Does Online Social Network Contribute to WOM Effect on Product Sales?

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In recent years, IT advancement has brought out the new Internet communication environment such as online social network services, where people are connected in global network without temporal and spatial limitation. The popular use of online social network helps people share their experience and preference for specific products and services, thus holding large potential to significantly affect firms' business performance through Word-of-Mouth (WOM). This study examines the role of online social network in raising WOM effect on the movie industry by comparing with the similar role of Internet portal, another major online communication channel. Analyzing 109 movies and data from both Twitter and Naver movie, we found that significant WOM effect exists simultaneously in both Twitter and Naver movie. However, we also found that different figures of online viral effects exist depending on the popularity of movies. In the hit movie group, before the movie release, the WOM effect occurs only in Twitter while the WOM effect arises in both Twitter and Naver movie at the same time after the movie release. In the less-popular (or niche) movie group, the WOM effect occurs in both Twitter and Naver movie only before the movie release. Our findings not only deepen theoretical insights into different roles of the two online communication channels in provoking the WOM effect on entertainment products but also provide practitioners with incentive to utilize SNS as strategic marketing platform to enhance their brand reputations.

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1. Introduction

The widespread use of information technologies, especially the Internet technologies, has drastically triggered word-of-mouth (WOM) effects in online environments and provided large amounts of impact on firms' business operations. WOM is the process of information delivery from person to person and influences people's decision-making of purchasing or using products and services (Engel et al., 1969; Richins and Root-Shaffer, 1988). Many of previous IS studies examined the

WOM effect on firm performance (e.g., sales or revenue), but these works mostly focused on the effect mediated by conventional online communication channels like Internet portals and online bookstores (Chevalier and Mayzlin, 2006; Godes and Mayzlin, 2004).

In recent years, another Internet communication channel, the online social network service (SNS), has been rapidly growing and transformed the way of communicating with other people in the manner of being connected anytime and anywhere. SNS is a Web-based communication service that allows users to construct a public or semi-public profile within a system, articulate a users list with shared connections, and observe their list of connections and those made by other people within the system (Boyd and Ellison, 2007).

Equipped with Internet technologies, SNS enables users to share diverse information and opinions regarding personal and social issues among members without spatial and temporal limitations (Howard, 2008). For purchasing any product and service, consumers can take advantage of SNS for their decision-makings. Within SNS, many consumers can leave their enquiries and opinions or look up their predecessors' reviews as a major benchmark before buying products and services. Especially, the capabilities of convenient, global and ubiquitous communications embedded in SNS make consumers' opinions more rapidly and broadly disseminated over the Internet and usually affect the performance of products and services in the market (Dellarocas et al., 2010). This is because contemporary firms are more interested in understanding and managing SNS in order to generate more favorable attitude of consumers toward their products and services.

Therefore, it is highly important to pay more attention to investigating WOM effects on the performance of a product or a service under SNS environments. In particular, information goods and entertainment products are relatively more vulnerable to WOM effects driven by SNS in terms of success in the market because the characteristics of these products are intangible, experiential, and more prone to be affected by network effects.

The focal context of the study is movie industry because movie is one of the representative entertainment products with sufficient features of information goods and experience goods. Customers can hardly figure out its utility before buying and using it. Many moviegoers are likely to directly or indirectly survey the opinion of other people who already experienced the same movie. Through this process of online enquiry, people can preemptively adjust their expectations to each candidate movie and decide which movie to go according to their predecessors' comments.

Nowadays, we may frequently find any example in which a specific movie achieves box office hit due to positive WOM effects from SNS. In May 2011, "Sunny (써니)," the most successful Korean movie in the first half of the year, was released. From the very first time of the release, a large amount of positive opinions on the movie were disseminated through SNS. The volume and speed of the transaction of movie-viewers' comments outnumbered other movies released at the same time. This is the typical example where we can insist that the WOM could be occurred in SNS and its effect is important for movie makers and distributors.

The current study is motivated by today's transformative phenomenon in online communications among people and aims to empirically understand viral effects on sales performance of movie industry associated with the emergence of online social network. The research questions that specify the study goal mentioned above are; (1) Do online WOM effects on movie sales exist in both SNS and Internet portal? (2) What are the social network-related factors that affect movie sales? (3) Do WOM effects on movie sales show different patterns depending on the types of online communication channels (e.g., SNS and Internet portal) and movie characteristics (e.g., popularity of movie)?

To answer these questions, the study collects online reviews on an Internet movie portal (i.e., Naver.com) and posted messages on SNS (i.e., Twitter) for 109 movies released in Korea during 2011. The study examines whether the WOM effect occurs in the movie industry through SNS and Internet portal depending on the popularity of movie and how long the WOM effect exists in groups of popular movies and less popular movies.

In short, the empirical results indicate that positive WOM effects exist over SNS and Internet portal in the movie industry, but the effects are presented in different shapes by the popularity of movie. The WOM effect of SNS in less popular movies is greater than that in popular movies. It is also found that the WOM effect on popular movies lasts longer than that on less popular movies; the WOM effect on less popular movies is found to increase in rapid pace but quickly decrease at its peak point.

These findings not only deepen our theoretical insights into the role of two different online communication channels (i.e., SNS and Internet portal) in provoking the WOM effect on entertainment products but also help practitioners plan their marketing strategies and promotions more effectively.

The rest of the study is organized as follows. Section 2 reviews previous studies on word of mouth (WOM) effects in online communication channels. Then research hypotheses that specify the study's objective are proposed in Section 3. Section 4 describes research methods incorporated in the current study including data collection and analysis models. The results of empirical analysis are explained in Section 5. Finally, in Section 6, the study concludes with discussion and implications of research findings.

