International Journal of Multimedia and Ubiquitous Engineering
Vol.10, No.7 (2015), pp.305-316
http://dx.doi.org/10.14257/ijmue.2015.10.7.32

A Study on the Activities of Touch Point and Consumer Information Search in the Multimedia Environment

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Abstract

The purpose of this study is, in the situation that consumers use not only online news but social media as information delivery media, based on web data, to examine the effect of touch point activities in two media different according to product types on consumer search activities. To do this, we traced the patterns of information diffusion according to time, by extracting the number of the web postings of the information about the products from on-line news and blogs on a weekly or monthly basis, and identified consumer search activities about the goods by using their search traffics provided on a weekly basis by portal sites

As a result of the study, it turned out that touch point activities and consumer search activities are different from each other in two media different according to product types. Specifically speaking, as for utilitarian goods, it appeared that there were correlations between the touch points and consumer search activities of the two different information media. In particular, more similarity in the patterns of information diffusion was found in the news sites than in the blogs.

In the case of hedonic goods, the correlations between touch points and consumer search activities showed different results according to the time intervals. A monthly analysis showed that the consumer search activities had correlations not with on-line news, but with blogs. On the contrary, a weekly analysis showed that they had higher correlations with blogs than with on-line news sites though having correlations with both the two.

Keywords: *Touch point, Product types, Social media, Search traffic, Information diffusion*

1. Introduction

In multimedia environment, for more effective competition in the world's competitive online market, various online media should be properly utilized [1]. When touch points are well managed and established in various media regarding products or services, they can positively influence consumer behaviors, so it is important to manage and organize touch points of various media based on consumer behaviors [2-4]. Thus, companies are developing diverse strategies to gain consumer interest through proper touch point activities, and academic circles are also performing various researches on touch point activities.

Presently, although information about products and services are diffusing through multimedia, not all the touch point activities from the time when information exposure first takes place to the time when information diffusion speed is reduced lead to consumer interest. Thus, this study, by considering what advanced researches could not consider, intends to examine the correlation between consumer interest patterns and touch point activities. Regarding this, this study seeks to determine the correlations based on the flow of time between consumer attention and touch points according to product types by

ISSN: 1975-0080 IJMUE

picking up particular on-line news paper (*i.e.*, general information media) and blog posting (*i.e.*, recently emerged social media).

In addition, by considering product lifecycle differences according to product types claimed by advanced researches, it tries to divide product types, and analyze media touch points and consumer interest by using a time-series analysis method.

The rest or paper is organized as follows. Section 2 provides a review of relevant literature. Section 3 provides research hypotheses. Section 4 provides analytical methods and results. Section 5 provides a conclusion and implications.

2. Literature Review

2.1. Multimedia Environment and Touch Point

The customer touch point service can be defined as direct interactions among people [5]. It means the channel where information providers and receivers can meet under the optimal condition. Media environment changed due to the appearance of social media. The way to receive consumer interest through various methods using various existing touch points is being focused. Thus, studies on strategies to effectively manage touch points regarding products or services, the effect of various touch point activities on consumers, and the correlation between touch point and word of mouth in multimedia are being actively conducted [2-3,6].

2.2 Advanced Research Using Search Traffic

Because search traffic provided by websites enables grasping market trends almost in real-time, it is possible to understand social phenomena and predict near future. Studies predicting social phenomena and analyzing consumption trends have been conducted by using search traffic [7-9]. Goel [10] found that, in music ranks of Billboard Hot 100 chart and first month sales of video games, it is possible to predict consumer behaviors by using search traffic. Web search traffic has a merit that it enables investigating a population because there are many users per day, so it could be considered to be a good analytical method in understanding consumer behaviors [11].

2.3 Hedonic Goods and Utilitarian Goods

Products and services can be divided into utilitarian goods and hedonic goods according to the types of benefits that consumers seek [12]. While utilitarian goods have a characteristic of utilitarian consumption resulted from instrumental attributes of the utilitarian aspect, hedonic goods have a characteristic of emotional consumption resulted from sensuous attributes of the emotional aspect [13-14].

