central limit theorem because there were more than 30 samples. Finally, for independence, the Durbin-Watson statistics was derived from approximately 1.8~2.0 in all relationships between the independent variables and the dependent variable. It revealed that there was no autocorrelation.

For the test of H1, the results of simple and multiple regression about the effect of complexity on consumer engagement are as follows. First of all, as a result of simple regression of each independent variable, content length (β = -0.0428, $p < .01$), hashtags (β = -0.0083, $p < .01$), long words (β = -0.1105, $p < .01$), average sentence length (β = -0.1597, $p < .01$) were shown to have significant negative effects on polarity. Therefore, H1 was accepted because the hypotheses about detailed complexity factors were accepted. The results of multiple regression to compare the influence of detailed factors are shown in <Table 9>. Content length (β = -0.0117, $p < .05$), hashtags (β = -0.0093, $p < .01$), long words (β = -0.0947, $p < .01$) and average sentence length (β = -0.0850, $p < .01$) have significant and negative effects on polarity.

As a result, the most negative influence on polarity was long words. In other words, as the proportion of long words increases, polarity decreases the most. Next, we confirmed that the negative influence was greater in order of average sentence length, content length, and hashtags based on the results of multiple regression. Additionally, focused on content length, Independent-samples t-test analyzed whether there is a difference in the average polarity between long and short content groups. The criteria for classifying groups is 0.139 which is the average content length. As a result, the null hypothesis that there is no difference in the average polarity based on the content length was rejected at the significance level of 0.05. So, it can be inferred that a longer content reduces the polarity based on t-value (t = -9.550, $p < 0.05$).

As a result of simple regression for the test of H2, the effect of emojis (β = 0.0030, p = 0.302) on polarity was not significant. Therefore, H2 that informality had positive effects on consumer engagement was rejected.

Lastly, the results of multiple regression focused on combined effect of complexity and informality are shown in <Table 10>. Same results as the test of H1 and H2, content length (β = -0.0109, $p < 0.05$),

<Table 9> The Results of Multiple Regression Focused on Complexity's Influence

	B	std err	T	R^2	Adj R^2	F
Intercept	0.3681***	0.003	217.803	0.152	0.151	254.3
Content length	-0.0117*	0.005	-2.278			
Hashtags	-0.0093***	0.002	-3.975			
Long words	-0.0947***	0.004	-23.306			
Average sentence length	-0.0850***	0.008	-10.336			

***$p < .001$, **$p < .01$, *$p < .05$
Note: Dependent variable is polarity.

<Table 10> The Results of Multiple Regression Focused on Combined Effect of Complexity and Informality

	B	std err	T	R^2	Adj R^2	F
Intercept	0.3664***	0.003	119.548	0.152	0.151	204.0
Content length	-0.0109*	0.005	-2.122			
Hashtags	-0.0091***	0.002	-3.909			
Long words	-0.0949***	0.004	-23.349			
Average sentence length	-0.0852***	0.008	-10.363			
Emojis	0.0044	0.003	1.596			

***$p < .001$, **$p < .01$, *$p < .05$
Note: Dependent variable is polarity.

hashtags (β = -0.0091, p < 0.01), long words (β = -0.0949, p < 0.01) and average sentence length (β = -0.0852, p < 0.01) have significant and negative effects on polarity. Otherwise, emojis (β = 0.0044, p = 0.110) was not significant on polarity.

The results of the tests in H1 and H2 supported RQ1 that complexity is an important factor. In particular, since complexity and informality are representative readability factors (Deng et al., 2020), it was determined based on the fact that the two factors can be compared. Furthermore, we can support existing studies (Deng et al., 2020; Hendriks et al., 2017; Pancer et al., 2019; Yeun Chun et al., 2014) that indicate that complexity is an important factor for consumer engagement and advertisement effect. For example, Hendriks et al. (2017) said that linguistic complexity must be eliminated as much as possible to increase advertising effectiveness. If complexity increases, advertising effectiveness will be negatively affected.

For the test of H3, multiple regression analysis (Baron and Kenny, 1986) was confirmed into three steps for each complexity factor. The results were interpreted in conjunction with the patterns of moderating effects. The basis for pattern is as shown in <Table 11> (Bae, 2015).

The results are listed in <Table 12> through 15. First, shoppable tags was the moderator with buffering effect between content length and polarity. The model's fitness was statistically significant in the third model in which the interaction variable (β = 0.0374, p < .05) was deployed, and R-square increased by 0.02 and 0.001 as the model was progressed from the first to the third. Second, shoppable tags was moderator with interference effect between hashtags and polarity. The model's fitness was significant in

<Table 11> Theoretical Assumption about the Pattern of Moderator in the Third Model

Patterns (effects)	X → Y : B1	M → Y : B2	X x M → Y : B3
Enhancing	(+)	(+)	(+)
	(-)	(-)	(-)
Buffering	(+)	(-)	(-)
	(-)	(+)	(+)
Interference	(+)	(+)	(-)
	(-)	(-)	(+)

<Table 12> Shoppable Tags' Moderating Effect on Content Length's Influence

Steps	Independent	β	R^2	Adj R^2	R^2(change)	F
1	Content length	-0.0428***	0.011	0.011		65.32***
2	Content length	-0.0371***	0.032	0.031	0.02	93.28***
	Shoppable tags	0.0164***				
3	Content length	-0.0696***	0.033	0.032	0.001	64.14***
	Shoppable tags	0.0105***				
	Interaction	0.0374*				

***p < .001, **p < .01, *p < .05

Note: Dependent variable is polarity and interaction was calculated as content length x shoppable tags.