2. Literature Review

2.1 Word of Mouse

In business transaction environment, word of mouth (WOM) refers to informal communications between customers who concern evaluations of products and services (Singh, 1988; Westbrook, 1987) rather than formal claims or complaints to firms. Based on this concept, previous studies examine the relationship between customer satisfaction (CS) and WOM. Early studies in the field mainly utilized survey, satisfaction index, experiment, and critics of magazine or newspaper as major data sources (Anderson, 1998). The mood of customer satisfaction can be positive, neutral, or negative. Examples of positive WOM include pleasant, vivid, or novel experience that consumers have ever received from the use of a product or service. Negative WOM includes unpleasant experience, rumor, and private complaining (Anderson, 1998). The CS-WOM studies generally emphasize that individual degree of satisfaction and dissatisfaction with consumption experience is regarded as the key precursor of product-related WOM (Bitner, 1990; Westbrook, 1987). These studies also find that the WOM effect arises more definitely in either extremely satisfied or dissatisfied customer groups (Anderson, 1998).

Several works conducting comparative study between WOM and conventional media advertisements advocate WOM effects on promoting sales of new products and services (Katz and Lazarsfeld, 1955). The major research findings from these studies indicate that WOM plays a significant role in influencing the purchase of household goods and food products. For instance, Arndt (1967) finds that consumers who have received positive WOM about a new food product are much more likely to purchase compared to those who have received negative WOM. The findings also indicate that WOM is seven times as effective as newspaper and magazine advertisements, four times as effective as personal selling, and twice as effective as radio commercials in influencing consumers to switch brands (Engel et al., 1969; Katz and Lazarsfeld, 1955).

For the movie industry, WOM also has been found to be a significant factor that influences attendance and sales of movies (Mahajan et al., 1984). Several studies maintain that negative critics have greater impact on the box office revenue (Basuroy et al., 2003), and the estimated seasonality underlying demand is much smaller and slightly different from the observed seasonality of sales in movie industry (Einav, 2007).

2.2 WOM Effects in Online Communication Channels

In online environments, online forum and review became more important as a proxy of WOM. Some studies find that online reviews and comments can offer easy and effective instrument to measure WOM (Godes and Mayzlin, 2004). Furthermore, the studies suggest that online recommendations are more influential than traditional offline recommendation sources (Cho and Kim, 2011; Choi and Lee, 2011; Senecal and Nantel, 2004). Although early studies of online WOM were conducted with online review system itself, some researchers investigated how firms strategically manipulate online forums especially when they intend to more actively engage in marketing communication with consumers by improving the quality of product information (Bolton et al., 2004; Dellarocas, 2006).

Upon the emergence of Internet technologies, many researchers have investigated WOM effects in more detailed research specifications (Nam et al., 2011). In particular, the relationship between online reviews and firm performance, such as sales and revenue, was examined in more sophisticated manners. There are several research subjects on which the WOM-firm performance studies have been deployed so far.

One stream of the studies is assessing the role of WOM. Associated with movie industry, online reviews with opinions related to early box office sales are defined as influencers, while those with opinions related to overall box office sales are defined as predictors. With such concepts of predictor and influencer, previous studies in this area seek to understand which roles WOM usually plays relatively better in improving firm performance (Elberse and Eliashberg, 2003; Reinstein and Snyder, 2005). But the studies generally come up with mixed results. Some studies indicate that online reviews with influencer feature make more contribution to box office revenue rather than those with predictor feature (Reinstein and Snyder, 2005; Boatwright et al., 2007), but other studies explain that WOM communication is an important predictor of box office revenue and the number of playing screens in subsequent weeks (Elberse and Eliashberg, 2003).

The second research stream is measuring the effects of volume (i.e., total amount of WOM) and valence (i.e., the nature of WOM messages in online channel). On one hand, some studies find the valence of WOM is a salient influencing factor to firm performance (Clemons et al., 2006; Li and Hitt, 2008). On the other hand, other works indicate that the volume of WOM has a positive effect on the revenue (Duan et al., 2008; Liu, 2006; Zhu and Zhang, 2010). Finally, it is also found that both volume and valence significantly affect firms' the revenue at the same time (Chevalier and Mayzlin, 2006; Dellarocas et al., 2007).

The third stream is evaluating the durability and timing of WOM. The effect of WOM is found to be decreased after movies are released (Liu, 2006; Duan et al., 2008) and have more positive impact on revenue at the first or early stage of movie release (Elberse and Eliashberg, 2003; Dellarocas et al., 2007).

Lastly, the degree of WOM effect may be different by external factors such as customer experience, product characteristics, and product sales. For instance, WOM effect becomes greater when customers has more Internet experience (Zhu and Zhang, 2010) because movie goers who are familiar with Internet use usually more tend to participate in online reviews not only for very obscure movies but also for very high-grossing movies (Dellarocas et al., 2010). Firms' promotion of reducing product price or introducing a product with new features can also generate greater WOM effects on the product and lead to more sales on that in return (Fan, 2011; Li and Hitt, 2010).

Although previous studies on WOM effect in SNS contribute to expanding the boundary of our knowledge toward newly emerging socio-technological phenomenon, the studies have their own limitations. These studies investigate the WOM in SNS mostly through survey and case study. They find that the engagement in WOM behavior in SNS is caused by tie strength, trust, normative influence, and informational influence (Chu and Kim, 2011) and in Starbucks Twitter case, they show the existence of positive and negative sentiment about Starbucks and its process of changing sentiment (Jansen et al., 2009). However, they could not explain the relationship between the WOM effect and performance of firm empirically.