Hedonic and utilitarian goods or services have differences in the demand pattern of products, and the characteristics of products or services themselves. [15]. Hedonic and utilitarian goods generally have different diffusion patterns [16-17]. Hedonic goods such as movies, music, and books have rapidly decreasing sales speed over time compared to utilitarian goods. This cycle turns out over a short period. On the other hand, the cycle of utilitarian goods often turns out over a long period, not just a few weeks.

3. Hypothesis

3.1 The Difference of the Cycle of Consumer Search According to Product Types

While for utilitarian goods, consumers can resolve the uncertainty of product or service information to some degree by using information provided by online or offline, for hedonic goods, due to high emotional involvement and symbolic values, it is hard for consumers to make a judgment before experiencing products or services[18-19]. In other words, due to product characteristics, the degree and range of information value and information search recognized by consumers are different according to product types. Thus, a hypothesis was set up as below.

Hypothesis 1: The cycle of consumer search would be different according to product types.

3.2 The Relationship between Touch Point Activities and Consumer Information Search in Information Delivery Media

The information types are varied according to product types, so is the on-line buying preference [20].

Factual information is referred to as information on the physical properties in which the characteristics of tangible goods can be directly perceived with sensory organs; evaluative information means information which holds the intangible aspects of goods as emotional and subjective impressions [21].

Objective information has more influence on consumers' attitudes since it can be evidenced with fewer search costs than subjective information.

Park *et al*. [22] identified a significant difference between product types and contents of the information, and found that empirical goods had more subjective contents than factual ones of word of mouth.

For utilitarian goods, not only news information based on the objective ground but information experienced by consumers in social media could be important. Before release of a product, related information is provided by news, and those interested in the product share the information in their social media. However, for utilitarian goods, consumers can know about the characteristics of products to some degree through news information, so it is judged that consumer search activity may be more related to news information than to social media information. On the contrary, for hedonic goods, information provided by news may be insufficient compared to that provided by social media. Because consumers cannot experience hedonic goods before purchase and they are based on various emotional bases, consumers may show different reactions. Therefore, it is judged that, for touch point of hedonic goods, social media information would have a higher correlation with the amount of consumer search activity than news information. Thus, hypotheses were set up as below.

Hypothesis 2: Touch point activities and the amount of consumer information search would have a correlation.

Hypothesis 2-a: For utilitarian goods, the amount of consumer information search will be more related to the information diffusion pattern of on-line news than to that of blogs.

Hypothesis 2-b: For hedonic goods, the amount of consumer search will be more related to the information diffusion pattern of blogs than to that of on-line news.

4. Analysis

4.1. Data Collection and Analytical Methods

For data collection, articles and materials containing product information provided by Naver news and Naver blogs of Naver, the most frequently used portal website in Korea, were collected, and web search traffic information provided by Naver Trend was used for the amount of consumer search.

In order to examine the difference of the amount of consumer search according to product types, products and services were divided into utilitarian goods and hedonic goods, and of them, representative goods were selected by referring to advanced researches [23,20,24]. In this study, smartphone was selected as the representative utilitarian goods, and song was selected as the representative hedonic goods, by considering the fact that the patterns of hedonic goods and utilitarian goods could vary with genres or the purpose of use.

For an estimation method, in order to examine the correlation between search traffic and information media, a time-series regression analysis was used.

4.2. Results

4.2.1 Comparison of the Information Diffusion Patterns of Media and Search Traffic According to Product Types

The Figure 1, 2 made it easier to compare the data with the horizontal axis representing time; and the vertical one having the number of the postings in each media as the main axis and their search traffics as the auxiliary one.

The Figure 1, 2 shows that each of the product types has its different product life cycle in the media, according to the amount of the information, the peak time, the duration of high season, and the amount of residues.

