Impact of Social Networks on Diffusion of Products

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Abstract

In light of the rapid growth of social networks around the world, this study analyses the impact of social networks on the diffusion of products and demonstrates the effective way to diffuse products in the society where social networks play an important role. We construct a consumer behaviour model by multi-agent simulation taking the movie market as an example. After validating it by using data from 13 US movies, we conduct simulations. Our simulation results show that the impact of social networks on the diffusion differs according to the customers' expectations and evaluation for a movie. We also demonstrate the effective weekly advertising budget allocations corresponding to the types of movies. We find that the difference of weekly advertising budget allocations gives greater impact on the diffusion with the growth of social networks. This paper provides firm's managers with important suggestions for diffusion strategy considering the impact of social networks.

Keywords: *Social networks, diffusion strategy, consumer behaviour model, multi-agent simulation.*

INTRODUCTION

Social networking services such as Twitter and Facebook have grown rapidly around the world and are generating a significant impact on changing consumer behaviour and the diffusion process of products. Contemporarily, many firms utilise social networking services to market their products. By optimally using social networking services, firms may diffuse their products more widely, even on a limited budget. Such a strategy will be critical, especially for firms in emerging economies, whose budgets are relatively small compared to those of large firms in developed economies. In order to devise an effective diffusion strategy, understanding the impact of social networks on consumer behaviour and the diffusion process of products is essential.

There are a large number of studies that attempt to clarify consumer behaviour and the diffusion process of products (Mansfield, 1961; Bass, 1969;

CHITKARA UNIVERSITY

Arai, Y.
Kajiyama, T.
Ouchi, N.

36

Mahajan et al., 1990; Meyer, 1994; Libai et al., 2009). For example, Bass (1969) developed a single first-purchase diffusion model, which assumes two types of adopters: innovators and imitators. Many researchers have developed diffusion models based on this model. However, they have not considered the role of social networks on consumer behaviour. Thus, how social networks influence consumer behaviour and, subsequently, the diffusion of products remains unclear.

Some researchers have attempted to link consumer behaviour and firms' strategies (Kamimura et al., 2006; Tilman et al., 2007; Duan et al., 2008). For example, Duan et al. (2008) used a dynamic simultaneous system to demonstrate how word-of-mouth (WOM) on the Internet influences consumer behaviour in the movie market. They revealed that there is a positive relationship between WOM volume and sales figures, and suggested that stimulating the volume of WOM about a product or service is an effective diffusion strategy. In addition, other studies have shown that the effective advertisement of products is important for increasing consumers' willingness to pay for those products (Tsui, 2012).

Additionally, Kamimura et al (2006) constructed a consumer behaviour model concerning the movie market and analysed the effective use of an advertising budget. During the advertising period (which starts a few weeks before a movie is released and lasts until the final week a movie is in theatres), firms allocate a certain amount of their budget to advertising each week. Kamimura et al (2006) demonstrated the impact of the different patterns of weekly advertising budget allocation on the cumulative number of movie viewers. However, there are some limitations in the study. It does not consider the existence of social networks. Furthermore, the characteristics of the movies are not considered, although such product features may well be a critical element of an effective diffusion strategy. Some research (Mittal et al., 1999; Plouffe et al., 2001) has argued that consumer attitudes and behaviours are affected by product characteristics. Given this, it is important to consider differences in product characteristics to devise effective diffusion strategies.

Given the above, the objectives of our study are as follows: (i) to clarify how social networks impact the diffusion process of products corresponding to product characteristics by constructing a consumer behaviour model that considers the impact of social networks, and (ii) to demonstrate effective diffusion strategies in order to increase the number of adopters of products. This study considers the movie market as a target market because it is strongly influenced by the effects of WOM and, is therefore, suitable for our study.

In section 2, we propose a consumer behaviour model that incorporates social networking effects. In section 3, we validate the accuracy of our

proposed model using empirical data of 13 US movies, clarify how social networks influence the diffusion process of products, and demonstrate effective diffusion strategies. Finally, in section 4, we briefly summarises the new findings, discuss strategy implications for firms, and provide some suggestions for future research.