3. Research Hypotheses

3.1 WOM Effects on Movie Attendance

SNS offers communicating networks between people with similar tendency or favor. Within SNS, members could have the same interest and feel the tie strength, homophiles and trust. Some studies regard these emotional effects as key influencers to increase WOM (Bansal and Voyer, 2000; Chu and kim, 2011). Specifically the tie strength and trust positively engage in WOM behaviors in SNS (Chu and kim, 2011), and peer effects among members eventually influence consumers' decision-makings of purchasing a product or a service (Bansal and Voyer, 2000). In a similar vein, micro-blogging (e.g. Twitter) is an online tool that facilitates WOM communications among consumers (Jansen et al., 2009), and WOM referrals through SNS is an effective way of promoting a new product compared with using conventional communication media (Trusov et al., 2009). Based on the argument, we expect that if WOM effects (represented as the number of related messages) on a specific movie arise over SNS, they should influence the movie attendance. Thus, the following hypothesis is proposed;

Hypothesis 1 *: An increase in the number of SNS postings is positively related to an increase in movie attendance.*

3.2 WOM Effects by the Popularity of Movie

Movie could be divided into two groups: popular and less popular movies. Each group has different characteristics because popular movies have more entertainment features than less popular movies do, and the degree of WOM effects could be different in each movie group. In the game industry, increase in online reviews positively influences the sales of product, and the effects becomes much greater especially in the case of newly released game products or products with lower reputation in the market (Zhu and Zhang, 2010).

Online reviews in movie portal sites are relatively open to the public, but SNS holds more private features in sharing reviews among inner-circled members. So it can be interpreted that the level of WOM effects can be different depending on the degree of tie strength among people (Granovetter, 1973), which is attributed to the system architecture of online communication channels (i.e., public architecture vs. private architecture).

Therefore, we expect that WOM effects in SNS should be greater for less popular movies than for popular movies because people who would like to see less popular movie usually have highly specialized preference compared to others, and these kinds of people are more likely to have strong tie with each other in SNS mediated by their common preference. Based on the argument, the following hypotheses are suggested;

Hypothesis 2a : *The effect of WOM in SNS is greater for less popular movies than for popular movies.*

Hypothesis 2b : *Online reviews in the movie portal site will lead to the smaller scale of WOM effects for less popular movies.*

3.3 Durability and Timing of WOM Effects on Movie Attendance

For marketing practitioners, the durability and timing of WOM effects are also important to manage marketing communications with consumers in SNS because understanding of time value of WOM could help firms develop appropriate marketing tools in timely manners.

In the context of movie industry, a number of studies examine when WOM effects occur and how long they exist. Some studies indicate that reviews are positively related to opening week revenues or could predict early sales (Elberse and Eliashberg, 2003; Dellarocas et al., 2007). Other studies find that the WOM effect lasts but decreases (Duan et al., 2008) or vanishes in 6 weeks after the movie release (Liu, 2006).

In the aspect of timing of WOM effects, time point in which the effects should arise can be different depending on features of a movie such as popularity of the movie (Dellarocas et al., 2007; Duan et al., 2008). For popular movies, people go and watch movies, and they tend to post reviews in movie portal sites or SNS after watching the movie. However, for less popular movies, people are more prone to leave their enquiries and expectations prior to watching movies, but they less tend to post reviews and comments after watching movies because there are little incentives for them to post reviews for the less popular movies with limited number of target audiences who hold a highly specialized preference. Thus, the argument leads to the following hypotheses;

Hypothesis 3a : *The effect of WOM in popular movies has a positive impact on movie attendances after movie release and lasts in longer time period.*

Hypothesis 3b : *The effect of WOM in less popular movies has a positive impact on movie attendances before movie release but quickly diminishes.*

4. Research Method

4.1 Data Collection

The data for 179 movies released from February 2011 to July 2011 were collected from Korea Film Council, a public institution which gathers movie's revenue, attendance and other movie information. The movie reviews were collected from Naver movie portal (movie.naver.com)-the most famous movie portal site in Korea. SNS message data were gathered from SocialMetrics.com, which is a SNS analytics site run by Daumsoft. In Naver portal, movie review ratings (ranged from 1 to 10) and the number of ratings was also collected. The SNS data include the number of SNS postings, the number of tweets, the number of blog postings, and the sum of top 10 retweet postings.

Among the original 179 movies, some movies were eliminated from the sample data set because some movie names caused search errors in SocialMetrics.com and did not retrieve sufficient amount of message-related data. Finally data for 109 movies were included in the sample. Movie data showed that average rating was 7.85, mean of the number of rating was 1,124, and mean of the number of SNS postings was 8,113. <Table 1> presents variable descriptions and <Table 2> shows summary statistics of the collected data.

We divided the sample into two groups using the median of movie attendance (44,102): popular movies and less popular movies. The data shows that average rating is not different between each group (7.80 and 7.92), but NumRating and NumSNS are much bigger in popular movies group. <Table 3> shows summary statistics of each movie group.

<Table 1> Variable Description and Measures

Variables	Description	Variables	Description
Competition	Number of movies released on the same day	Site	No official Website = 0, Official Website = 1
Released	Period of screening	Revenue(in millions)	Total revenue of the movie
MAPP	Under age of 18 = 0, Above age of 18 = 1	Audience	Total attendances of the movie
Domestic	Korea movie = 0, Foreign movie = 1	NumSNS	The number of SNS postings
Screens	Total screens number	NumTweet	The number of tweets
Rating	Rating score in Naver Movie	NumBlog	The number of blog postings
NumRating	The number of raters in Naver Movie	NumRetweet	The sum of top 10 retweet postings
Time	Showing time of the movie		

<Table 2> Summary Statistics for Movies : All Movies

Variables	N	Min.	Max.	Mean	StsDev
Competition	109	3	77	8.06	9.09
Released	109	6	182	45.37	31.15
MAPP	109	1	4	2.42	1.03
Domestic	109	0	1	.73	.44
Screens	109	1	1,251	193	219
Rating	109	3.52	9.77	7.85	1.06
NumRating	109	10	12,534	1,124	2,193
Showtime	109	59	152	105	17.92
Site	109	0	1	.89	.30
Revenue(in millions)	109	1.089	74,800	4,186	10,876
Audience	109	207	7,790,298	503,795	1,275,240
NumSNS	109	68	98,513	8,113	19,649
NumTweet	109	24	76,753	6,236	15,328
NumBlog	109	9	31,190	1,877	4,544
NumRetweet	109	0	1,167	96.4	173.34