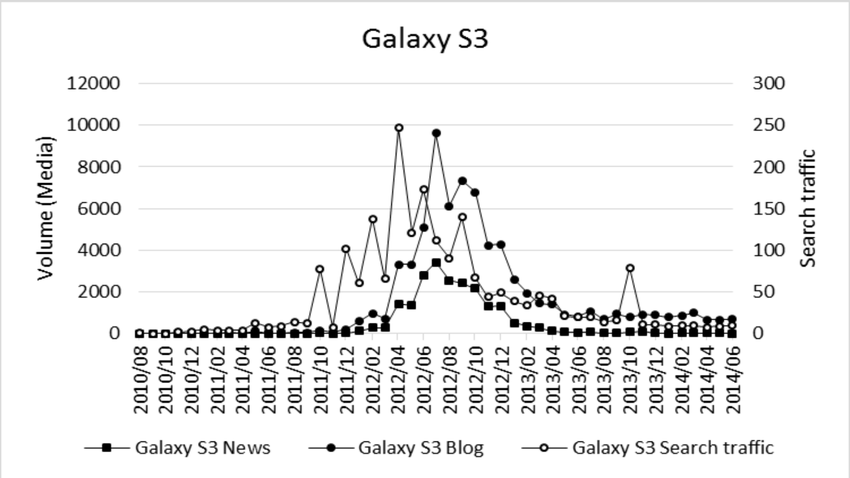

Figure 1. Comparison of Information Diffusion and the Amount of Search in each Media for Smartphone

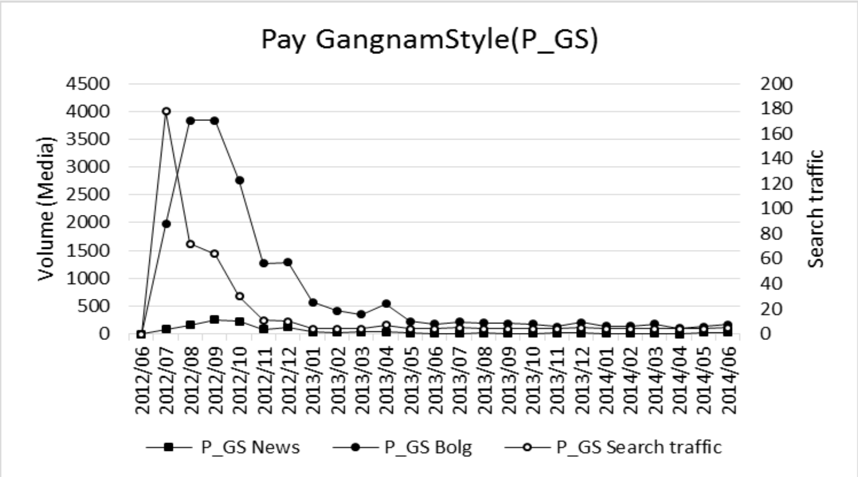

Figure 2. Comparison of Information Diffusion and the Amount of Search in each Media for Song

In the case of smart phone, it can be seen that consumers made efforts to attain information about the products through the web search activities before they were released on the market as representing utilitarian goods.

In contrast, in the case of song, it was found that consumers did the most of their search activities after they were released as hedonic goods on the market.

It can be confirmed that utilitarian goods had longer product life cycles and longer duration of high season than hedonic goods

Thus, Hypothesis 1 was supported.

4.2.2 Results of Comparing Search Traffic and Information Delivery Media

In order to grasp the information diffusion correlation between information delivery media and search traffic, a regression analysis was conducted for time-series data. First, the autocorrelation of error term was examined and a regression analysis was conducted. The amount of search traffic according to product types was set as a dependent variable, and then the amount of news exposure and the amount of blog registration were analyzed. The results are shown in the table below. As a result of trying various ARIMA models considering the autocorrelation, ARIMA (0,1,0) and ARIMA (1,0,0) were the most appropriate for IT devices and music, respectively. The significance probability of the Ljung-Box value turned out to be higher than 0.05, which indicates that there is no autocorrelation to residual. As a result of the analysis, the significance probability turned out to be lower than 0.05, which indicates that search traffics of news and blogs have a significant correlation, which shows that search trends are influenced by media.