MODEL CONSTRUCTION

In this study, we developed a consumer behaviour model considering social networks' effects by multi-agent simulation using the movie market as an example[1]. Multi-agent simulation is a class of computational models for simulating the actions and interactions of agents to assess their effects on the system as a whole. Multi-agent simulation is an especially appropriate model for observing individual actions and interactions between consumers in society. Because this study is geared towards constructing a model that considers the effects of individual agents on a society, multi-agent simulation is suitable. We used the software 'artisoc' produced by Kozo Keikaku Engineering Inc. to conduct the simulations. In our model, 1,000 agents are created in a grid size of 50×50 cells.

According to Kamimura (2006), internal and external factors may contribute to consumers' motivations for watching a movie. Internal factors represent consumers' interests in movie, and external factors consist of advertising and WOM. Further, the degree to which value is placed on internal or external factors varies by consumer. For example, while some consumers watch a movie once they have developed an interest in it, others may refer to WOM before making a decision regarding the film. To account for these variations, we set the decision-making process as follows: agent i decides whether or not to watch a movie at week t, by comparing the weighted sum of 'individual preference' ($P_{i,t}$) and 'effects from advertising and WOM' ($E_{i,t}$) with 'individual threshold' (T_i). By using weighted parameter (a_i), the condition where agent i decides to watch a movie is defined as depicted in inequality (1).

$$a_i \cdot P_{i,t} + (1 - a_i) \cdot E_{i,t} > T_i \qquad (1)$$

To account for characteristics of individual consumers, we assume is a random number between 0 and 1. If is close to 1, agents value their interests for a movie. On the other hand, agents value WOM if is close to 0. 'Individual preference' () represents agent i's degree of preference for the movie. $P_{i,t}$ is computed with equation (2).

$$P_{i,t} = (pb + adv + pre) \cdot F^P(t) \cdot I_i^P \cdot D_i^{\ P} \qquad (2)$$

Arai, Y.
Kajiyama, T.
Ouchi, N.

where, *pb* is the effect of production budgets, *adv* represents the effect of advertising, *pre* depicts the effect of previous movies and original novels, $F^p(t)$ is the time variation of consumers' interests in a new movie, I_i^P represents the individuality of agent *i*, and D_i is a dummy variable that denotes whether or not agent *i* has an interest in the movie's genre (D_i=1 if agent *i* has an interest, D_i=0 if otherwise).

The variables *pb*, *adv* and *pre* are rated on a scale of one to ten. We consider *pb*, *adv* and *pre* to be components of $P_{i,t}$ because they represent key factors related to a movie's attractiveness. Because consumers' interests in a movie wane as time passes, $F^p(t)$ is a decreasing function of t. In our model, we set $F^p(t) = 0.94^t$ following Kamimura et al (2006). With respect to the value of I_i^P, we assign agents a random number between 0 and 1 because receptivity can vary among consumers.

Consumers' film genre preferences also influence their decision to watch a movie. Therefore, we created a dummy variable (D_i) to represent whether or not agent *i* is interested in the genre of the movie. To determine the percentage of agents who are interested in the movie genre, we referred to the results of a questionnaire provided by Kamimura et al (2006), as denoted in Figure 1. Figure 1, for example, shows that the percentage of consumers who are interested in the Action/Adventure movie is 69%. Following Kamimura et al (2006), we use the percentages outlined in Figure 1 as relevant data.
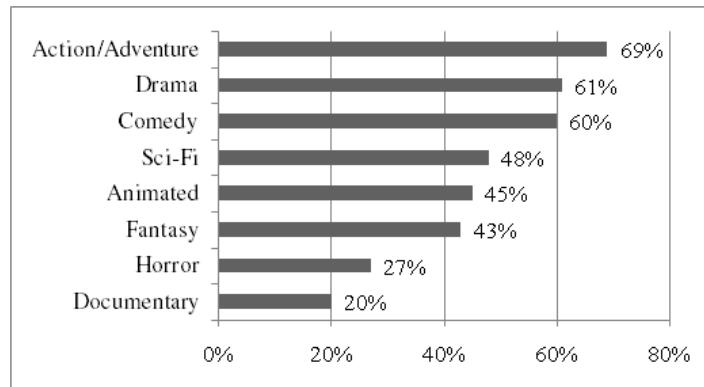

Figure 1: Percentage of consumers who are interested in the genre of the movie
Source: Kamimura et al (2006)

'Effects of advertising and WOM' ($E_{i,t}$) is the sum of the 'effects of advertising' ($A_{i,t}$) and the 'effects of WOM' ($W_{i,t}$) as depicted in equation (3).

$$E_{i,t} = A_{i,t} + W_{i,t} \qquad (3)$$

is computed by equation (4).

$$A_{i,t} = adv \cdot R^A \cdot I_i^A \cdot G^A(t) \tag{4}$$

where R^A is the reliability of mass media, I_i^A represents agent i's responsiveness to advertising, and $G^A(t)$ relates to time variation concerning the effect of advertising.