<Table 3A> Summary Statistics : Popular Movies

Variables	N	Min.	Max.	Mean	StdDev
Rating	64	3.52	9.35	7.8	1.04
NumRating	64	86	12,534	1,825	2,647
NumSNS	64	171	98,513	12,953	24,513
NumTweet	64	41	76,753	9,952	19,138
NumBlog	64	130	31,190	3,001	5,677
NumRetweet	64	0	1,167	124	205.03
Revenue(in millions)	64	3.04	74,800	702.04	13,442
Audience	64	45,752	7,790,298	852,563	1,577,480

<Table 3B> Summary Statistics : Unpopular Movies

Variables	N	Min.	Max.	Mean	StdDev
Rating	45	4.13	9.77	7.92	1.11
NumRating	45	10	1,302	128.13	208.28
NumSNS	45	68	12,804	1,229	2,182
NumTweet	45	24	11,037	950.68	1,892
NumBlog	45	9	1,767	278.73	313.73
NumRetweet	45	0	591	59.35	109.12
Revenue(in millions)	45	1.089	328	63.32	83.37
Audience	45	207	40,615	7,768	10,317

4.2 Empirical Models

To examine WOM effects in both SNS and the movie portal site, we develop the following model specifications. We use movie attendance as dependent variable. The reason for not using revenue as a performance indicator in the study is that movie ticket price is various according to the movie screening facilities. For example, 3D movie price is twice the price of normal screen movie which is the same movie of 3D. Therefore, revenue is not suitable to measure the performance of movies.

$$\begin{aligned} ln(Attendance)_i &= \beta_2 ln(NumRating)_i \\ &+ \beta_3 ln(NumSNS)_i + \mu_i + \epsilon_i \end{aligned} \tag{1}$$

$$\begin{aligned} ln(Attendance)_i &= \alpha + \beta_1 Rating_i \\ &+ \beta_2 ln(NumRating)_i \\ &+ \beta_3 ln(NumRerweet)_i + \mu_i + \epsilon_i \end{aligned} \tag{2}$$

Let i = 1, ⋯ N index the movies and μ is the fixed effect of movie attendance. We use natural log transformation to cope with potential nonlinearity. We develop another empirical model to estimate the durability of WOM effects.

$$\begin{aligned} ln(Attendance)_i &= \alpha + \beta_1 Rating_{i,t-1} \\ &+ \beta_2 ln(NumRating)_{i,t-1} \\ &+ \beta_3 ln(NumSNS)_{i,t-1} \\ &+ \mu_{i,t-1} + \varepsilon_{i,t-1} \end{aligned} \tag{3}$$

For each week separately (t = 1, ⋯, M), where i denotes each movie (i = 1, ⋯ N). In this equation, we also use natural log for the attendance and the number of rating and SNS.

5. Analysis Results

<Tables 4>~<Table 6> summarize analysis results of equation (1). <Tables 4> is about the regression result to the all movie audience and <Tables 5> and <Table 6> present the result of popular and unpopular movies. In each table, Model 1 consists of movie variables (Competition, Released, MAPP, Domestic, Screens, Showtime, and Site), Model 2 includes Internet portal variables (Rating and NumRating), and Models 3, 4, and 5 include SNS variables (NumSNS, NumTweet, and NumBlog).

<Table 4> presents Rating, NumRating, NumSNS, and NumBlog have significant results but NumTweet does not have a significant effect on the movie audience. The results indicate that the WOM effect in SNS could exist, and H_1 is partially supported. In addition, in popular movie group, <Table 5> shows NumTweet have a significant effect but does not have a positive effect in unpopular movie group (see <Table 6>). Therefore, the effect of WOM in Twitter is partially appeared and the WOM effect in Blog is generally generated. This result also partially supports H1.

The coefficient of NumSNS and NumBlog in unpopular movies is higher (NumSNS : .271 < .365, NumBlog : .396 < .434) than popular movies. This result shows that the effect of SNS is bigger in unpopular movies than popular movies, and H2a could be supported. Moreover, in <Table 6>, NumRating has no positive effect in unpopular movies but a significant effect in popular movie in <Table 5>. This result indicates that online reviews in movie portal site have less WOM effect in unpopular movies and could support H2b.

<Table 4> Results of Regression Analysis : All Movies

	Models				
	1	2	3	4	5
Competition	.000 (.015)	.008 (.012)	.009 (.012)	.009 (.012)	.012 (.012)
Released	.008 (.005)	.003 (.004)	.001 (.004)	.000 (.004)	.003 (.004)
MAPP	257 (.384)	.396 (.309)	.454 (.306)	.444 (.309)	.376 (.297)
Domestic	.397 (.330)	.385 (.254)	.452* (.253)	.435* (.255)	.476* (.247)
Screens	.009*** (.001)	.005*** (.001)	.004*** (.001)	.004*** (.001)	.004*** (.001)
Showtime	.010 (.009)	.009 (.007)	.009 (.007)	.009 (.007)	.008 (.007)
Site	1.882*** (.501)	1.126*** (.403)	1.097*** (.398)	1.112*** (.402)	.959** (.392)
Rating		.193* (.109)	.182* (.108)	.187* (.109)	.171 (.105)
NumRating		.827*** (.101)	.724*** (.114)	.764*** (.111)	.635*** (.117)
NumSNS			.233* (.123)		
NumTweet				.140 (.164)	
NumBlog					.447*** (.150)
Observations	109	109	109	109	109
R^2	.738	.848	.853	.851	.860

Note) Standard errors in parentheses, $^{*}P$ > 0.1, $^{**}P$ > 0.05, $^{***}P$ > 0.01.