Table 1. Results of the ARIMA Regression Analysis for Media and Searching Traffic

Variables	ARIMA model	Model statistics		Model parametric statistics			
		R squared	Ljung-Box significant probability	Beta	SE	t	Significant probability
▲ N→S	(0, 1, 0)	0.809	0.271	0.028	0.008	**3.343***	**0.002**
▲ B→S	(0, 1, 0)	0.749	0.109	0.009	0.004	**2.304***	**0.026**
△ N→S	(1, 0, 0)	0.259	1.000	0.255	0.128	1.996	0.059
△ B→S	(1, 0, 0)	0.411	1.000	0.021	0.006	**3.510***	**0.002**
▽ N→S	(1, 0, 0)	0.294	0.976	0.235	0.067	**3.510***	**0.001**
▽ B→S	(1, 0, 0)	0.411	1.000	0.021	0.006	**3.510***	**0.002**

(News: N, Blog: B, Search traffic: S, ▲: Galaxy S3 monthly, △: Psy gangnamstyle monthly, ▽: Psy gangnamstyle weekly, *P < 0.05)

The results above indicate that consumer information search is influenced by both news and blogs. That is, media activities may be significant in explaining consumer information search activities. And the fact that the degree of the correlation between media and consumer search activities varies with information types seems to be a significant result.

Thus, Hypothesis 2 was supported.

4.2.3. Cross Correlation Analysis

We first conducted a conversion process in which the factors affecting the changes in the time series data were screened out, and then utilized the results in the analysis process, in order to analyze the correlations according to time difference between time series data, based on the types of the media and the goods

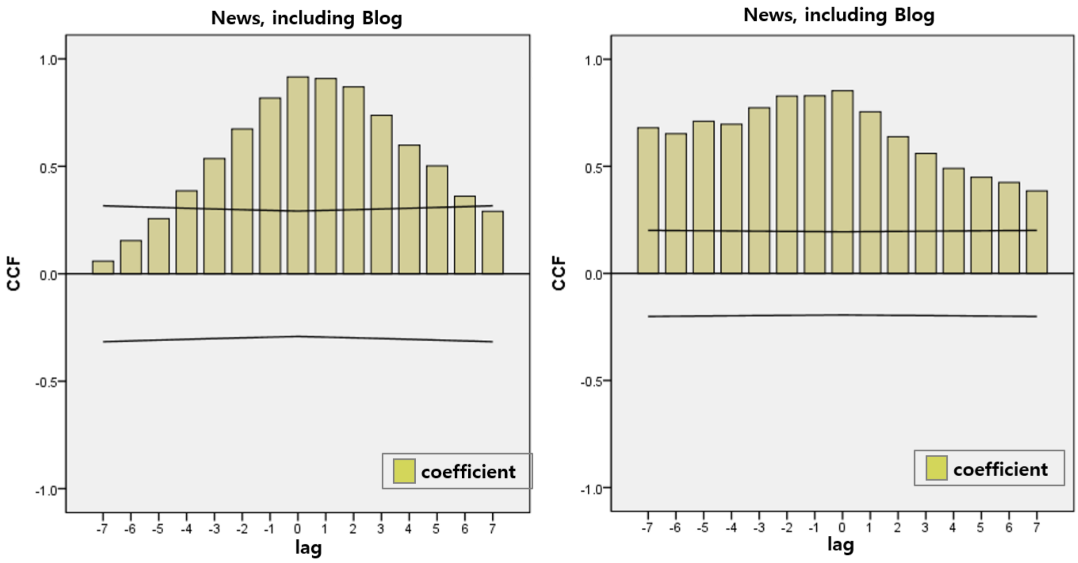

Figure 3. Results of the Cross Correlation Coefficient for the News and Blog (Left: Smartphone, Right: Song)

According to Figure 3, in the case of smart phone, the results of the analysis of the cross correlation between news sites and blogs show the highest correlation efficient in the zeroth session.