<Table 13> Shoppable Tags' Moderating Effect on Hashtags' Influence

Steps	Independent	β	R^2	Adj R^2	R^2(change)	*F*
1	Hashtags	-0.0083**	0.002	0.002		11.34***
2	Hashtags	-0.0097***	0.026	0.026	0.024	75.90***
	Shoppable tags	0.0177***				
3	Hashtags	-0.0606***	0.037	0.037	0.011	72.96***
	Shoppable tags	-0.0124**				
	Interaction	0.0585***				

***p < .001, **p < .01, *p < .05

Note: Dependent variable is polarity and interaction was calculated as hashtags x shoppable tags.

<Table 14> Shoppable Tags' Moderating Effect on Long Words' Influence

Steps	Independent	β	R^2	Adj R^2	R^2(change)	*F*
1	Long words	-0.1105***	0.129	0.129		840.7***
2	Long words	-0.1062***	0.140	0.140	0.011	464.3***
	Shoppable tags	0.0124***				
3	Long words	-0.1611***	0.143	0.142	0.002	316.0***
	Shoppable tags	-0.0181*				
	Interaction	0.0593***				

***p < .001, **p < .01, *p < .05

Note: Dependent variable is polarity and interaction was calculated as long words x shoppable tags.

<Table 15> Shoppable Tags' Moderating Effect on Average Sentence Length's Influence

Steps	Independent	β	R^2	Adj R^2	R^2(change)	*F*
1	Average sentence length	-0.1597***	0.068	0.068		414.4***
2	Average sentence length	-0.1532***	0.085	0.085	0.017	265.5***
	Shoppable tags	0.0152***				
3	Average sentence length	-0.3002***	0.090	0.090	0.005	188.3***
	Shoppable tags	-0.0373***				
	Interaction	0.1599***				

***p < .001, **p < .01, *p < .05

Note: Dependent variable is polarity and interaction was calculated as average sentence length x shoppable tags.

the third model in which the interaction variable (β = 0.0585, p < .01) was deployed, and R-square increased by 0.024 and 0.011. Third, shoppable tags was moderator with interference effect about long words' influence. The model's fitness was significant in the third model in which the interaction variable (β = 0.0593, p < .01) was deployed, and R-square increased by 0.011 and 0.002. Lastly, shoppable tags was moderator with interference effect about average sentence length's influence. The model's fitness was statistically significant in the third model in which the interaction variable (β = 0.1599, p < .01) was deployed, and R-square increased by 0.017 and 0.005.

As a result, H3 was accepted. This result supported the RQ2 that the commerce feature of shoppable tags would mitigate the negative effects of complexity.

Ⅴ. Conclusion

5.1. Discussion and Implications

In this study, we confirmed the importance of complexity for content readability and analyzed the moderating effect of the commerce feature on the negative influence of these factors on consumer engagement. The analysis results are as follows.

First, content length, hashtags, long words and average sentence length have significant negative effects on consumer engagement. This supports existing research findings (Jones et al., 2004; Schultz, 2017) that the more complex the linguistic style of content, the more the consumer is fatigued (Pancer et al., 2019). Schultz (2017) found that Content length, measured in words, has a negative effect on the number of likes, comments and shares. Jones et al. (2004) said online users tend to respond to more concise messages in an overloaded interactive environment. It can be inferred because users mainly view social media on a small mobile screen, long words or sentences are expressed in multiple lines rather than in a single line, leading to reader fatigue.

Second, before testing the importance of complexity, the effect of emojis—which is a detailed factor of informality—was not significant on consumer engagement. This contrasts with previous research findings (Dwyer, 2007) that emojis create positive consumer engagement toward content in the context of social media. Therefore, we can question whether the frequent use of emojis in content is correct to increase positive consumer sentiment. Based on the fact that readability is centered on complexity and informality, these results highlighted the influence of complexity and confirmed its importance. This result supports existing findings (Deng et al., 2020; Pancer et al., 2019; Yeun Chun et al., 2014) that emphasize the importance of complexity. In particular, these results are consistent with studies (Pancer et al., 2019) in which clients preferentially check the overall structure of words and sentences to determine whether the sentence is easy to read.