<Table 5> Results of Regression Analysis : Popular Movies

	Models				
	1	2	3	4	5
Competition	.091** (.040)	.046 (.159)	.046 (.029)	.049 (.030)	.042 (.028)
Released	.007* (.004)	.002 (.004)	.002 (.003)	.001 (.003)	.002 (.003)
MAPP	.125 (.309)	.114 (.246)	.027 (.229)	.010 (.236)	.004 (.220)
Domestic	.125 (.277)	.068 (.216)	.110 (.198)	.098 (.204)	.136 (.192)
Screens	.005*** (.001)	.004*** (.001)	.003*** (.001)	.003*** (.001)	.003*** (.001)
Showtime	.006 (.008)	.000 (.006)	.000 (.005)	.001 (.006)	.001 (.005)

Site					
Rating		.155* (.083)	.178** (.076)	.180** (.078)	.164** (.073)
NumRating		.493*** (.088)	.295*** (.099)	.329*** (.101)	.264*** (.097)
NumSNS			.271*** (.080)		
NumTweet				.194*** (.068)	
NumBlog					.396*** (.099)
Observations	64	64	64	64	64
R^2	.743	.853	.879	.872	.886

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

<Table 6> Results of Regression Analysis : Unpopular Movies

	Models				
	1	2	3	4	5
Competition	.001 (.013)	.003 (.012)	.003 (.011)	.003 (.011)	.005 (.011)
Released	.021*** (.005)	.016*** (.005)	.010* (.006)	.011* (.005)	.010* (.005)
MAPP	.038 (.384)	.073 (.385)	.030 (.373)	.023 (.377)	.164 (.373)
Domestic	.747* (.386)	.850** (.364)	.923** (.355)	.904** (.357)	.923** (.353)
Screens	.025*** (.004)	.020*** (.005)	.021*** (.004)	.021*** (.004)	.202*** (.004)
Showtime	.012 (.011)	.010 (.010)	.009 (.010)	.009 (.010)	.009 (.009)
Site	.347 (.412)	.370 (.387)	.243 (.381)	.252 (.384)	.190 (.383)
Rating		.356** (.148)	.292* (.148)	.304** (.148)	.303** (.146)
NumRating		.307* (.155)	.205 (.160)	.243 (.156)	.178 (.164)
NumSNS			.365* (.199)	.	
NumTweet				.262 (.157)	
NumBlog					.434* (.223)
Observations	45	45	45	45	45
R^2	.600	.682	.710	.706	.714

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

<Table 7> Results of Retweet Effect

	All	Popular	Unpopular
Rating	.196* (.109)	.152* (.077)	.321** (.147)
NumRating	.842*** (.100)	.463*** (.085)	.301* (.152)
NumRetweet	.077 (.305)	.138** (.052)	.180 (.111)

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

Furthermore, we add NumRetweet variable and its result, as appeared in <Table 7>, presents that NumRetweet is only significant in popular movie group. This result shows similar result of NumTweet variable and those results show the WOM effect in Twitter only exist in popular movie group.

<Table 8> shows that the WOM effects of SNS (NumSNS, NumTweet and NumBlog) are significant in every week excepting second and fifth week and the review WOM effects (Rating and NumRating) are significant in every week. Those results indicate that there exists the long durability of WOM in both SNS and Internet movie portal for all movie dataset.

However, there are different results in popular and unpopular movie groups on those results. In popular movies (see <Table 9>), NumSNS have a positive effect on movie audience to the fourth week but Rating and Num-Ratings have a positive effect on after first week. Therefore, before releasing, the effect of WOM in SNS only exists and review effect occurs after movie releasing with SNS effect simultaneously. The WOM effect in SNS and Internet portal are lasting four weeks and those results support H3a.

In unpopular movies (see <Table 10>), Rating, NumSNS, and NumTweet are significant to the first week audience but its effect is not lasting after second week clearly. Therefore, the WOM effect in unpopular movie group is higher before movie released and this result support H3b.

In addition, there are different WOM effects between Twitter and Blog. NumTweet is significant from the first week to the fourth week but NumBlog has a positive effect on the third and fourth week in the popular movie group. In addition, Numtweet has a positive effect on the first and fourth week but NumBlog is only significant in the third week in unpopular movie group. Therefore, the WOM effect in Twitter is more quickly appeared than the WOM effect in Blog.

6. Conclusion

The objective of this research is to investigate the WOM effect on movie industry in both SNS and Internet portals. The research results present salient theoretical and practical insights that help researchers and practitioners figure out more efficient way of manipulating SNS for better business performance.

First, the study finds that the WOM effect exists in SNS, and its effect is stronger in less popular movies. These results imply that SNS sufficiently becomes another major online

<Table 8> Results of Durability of WOM : All Movies

	Weeks				
	1	2	3	4	5
Rating	$.559^{***}$ (.149)	$.204^{**}$ (.102)	$.611^{***}$ (.141)	$.574^{***}$ (.210)	$.513^{***}$ (.192)
NumRating	$.403^{***}$ (.102)	$.831^{***}$ (.094)	$.472^{***}$ (.136)	$.573^{***}$ (.209)	$.637^{***}$ (.162)
NumSNS	$.412^{***}$ (.127)	.177 (.107)	$.390^{***}$ (.154)	$.590^{***}$ (.223)	.258 (.167)
Observations	109	107	99	85	63
R^2	.798	.883	.806	.735	.803
Rating	$.570^{***}$ (.150)	$.202^{**}$ (.102)	$.610^{***}$ (.142)	$.608^{***}$ (.211)	$.528^{***}$ (.191)
NumRating	$.428^{***}$ (.102)	$.847^{***}$ (.090)	$.517^{***}$ (.133)	$.589^{***}$ (.209)	$.660^{***}$ (.167)
NumTweet	$.342^{***}$ (.109)	.140 (.085)	$.266^{**}$ (.122)	$.468^{**}$ (.179)	.227 .(157)
Observations	109	107	99	85	63
R^2	.796	.883	.803	.735	.813
Rating	$.534^{***}$ (.153)	$.204^{*}$ (.104)	$.665^{***}$ (.135)	$.603^{***}$ (.214)	$.509^{**}$ (.195)
NumRating	$.356^{***}$ (.108)	$.866^{***}$ (.109)	$.400^{***}$ (.135)	$.656^{***}$ (.212)	$.661^{***}$ (.162)
NumBlog	$.429^{***}$ (.163)	.082 (.154)	$.612^{***}$ (.188)	$.483^{*}$ (.250)	.250 (.191)
Observations	109	107	99	85	63
R^2	.798	.881	.806	.724	.795