Also, Figure 3 shows that in the case of songs, the results of the analysis of the cross correlation between the news sites and blogs show the highest correlation efficient in the zeroth session.

Thus, it can be thought that there is a high correlation between the news sites and the blogs, but that it is not affected by the time difference.

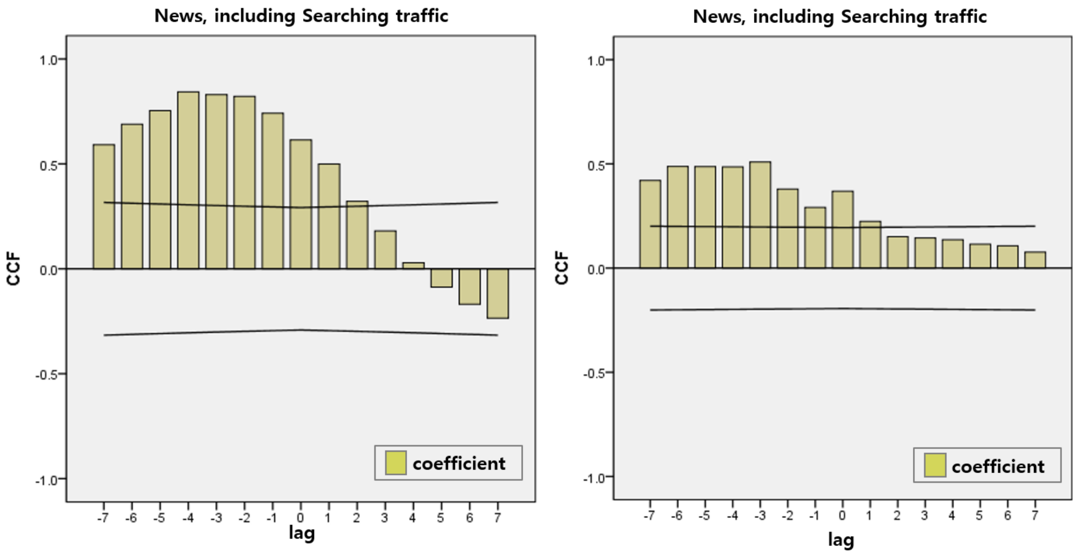

Figure 4. Results of the Cross Correlation Coefficient for the News and Search Traffic (Left: Smartphone, Right: Song)

Thus, it can be thought that there is a high correlative relationship between the news sites and the blogs, but that it is not affected by the time difference.

On the contrary, in the case of songs in Figure 4, the results of the weekly analysis of the cross correlation between the news sites and their search traffics show that the two-way influence, though high prior to the third session, had a low explanatory power since it had the lowest coefficient (less than 0.5).