Sources of information, such as mass media and WOM, differ in terms of their respective reliabilities. In this model, we assume $R^A = 1$. I_i^A is a random number between 0 and 1 because receptivity can also vary among consumers. Because the effects of advertising decrease as time passes, we set $G^A(t) = B^A \cdot F^A(t)$. B^A is a base value for time variation related to the advertising effect. According to Miyata and Ikeda (2008), who investigated how consumers gather information related to movies, 30.6% of all consumers seek information related to movies from advertising. Therefore, we set B^A =0.306 in this model. F^A *(t)* =0.7 (t < 0) and F^A *(t)* *(t ≥ 0),* in accordance with Kamimura et al (2006). In section 3.3, we change F^A *(t)* to correspond with advertising budget allocation patterns.

With respect to $W_{i,t}$, we consider three sources of WOM: 'neighbours', 'Internet sites', and 'social networks'. $W_{i,t}$ is the sum of the effects of neighbours' WOM ($\sum_{j=1}^{N_N} w_{i,j,t}$), the effects of the Internet's WOM ($\sum_{k=1}^{N_I} w_{i,k,t}$) and the effects of social networks' WOM ($\sum_{l=1}^{N_S} w_{i,l,t}$) as depicted in equation (5).

$$W_{i,t} = \sum_{j=1}^{N_N} w_{i,j,t} + \sum_{k=1}^{N_I} w_{i,k,t} + \sum_{l=1}^{N_S} w_{i,l,t} \tag{5}$$

where $w_{i,j,t}$, $w_{i,k,t}$ and $w_{i,l,t}$ represent the respective WOM effects agent i received from agent j, k and l, respectively N_N, N_I and N_S respectively represent the number of agents who can influence the impact of neighbours' WOM, the Internet's WOM, and social networks' WOM on agent i.

Although consumers can acquire information widely via the Internet, there are physical limitations associated with receiving WOM from neighbours. As a result, the number of agents who can affect the impact of Internet's WOM is greater than the number of agents that can influence neighbour's WOM. As such, we model N_N and N_I within 3×3 cells and 21×21 cells around agent i, respectively. Social networks represent specific connections between consumers on the Internet. Therefore, we assume that N_S is the number of agents who have a link with agent i and are within 21×21 cells around agent i.

A scale-free network (Barabasi and Albert, 1999) can be used to describe social networks. A scale-free network is a network with the property that the number of links originating from a given node exhibits a power law distribution. The network denotes the condition that few consumers have a large number of

Arai, Y.
Kajiyama, T.
Ouchi, N.

links, while other majorities have a few links. We use a scale-free network to create the links between agents, which denote social networks.

$w_{i,j,t}$ is computed as depicted in equation (6). $w_{i,k,t}$ and $w_{i,l,t}$ are computed in a similar manner.

$$w_{i,j,t} = \begin{cases} (pb + adv + pre) \cdot R^W \cdot I_i^W \cdot O_j \cdot G^W(t) \ (before\ release) \\ RatingScore \cdot R^W \cdot I_i^W \cdot O_j \cdot G^W(t) \ (after\ release) \end{cases} \quad (6)$$

where R^W represents the reliability of WOM, I_i^W is agent i's responsiveness to WOM, O_j depicts agent j's ability to spread information and $G^W(t)$ signifies variation in time related to the frequency with which an agent chats about the movie.

Following a movie's release date, the effect of WOM is largely contingent on the movie's rating score. However, consumers cannot obtain information concerning the movie's rating score prior to its release. Therefore, a movie's attractiveness prior to its release date is dependent on pg, adv and pre.