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

<Table 9> Results of Durability of WOM : Popular Movies

	Weeks				
	1	2	3	4	5
Rating	.142 (.108)	$.399^{***}$ (.113)	1.031^{***} (.206)	$.751^{**}$ (.365)	.382 (.321)
NumRating	.031 (.060)	$.426^{***}$ (.159)	.383 (.240)	.680 (.404)	$.654^{**}$ (.258)
NumSNS	$.164^{**}$ (.065)	$.277^{**}$ (.113)	$.598^{***}$ (.206)	$.750^{**}$ (.337)	.252 (.202)
Observations	64	64	63	52	39
R^2	.808	.808	.793	.772	.838
Rating	.143 (.108)	$.398^{***}$ (.113)	1.031^{***} (.210)	$.718^{*}$ (.373)	.427 (.328)

NumRating	.036 (.060)	.451*** (.153)	.396 (.249)	.806* (.403)	.638** (.285)
NumTweet	.152*** (.057)	.398** (.113)	.447** (.171)	.473* (.264)	.225 (.201)
Observations	64	64	63	52	39
R^2	.811	.807	.787	.763	.837
Rating	.127 (.112)	.395*** (.117)	1.042*** (.202)	.765** (.368)	.323 (.318)
NumRating	.026 (.063)	.529*** (.167)	.440** (.216)	.766* (.382)	.694*** (.240)
NumBlog	.125 (.084)	.185 (.155)	.811*** (.243)	.812** (.369)	.284 (.216)
Observations	64	64	63	52	39
R^2	.794	.792	.801	.771	.839

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

<Table 10> Results of Durability of WOM : Unpopular Movies

	Weeks				
	1	2	3	4	5
Rating	.384** (.156)	.161 (.180)	.123 (.172)	.027 (.203)	.649 (.259)
NumRating	.254 (.152)	.389 (.228)*	.295 (.233)	.175 (.242)	.800 (.544)
NumSNS	.626** (.238)	.379 (.247)	.419* (.236)	.603** (.238)	.110 (.388)
Observations	45	43	36	33	24
R^2	.708	.684	.751	.670	.578
Rating	.381** (.155)	.160 (.180)	.140 (.181)	.006 (.254)	.686 (.371)
NumRating	.309* (.154)	.418* (.222)	.359 (.239)	.030 (.254)	.875 (.556)
NumTweet	.455** (.182)	.298 (.194)	.256 (.197)	.616*** (.197)	.154 (.371)
Observations	45	43	36	33	24
R^2	.703	.684	.737	.716	.603
Rating	.368* (.182)	.192 (.186)	.228 (.136)	.137 (.226)	.670 (.553)
NumRating	.206 (.176)	.477* (.256)	.307 (.180)	.368 (.283)	.773 (.547)
NumBlog	.347 (.364)	.131 (.397)	.499** (.221)	.137 (.226)	.232 (.532)
Observations	45	43	36	33	24
R^2	.658	.661	.825	.585	.549

Note) Standard errors in parentheses, $^{*}P > 0.1$, $^{**}P > 0.05$, $^{***}P > 0.01$.

communication channel in which WOM effects can be possibly more amplified compared to other conventional communication media. Thus, the fact provides much incentive for firms regards SNS as strategic marketing platform to enhance their brand reputations. Also stronger WOM effects in less popular movies imply that product features may be a significant influencer for the degree of WOM effects, and SNS would be the plausible choice for any marketing promotion for niche products and marketing strategy with low budget but high return.

The study provides another result that the effect of WOM relatively last long in popular movies but disappears quickly in unpopular movies. This result provides significant implication for marketers. Practitioners should take more care of conducting marketing promotion for low-budget or independent art films prior to the movie release while, for blockbuster movies, they need to concentrate on marketing promotions after movie release. In addition, the WOM effect in Twitter is appeared only in popular movie and early stage of movie release. In more general sense, the finding implies that to make their marketing promotions more productive and successful, firms need to utilize diversified communication channels including online and offline across the life cycle of products and services because consumers' perception and opinion on the products and services can be frequently changed at each stage of the life cycle.

Although the study sheds light on relatively new theoretical perspective for understanding the role of WOM on SNS in promoting the sales of products and services, this study still has some limitations.

First, the study only focuses on online contexts and movie industry. Since there are many other experience goods such as music, games, and software, future study needs to be expanded to broader research context and present more generalized results applicable to diversified business environment.

Second, generally, the age of Internet user is lower than consumers who mostly use conventional media channel, so the current version of the study does not represent behavioral attitudes of all class consumers, and there is possibility to occur different results in other industries. Thus, examining different industries and considering overall population should be required for future research.

Third, the study does not consider the sentiment of messages posted on SNS. For the next research, manipulating social sentiment information can help us discover more sophisticated WOM communication patterns among consumers and explore more detailed causal relationship between information diffusion and elaboration mechanism and sales performance of products and services.

References

Arndt, J., "Role of Product-related Conversations in the Diffusion of a New Product", *Jour-*

nal of Marketing Research, Vol.4, No.3 (1967), 291~295.