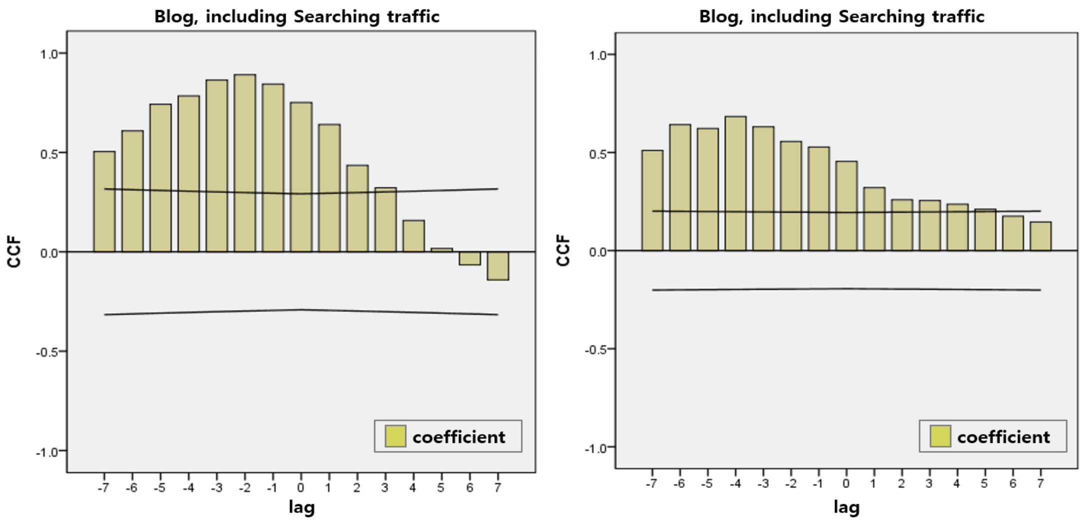

Figure 5. Results of the Cross Correlation Coefficient for the Blog and Search Traffic (Left: Smartphone, Right: Song)

According to Figure 5, it can be thought that as for smart phone, the results of the analysis of the cross correlation between the blogs and their search traffics show that the two-way influence has an explanatory power as it has the highest coefficient in the third session.

On the contrary, in the case of songs in Figure 5, the results of the analysis of the cross correlation between the blogs and their search traffics show that the two-way influence had an explanatory power since it had the highest coefficient in the fourth session, which was to say that the exposure to the blogs had less influence than the news sites did on the consumers' search activities.

4.2.4. Granger Causality Test

Granger causality test is among the methods of the causality analysis utilizing the time series data.

This test method is a method for analyzing the causal relationship among the variants by testing how well the present value of one variant accounts for the past value of another variant in the analysis of time series data.

Granger Causality Test is commonly used in testing the causal relationship among random variants by making use of the traditional F statistics.

By Granger's definition, there exists the causality direction from X to Y, if predicting Y by taking into account the past value of X as well as the past value of Y is more accurate than only with the past value of Y.

Likewise, there exists the causality direction from Y to X, if predicting X depending solely on its past value is more accurate than with combination of the past values of X and Y.

If these relations come into existence in both ways, there exists a mutually dependent relationship between X and Y.

Granger Causality Test is a test for a null hypothesis that one variant does not contribute to predicting another variant, and its analysis model can manifest itself as the following two autoregressive models [25].

$$Y_t = \sum_{i=1}^{p} \alpha_i X_{t-i} + \sum_{j=1}^{p} \beta_j Y_{t-j} + \varepsilon_{1t}$$

$$X_t = \sum_{i=1}^{n} \gamma_i X_{t-i} + \sum_{j=1}^{n} \delta_j Y_{t-j} + \varepsilon_{2t}$$

This study aims to perform Granger Causality Test on the relations between the activities of touch point and the consumer search and to examine the results.

Table 2. Granger Causality Tests on the Relationship between Smartphone News and Search Traffic

Lags	Null hypothesis	Observed value	F-statistics	Probability	Test results
1	GalaxyS3 trend does not Granger Cause News	46	26.6860	6.E-06	Reject
	News does not Granger Cause GalaxyS3 trend	46	0.00199	0.9647	Do not reject
2	GalaxyS3 trend does not Granger Cause News	45	17.8683	3.E-06	Reject
	News does not Granger Cause GalaxyS3 search traffic	45	10.8853	0.0002	Reject
3	GalaxyS3 trend does not Granger Cause News	44	10.7585	3.E-05	Reject
	News does not Granger Cause GalaxyS3 search traffic	44	6.41621	0.0013	Reject
4	GalaxyS3 trend does not Granger Cause News	43	6.57755	0.0005	Reject
	News does not Granger Cause GalaxyS3 search traffic	43	6.40846	0.0006	Reject
5	GalaxyS3 trend does not Granger Cause News	42	9.54155	1.E-05	Reject
	News does not Granger Cause GalaxyS3 search traffic	42	4.50734	0.0033	Reject
6	GalaxyS3 trend does not Granger Cause News	41	7.50529	7.E-05	Reject
	News does not Granger Cause GalaxyS3 search traffic	41	3.54673	0.0097	Reject
7	GalaxyS3 trend does not Granger Cause News	40	5.60610	0.0006	Reject
	News does not Granger Cause GalaxyS3 search traffic	40	3.56271	0.0086	Reject