Finally, the commerce feature moderates the relationship between all the complexity factors presented in this study and consumer engagement. First, the commerce feature reduces the negative effect of content length. It can be inferred that the key or potential consumers who encounter shoppable content (i.e., shoppable posts and tags) find a significant amount useful product information (Ranganathan and Ganapathy, 2002). Next, for hashtags, long words, and average sentence length, the commerce feature has interference effects. Therefore, these complexity factors form a positive effect on shoppable content. This supports existing research that advertising explicitness creates consumers' positive emotion and the introduction purpose of shoppable tags is convenience. In addition, it can be assumed that the event content using shoppable tags reflects the high participation rate of consumers and positive responses. This is because it is enough to attract consumers' attention by creating a long explanation of the events and stating the reward of participation together because consumers' interest in the events leads to a positive perception of the brand (Kim et al., 2019a; Labrecque, 2014). This is also consistent with brand SNS usage behavior and consumer response to this form of event content in that it increases search accessibility by utilizing suitable exposed hashtags (Kim et al., 2019b).

Based on these discussions, the theoretical and managerial implications or our study are as follows. For theoretical implications, the study supports or contradicts existing research. The results supporting existing studies on the negative influence of complexity detail factors include that the detailed factors used in this study explain the concept of content complexity over a certain level. Thus, when detailed factors related to content complexity are defined in future studies, the potential role of these factors can be confirmed. Moreover, results that contrast the positive influence of informality with existing findings mean that additional exploration of informality is required. In future studies, as a detailed factor of informality, it will be necessary to reconfirm the possibility of roles in defining emojis. Therefore, this study provides theoretical implications for the need for future content engineering research.

In terms of managerial implications, first, hashtags must be recognized as a word in content and word and sentence-centric content engineering processes are required to minimize the negative influence caused by complexity. Since the negative influence is large in order of long words, average sentence length, content length, and hashtags, it is necessary to set a standard for the proper length of words and sentences to resolve complexities. The proportion of words and sentences longer than the criteria should be abbreviated or divided. In addition, it is necessary to measure the level of complexity experienced by consumers who come into contact with the content after a company's own examination and modification. It would be beneficial to introduce not only content producers and experts, but also those who are familiar and those who are unfamiliar with the brands and brand content, into the measurement process to collect opinions on content complexity and detailed factors. Second, we have confirmed the utility of commerce features, so companies should actively utilize them. Additional related features need to be introduced in the future, considering the importance of maintaining advertising explicitness. Third, companies must recognize that even if they take advantage of effective commerce features, the negative influence of content length will not change to positive but will be reduced to a certain level－content length should be considered so that it does not become excessively long under any circumstances. Fourth, companies should consider that although commerce features positively change some of the complexity factors' influence, efforts should be made to maintain appropriate length criteria when using commerce features. Finally, to minimize content complexity, companies should ensure they do not lose information during the revision of content because accurate and sufficient information delivery is one the essence of advertising content (Ranganathan and Ganapathy, 2002).

the results of this study can be utilized as a guideline for contents engineering. In particular, the strategic insight derived from this approach is expected to be applied regardless of companies' scale. Because contents marketing using SNS does not have a high barrier (Choi, 2011), start-up companies that do not have an official website can promote their products and compete with other companies.

5.2. Limitations and Future Research

This study has the following limitations. First, the same number of companies were selected for each industry but were not classified by industry during the analysis process. If the marketing and communication strategies proposed as a result of research can be categorized by industry, the actual utilization will be even higher. Therefore, in future studies, industry-specific distinctions are needed. Second, in this study, complexity and informal factors were quantified from content. Other readability factors that reflect the context of social media ought to be made available in future studies. In addition, using external variables that affect companies' sales will further reduce the correlation between the variables. Third, data were collected from Instagram shopping posts that utilized shoppable tags, and other social media platforms such as Facebook and YouTube—which have similar shopping features—were not considered. This is because we prioritized SNS where commerce features are the most actively utilized. In future research, after confirming that commerce features will be used stably on various SNSs, we can expand the channels to be analyzed. Finally, our study focused on South Korea, and future research should focus on additional countries.

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<Appendix A> The Result of Data Collection

Brand name	Industries	Total content	More than one comment	ST content
ETUDE	Beauty	264	262	207
innisfree		258	253	242
nature republic		288	273	253
Gmarket	E-commerce	288	268	258
LOTTE Homeshopping		288	125	99
11st		276---	197	173
Lotte Confectionery	FMCG food	288	280	211
Binggrae		288	288	254
Nongshim		252	252	202
Uniqlo	Fashion	288	176	165
Stylenanda		264	235	218
Chuu		276	144	131
Emons	Home & Living	288	130	126
Locknlock		288	198	154
Hyundailnc		276	116	109
Goodfeel	Household goods	288	182	133
Huggies		264	263	219
Happyhome		288	83	76
Oliveyoung	Retail	252	251	211
Wconcept		264	125	124
Olens		276	268	196
Gongcha Korea	Retail food	264	262	213
SPC Group		264	177	117
Paris Baguette		276	255	206
FILA Korea	Sporting goods	288	236	199
Reebok Classic Korea		264	149	125
Discovery Expedition		288	240	218

Note: “Total content” means “Total number of content”, “More than one comment” means “Total number of content with more than one content” and “ST content” means “Total number of content using shoppable tags”

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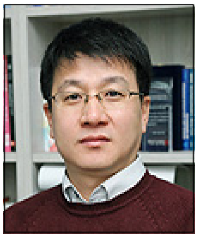

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