A rating score is an evaluation of a movie's value on a scale of one to ten, which is quoted from 'The Numbers' (The Numbers, 2011). Because the reliability of WOM (R^W) can differ as a function of the strength of the connection between consumers, we assume that $R^W_{neighbors} = 2.0$, $R^W_{internet\ sites} = 1.0$ and $R^W_{social\ networks} = 1.5$, respectively. I_i^W is a random number between 0 and 1 because receptivity differs among consumers. Because agents' ability to spread information can also differ among consumers, O_J is a random number around 1, between 0.5 and 1.5. We assume that the effects of WOM decrease as time passes, and set $G^W(t) = B^W \cdot F^W(t)$. B^W is a base value of the WOM effect, which we set as $B^W_{neighbors} = 0.32$, $B^W_{internet\ sites} = 0.16$ and $B^W_{social\ networks} = 0.24$, respectively. Similar to B^A, we set the values of $B^W_{neighbors}$ and $B^W_{internet\ sites}$ in accordance with the work of Miyata and Ikeda (2008). We set $B^W_{social\ networks}$ to be between $B^W_{neighbors}$ and $B^W_{internet\ sites}$ because Miyata and Ikeda (2008) did not investigate the social networks. We considered the base value of social networks' WOM effect to be larger than that of the Internet but smaller than that of neighbours. Also in parallel with Kamimura et al. (2006), $F^W(t) = e^t (t < 0)$ and $F^W(t) = 0.94^t (t \geq 0)$. The parameters for B^W and R^W are outlined in Table 1.

Table 1: Differences among the three WOM sources

WOM source	R^w	B^w
Neighbour	High ($R^w_{neighbors} = 2.0$)	High ($B^w_{neighbors} = 0.32$)
Internet sites	Low ($R^w_{internet\ sites} = 1.0$)	Low ($B^w_{internet\ sites} = 0.16$)
Social networks	Medium ($R^w_{social\ networks} = 1.5$)	Medium ($B^w_{social\ networks} = 0.24$)

(): Parameters used in the model

The individual threshold is computed by equation (7).

$$T_i = \alpha + \beta \cdot r \qquad (7)$$

where α, β refers to the respective coefficients that determine the individual threshold and r is a random number between 0 and 1.

Agents are characterised as innovators, early adopters, early majority, late majority, and laggards, in accordance with Rogers' diffusion theory (Rogers, 1962). The values of α and β differ depending on these characteristics, as illustrated in Table 2.

Table 2: Parameters for individual thresholds

Category	Proportion (%)	α	β
Innovators	2.5%	4	1
Early adopters	13.5%	6	3
Early majority	34%	9	6
Late majority	34%	11	6
Laggards	16%	13	3

SIMULATION AND APPLICATION TO DIFFUSION STRATEGIES

Model Verification

We validated the proposed model by comparing our simulation results with actual data related to the cumulative number of weekly movie viewers. To this end, we selected 13 movies (see Table 3). They include the top five movies in terms of box office take in 2010 and 'The King's Speech', the Academy Award winner for Best Motion Picture in 2010. The data in Table 3 are available at 'The Numbers (The Numbers, 2001).

Table 3: List of the 13 movies used in the study

Title	Sales Figure
Toy Story 3	$415,004,880
Alice in Wonderland	$334,191,110
Iron Man 2	$312,433,331
The Twilight Saga: Eclipse	$300,531,751
Inception	$292,568,851
Harry Potter and the Deathly Hollows: Part I	$294,980,434
Shrek Forever After	$238,319,043
The Book of Eli	$94,822,707

Arai, Y.
Kajiyama, T.
Ouchi, N.

42

Title	Sales Figure
The Social Network	$96,619,124
The Town	$92,173,235
Red	$90,356,857
Percy Jackson & the Olympians: The Lightning Thief	$88,761,720
The King's Speech	$138,797,449

To exclude the influence of random numbers, we conducted 30 simulations for each movie and calculated the average value of these results, following Kamimura et al (2006). For each movie, the simulation period began four weeks before the movie's release date (t= -4). Table 4 outlines the parameters used in the simulation. pb is standardised on a scale from one to ten in correspondence to each production budget. Similarly, adv is standardised on a scale from one to ten corresponding to estimated advertising budgets. Because advertising budgets of movies are available only from 2002 to 2004, and the amount of advertising budgets are unlikely to have changed over the past decade, we estimated the advertising budgets of target movies to be within a range of $30,000,000 to $70,000,000, based on the available data. These data were obtained from 'The Numbers (http://www.the-numbers.com/box-office/2010).' pre is rated on a scale from one to ten corresponding to sales figures of previous movies and original novels. These data are available at 'The Numbers (http://www.the-numbers.com/box-office/2010),' and 'The Comics Chronicles (http://www.comichron.com/titlespotlights.html),' respectively.