Anderson, E. W., "Customer Satisfaction and Word of Mouth", *Journal of Service Research*, Vol.1, No.1(1998), 5~17.

Bansal, H. S. and P. A. Voyer, "Word-of-Mouth Processes within a Services Purchase Decision Context", *Journal of Service Research*, Vol.3, No.2(2000), 166~177.

Basuroy, S., S. Chatterjee and S. A. Ravid, "How Critical are Critical Reviews? The Box Office Effects of Film Critics, Star Power, and Budgets", *Journal of Marketing*, Vol. 67, No.4(2003), 103~117.

Bitner, M. J., "Evaluating Service Encounter : The Effects of Physical Surroundings and Employee Responses", *Journal of Marketing*, Vol.54, No.2(1990), 69~82.

Boatwright, P., S. Basuroy and W. Kamakura, "Reviewing the Reviewers : The Impact of Individual Film Critics on Box Office Performance", *Quantitative Marketing and Economics*, Vol.5, No.4(2007), 401~425.

Bolton, G. E., E. Katok and A. Ockenfels, "How Effective Are Electronic Reputation Mechanisms? An Experimental Investigation", *Management Science*, Vol.50, No.11(2004), 1587~1602.

Boyd, D. M. and N. B. Ellison, "Social network sites : Definition, History, and Scholarship", *Journal of Computer-mediated Communication*, Vol.13, No.1(2007), 210~230.

Chevalier, J. A. and D. Mayzlin, "The Effect of Word of Mouth on Sales : Online Book Reviews", *Journal of Marketing Research*, Vol.43, No.3(2006), 345~354.

Cho, I. and N. Kim, "Recommending Core and Connecting Keywords of Research Area Using Social Network and Data Mining Techniques", *Journal of Intelligence and Information Systems*, Vol.17, No.1(2011), 127~138.

Choi, J. and H. J. Lee, "The Effects of Customer Product Review on Social Presence in Personalized Recommender Systems", *Journal of Intelligence and Information Systems*, Vol.17, No.3(2011), 115~130.

Chu, S.-C. and Y. Kim, "Determinants of Consumer Engagement in Electronic Word-of-Mouth (eWOM) in Social Networking Sites", *International Journal of Advertising*, Vol. 30, No.1(2011), 47~75.

Clemons, E. K., G. G. Gao and L. M. Hitt, "When Online Reviews Meet Hyper differentiation : A Study of the Craft Beer Industry", *Journal of Management Information Systems*, Vol.23, No.2(2006), 149~171.

Dellarocas, C., "Strategic Manipulation of Internet Opinion Forums : Implications for Consumers and Firms", *Management Science*, Vol.52, N0.10(2006), 1577~1593.

Dellarocas, C., G. G. Gao and R. Narayan, "Are Consumers More likely to Contribute Online Reviews for Hit or Niche Products?" *Journal of Management Information Systems*, Vol.27, No.2(2010), 127~157.

Dellarocas, C., X. Zhang and N. F. Awad, "Exploring the Value of Online Product Reviews in Forecasting Sales : The Case of Motion Pictures", *Journal of Interactive Marketing*, Vol.21, No.4(2007), 23~45.

Duan, W., B. Gu and A. B. Whinston, "The

Dynamics of Online Word-of-Mouth and Product Sales : An Empirical Investigation of the Movie Industry", *Journal of Retailing*, Vol.84, No.2(2008), 233~242.

Duan, W., B. Gu and A. B. Winston, "Do Online Reviews Matter? An Empirical Investigation of Panel Data", *Decision Support Systems*, Vol.45, No.4(2008), 1007~1016.

Einav, L., "Seasonality in the U.S. Motion Picture Industry", *The RAND Journal of Economics*, Vol.38, No.1(2007), 127~145.

Elberse, A. and J. Eliashberg, "Demand and Supply Dynamics for Sequentially Released Products in International Markets : The Case of Motion Pictures", *Marketing Science*, Vol. 22, No.3(2003), 329~354.

Engel, J. F., R. D. Blackwell and R. J. Kegerreis, "How Information Is Used to Adopt an Innovation", *Journal of Advertising Research Special Classics Issue*, Vol.9, No.4(1969), 3~8.

Fan, J., "Research on the External Factors of Consumers Releasing Online Comments." *In Proceedings of 2011 International Conference on Electronic and Mechanical Engineering and Information Technology*, EMEIT 2011, 3819~3823.

Godes, D. and D. Mayzlin, "Using Online Conversations to Study Word-of-Mouth Communication", *Marketing Science*, Vol.23, No.4 (2004), 545~560.

Granovetter, M. S., "The Strength of Weak Ties", *American Journal of Sociology*, Vol.78, No. 6(1973), 1360-1380.

Howard, B., "Analyzing Online Social Networks", *Communications of the ACM*, Vol.51, No. 11(2008), 14~16.

Jansen, B. J., M. Zhang, K. Sobel and A. Chowdury, "Twitter Power : Tweets as Electronic Word of Mouth", *Journal of the American Society for Information Science and Technology*, Vol.60, No.11(2009), 2169~2188.

Katz, E. and P. Lazarsfeld, Personal Influence, The Free Press, New York, NY, 1955.

Li, X. and L. M. Hitt, "Self-Selection and Information Role of Online Product Reviews", *Information Systems Research*, Vol.19, No.4 (2008), 456~474.

Li, X. and L. M. Hitt, "Price Effects in Online Product Reviews : An Analytical Model and Empirical Analysis", *MIS Quarterly*, Vol.34, No.4(2010), 809~837.

Liu, Y., "Word Mouth for Movies : Its Dynamics and Impact on Box Office Revenue", *Journal of Marketing*, Vol.70, No.3(2006), 74~89.