(Significant the rejection of the null hypothesis that there is no Granger causality in *p<0.1, **p<0.05, ***p<0.01)

Table 3. Granger Causality Tests on the Relationship between Song News and Search Traffic

Lags	Null hypothesis	Observed value	F-statistics	Probability	Test results
1	Song search traffic does not Granger Cause News	105	0.08554	0.7705	Do not reject
	News does not Granger Cause Song search traffic	105	0.47470	0.4924	Do not reject
2	Song search traffic does not Granger Cause News	104	1.90269	0.1546	Do not reject
	News does not Granger Cause Song search traffic	104	0.15439	0.8571	Do not reject
3	Song search traffic does not Granger Cause News	103	6.24628	0.0006	Reject
	News does not Granger Cause Song search traffic	103	4.52538	0.0052	Reject

4	Song search traffic does not Granger Cause News	102	5.88170	0.0003	Reject
	News does not Granger Cause Song search traffic	102	0.13575	0.9687	Do not reject
5	Song search traffic does not Granger Cause News	101	7.37052	8.E-06	Reject
	News does not Granger Cause Song search traffic	101	6.17467	6.E-05	Reject
6	Song search traffic does not Granger Cause News	100	5.92802	3.E-05	Reject
	News does not Granger Cause Song search traffic	100	3.66388	0.0027	Reject
7	Song search traffic does not Granger Cause News	99	7.26165	9.E-07	Reject
	News does not Granger Cause Song search traffic	99	6.38499	5.E-06	Reject

(Significant the rejection of the null hypothesis that there is no Granger causality in *p<0.1, **p<0.05, ***p<0.01)

In the case of songs, the results of the Granger causality test on the news sites and their search traffics showed a causal relationship between them with significant results in the third, the fifth, the sixth, and the seventh session.

In the case of song, the results of the Granger causality test on the news sites and their search traffics showed a causal relationship between them with significant results in the third, the fifth, the sixth, and the seventh session.

Table 4. Granger Causality Tests on the Relationship between Smartphone Blog and Search Traffic

Lags	Null hypothesis	Observed value	F-statistic	Probability	Test results
1	GalaxyS3 search traffic does not Granger Cause Blog	46	25.4715	9.E-06	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	46	0.21514	0.6451	Do not reject
2	GalaxyS3 search traffic does not Granger Cause Blog	45	15.0464	1.E-05	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	45	5.85278	0.0059	Reject
3	GalaxyS3 search traffic does not Granger Cause Blog	44	7.72853	0.0004	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	44	2.72766	0.0578	Reject
4	GalaxyS3 search traffic does not Granger Cause Blog	43	5.41903	0.0017	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	43	2.49944	0.0608	Reject
5	GalaxyS3 search traffic does not Granger Cause Blog	42	7.52795	0.0001	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	42	1.59705	0.1902	Do not reject
6	GalaxyS3 search traffic does not Granger Cause Blog	41	5.65867	0.0006	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	41	1.63217	0.1753	Do not reject
7	GalaxyS3 search traffic does not Granger Cause Blog	40	4.59830	0.0020	Reject
	Blog does not Granger Cause GalaxyS3 search traffic	40	1.49844	0.2133	Do not reject

(Significant the rejection of the null hypothesis that there is no Granger causality in *p<0.1, **p<0.05, ***p<0.01)

Granger Causality Test on the blogs on IT devices and their search traffics showed significant results in the second, the third, and the fourth session, which was to say that there was a correlative relationship according to the time intervals.

In the case of the blogs, there was less amount of information than that of consumer attention, and the amount of information gets larger when the attention was lower.

It can be said that this is due to the evolution of the series of smart phones influenced by the previous model of GalaxyS2.

Thus, as shown in the causality analysis, it can be said that the search traffics played a bigger role in this phenomenon than blogs.

Table 5. Granger Causality Tests on the Relationship between Song Blog and Search Traffic

Lags	Null hypothesis	Observed value	F-statistics	Probability	Test results
1	Song search traffic does not Granger Cause Blog	105	13.6977	0.0003	Reject
	Blog does not Granger Cause Song search traffic	105	2.14789	0.1458	Do not reject
2	Song search traffic does not Granger Cause Blog	104	7.80543	0.0007	Reject
	Blog does not Granger Cause Song search traffic	104	0.53250	0.5888	Do not reject
3	Song search traffic does not Granger Cause Blog	103	10.2481	6.E-06	Reject
	Blog does not Granger Cause Song search traffic	103	19.5766	6.E-10	Reject
4	Song search traffic does not Granger Cause Blog	102	10.5535	4.E-07	Reject
	Blog does not Granger Cause Song search traffic	102	8.66857	5.E-06	Reject
5	Song search traffic does not Granger Cause Blog	101	19.7570	3.E-13	Reject
	Blog does not Granger Cause Song search traffic	101	8.82108	8.E-07	Reject
6	Song search traffic does not Granger Cause Blog	100	15.6685	4.E-12	Reject
	Blog does not Granger Cause Song search traffic	100	8.89727	1.E-07	Reject
7	Song search traffic does not Granger Cause Blog	99	11.6797	3.E-10	Reject
	Blog does not Granger Cause Song search traffic	99	9.73748	8.E-09	Reject

(Significant the rejection of the null hypothesis that there is no Granger causality in *p<0.1, **p<0.05, ***p<0.01)

In the case of songs, Granger Causality Test on the blogs and their search traffics showed significant results in the third, the fourth, the fifth, the sixth and the seventh session, which was to say that there was a correlative relationship according the time intervals.

5. Conclusion and Implications

This study, through the amount of search traffic provided by websites, determined consumer search behaviors different according to product types. In addition, it examined the correlation between touch point activities and consumer search activities different according to product types. In conclusion, looking at the relationship between information delivery media and information receivers, for smartphone, although both news and blogs are related to search traffic, it has a higher correlation with on-line news. And song is more related to blogs than to on-line news.

As for utilitarian goods, consumers are trying to attain factual information about the objective characteristics of the products rather than subjective thoughts or opinions.

Thus, it is thought that utilitarian goods have more of a correlative relationship with on-line news information, though the exposure to the two media (*i.e.*, news sites and blogs) is linked to the degree of consumer attention.

It is found that hedonic goods (*e.g.*, songs) had a higher correlative relationship with the blogs than with the on-line news sites.

As shown in the argument of Nelson [26] that since information search is done mainly with word of mouth and ads, consumers depend all the more on the empirical information search for hedonic goods through others's experience, consumer search appears to be more highly linked to indirect experience and word of mouth through blogs than to the news information centered on objective facts.

Thus, this study offers the following contributions, implications, and limitations.

It contributed to analyzing consumer behaviors by focusing solely on the on-line data, unlike the previous studies, most of which analyzed whether difference in the product types had influence on media, and whether consumer behaviors varied according to product types by applying questionnaires as a methodological approach.

In the environment where different media co-exist, it is needed to perform marketing to raise consumer interest at proper times by understanding touch points of each media and consumer search behaviors over time, and by considering media characteristics. Future studies may have to consider more various products or services.

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