Mahajan, V., E. Muller and R. A. Kerinet, "Introduction Strategy for New Products with Positive and Negative Word-of-Mouth", *Management Science*, Vol.30, No.12(1984), 1389~404.

Nam, Y., I. Son and D. Lee, "The Impact of Message Characteristics on Online Viral Diffusion in Online Social Media Services : The Case of Twitter", *Journal of Intelligence and Information Systems*, Vol.17, No.4(2011), 57~76.

Reinstein, D. A. and C. M. Snyder, "The Influence of Expert Reviews on Consumer Demand for Experience Goods : A Case Study of Movie Critics", *Journal of Industrial*

Economics, Vol.53, No.1(2005), 27~51.

Richins, M. L. and T. Root-Shaffer, "The Role of Involvement and Opinion Leadership in Consumer Word-of-Mouth : An Implicit Model Made Explicit", *Advances in Consumer Research*, Vol.15, No.1(1988), 32~36.

Senecal, S. and J. Nantel, "The Influence of Online Product Recommendations on Consumers' Online Choices", *Journal of Retailing*, Vol.80, No.2(2004), 159~169.

Singh, F., "Consumer Complaint Intentions and Behavio r : A Review and Prospective", *Journal of Marketing*, Vol.52, No.1(1988), 93~107.

Trusov, M., R. E. Bucklin and K. Pauwels, "Effects of Word-of-Mouth versus Traditional Marketing : Findings from an Internet Social Networking Site", *Journal of Marketing*, Vol.73, No.5(2009), 90~102.

Westbrook, R. A., "Product/Consumption-based Affective Responses and Post-purchase Processes", *Journal of Marketing Research*, Vol.24, No.3(1987), 258~270.

Zhu, F. and X. M. Zhang, "Impact of Online Consumer Reviews on Sales : The Moderating Role of Product and Consumer Characteristics", *Journal of Marketing*, Vol.74, No.2(2010), 133~148.

Abstract

온라인 소셜네트워크의 제품판매 관련 구전효과에 대한 기여도 분석

이주윤* · 손인수** · 이동원***

온라인 소셜네트워크의 확산으로 인해 사용자들은 특정제품과 서비스에 대한 자신의 생각과 경험을 보다 손쉽게 공유 할 수 있게 되었으며 이러한 환경변화는 기업의 사업성과에 영향을 미칠 수 있는 소비자 구전효과의 영향을 심화시킬 것으로 예상된다. 본 연구의 목적은 영화산업에서의 온라인 소셜네트워크의 구전효과 발생에 대한 기여도를 또 다른 온라인 매체인 인터넷 포탈과의 비교를 통해 검증하는데 있다. 이를 위해 2011년 2월부터 6월 사이에 국내 개봉된 영화 및 이들 영화와 관련된 트위터 메시지 그리고 네이버 무비상의 리뷰를 수집 분석하였다. 분석결과 온라인 소셜네트워크(트위터)와 인터넷 포털 모두에서 영화의 흥행과 관련한 구전효과가 존재하고 있음을 발견하였다. 또한 영화의 인기도에 따라 온라인 소셜케트워크와 인터넷 포털의 구전효과 발생에 대한 영향도가 다르게 나타나는 점도 발견하였다. 인기영화(블록버스터 영화)의 경우 개봉이전에는 온라인 소셜네트워크에 의한 구전효과가 유의하게 발생하였으며 개봉이후에는 온라인 소셜네트워크와 인터넷 포털에 의한 구전효과가 유의하게 발생함을 알 수 있었다. 비인기영화의 경우 개봉이전에만 온라인 소셜네트워크와 인터넷 포털에 의한 구전효과가 유의하게 발생함을 발견하였다. 본 연구의 결과는 영화와 같은 문화상품과 관련한 구전효과 발생에 있어 온라인 소셜네트워크의 영향에 관한 학문적 지식을 증대시키고 실무적으로 기업이 제품 및 서비스에 대한 브랜드가치 재고를 위해 온라인 소셜네트워크를 어떻게 전략적으로 활용할 수 있는가에 방향을 제시 할 것이라 기대된다.

Keywords : 인터넷 포털, 영화산업, 온라인 소셜네트워크, 트위터, 구전효과

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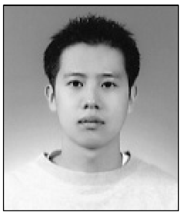
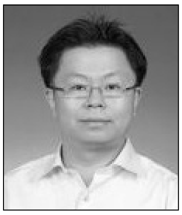
저 자 소 개



이주윤
고려대학교 경영대학 경영학석사 및 동 대학원 MIS 석사학위를 취득하였다. 관심분야는 the role of online social media in marketing promotion이다. 현재 새마을금고 중앙회에서 근무하고 있다.

손인수
현재 고려대학교 경영대학 대학원 박사과정 재학 중이다. 고려대학교 경제학사, University of Wisconsin-Madison 경영학 석사(MBA), Carnegie-Mellon University 경영정보학 석사(MISM)를 취득하였으며 LG-CNS 컨설팅 부문에서 근무하였다. 주요 관심분야는 E-business, Service-oriented computing, Technology-based innovation, Business value of IT, Consumer behaviors under social network environment이다.



이동원
현재 고려대학교 경영대학 교수로 재직 중이다. 서울대학교에서 경영학사 및 경영학 석사, University of Arizona에서 MIS 석사, University of Minnesota에서 경영학 박사를 취득하였다. 주요 관심분야는 전자상거래 가격 전략, 온라인 소비자 행동 분석, 소셜미디어, 클라우드 컴퓨팅 등이다. Review of Economics and Statistics, Journal of AIS, Journal of MIS, International Journal of Electronic Commerce, Communications of the AIS, Information Systems Frontier, Electronic Markets, Journal of Global Information Technology Management, ACM Crossroads 등을 비롯한 다수의 국내외 학술지에 논문을 발표하였다.