Table 4: Characteristics of the target movies

Title	pb	adv	pre	Genre	Rating Score
Toy Story 3	10.0	6.2	3.8	Adventure	8.84
Alice in Wonderland	10.0	5.7	5.0	Adventure	7.18
Iron Man 2	8.5	5.9	8.8	Adventure	7.27
The Twilight Saga: Eclipse	3.4	4.7	9.6	Drama	6.86
Inception	8.0	5.5	0.0	Sci-Fi	8.25
Harry Potter and the Deathly Hallows: Part I	6.3	6.3	4.7	Adventure	7.92
Shrek Forever After	8.3	5.8	3.7	Adventure	5.75
The Book of Eli	4.0	4.2	0.0	Action	6.33
The Social Network	2.0	4.0	0.0	Drama	8.23
The Town	1.8	3.8	0.0	Drama	8.54
Red	3.0	3.9	0.0	Action	7.80

Title	pb	adv	pre	Genre	Rating Score
Percy Jackson & the Olympians: The Lightning Thief	4.8	3.5	0.0	Adventure	7.03
The King's Speech	0.8	4.1	0.0	Drama	8.25

Figure 2 shows examples of trends in the cumulative adoption rate of actual data and the results of our simulation. We calculated the cumulative adoption rate by dividing the number of cumulative movie viewers at week t by the total number of movie viewers of Toy Story 3 (the movie with the highest box-office take among the 13 sample movies).
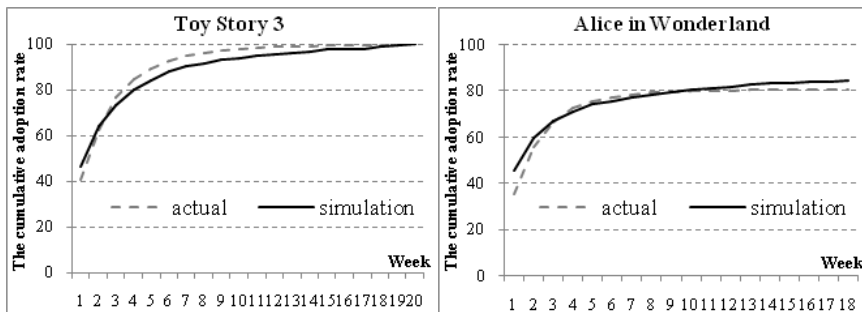

Figure 2: Trends in actual data and results of the simulation (%).

Table 5 summarises the mean error rate. The error rate at week t is computed by equation (8).

$$Er_t = \frac{|S_t - A_t|}{A_t} \qquad (8)$$

where Er_t is the error rate at week t, S_t represents the simulation results at week t and A_t is the actual data at week t.

Table 5: Mean error rates

Title	Mean error rate (%)
Toy Story 3	3.73
Alice in Wonderland	3.99
Iron Man 2	2.37
The Twilight Saga: Eclipse	9.51
Inception	4.01
Harry Potter and the Deathly Hallows: Part I	3.60

Arai, Y.
Kajiyama, T.
Ouchi, N.

Title	Mean error rate (%)
Shrek Forever After	8.56
The Book of Eli	6.60
The Social Network	9.43
The Town	8.67
Red	7.07
Percy Jackson & the Olympians: The Lightning Thief	6.24
The King's Speech	11.40

As shown in Table 5, the resulting mean error rates can be considered small. Therefore, these results demonstrate that our proposed model can describe actual consumer behaviour.

Simulations for clarifying the impact of social networks on consumer behaviour

In this section, we conducted simulations to clarify the impact of social networks on consumer behaviour and the diffusion process of products. In order to consider the characteristics of products, we classified movies into four types by consumers' expectations for a movie and the rating score as shown in Table 6. Consumers' expectations can be represented by.We analysed the impact of the characteristics of movies on the number of movie viewers.

Table 6: Four movie types

Type	Expectations	Rating score
1	High (9.0)	High (8.5)
2	Low (3.5)	High (8.5)
3	High (9.0)	Low (4.5)
4	Low (3.5)	Low (4.5)

In addition, in order to clarify the impact of social networks on the number of movie viewers, we set the following two conditions: (a) social networks' WOM is not considered and (b) social networks' WOM is considered.

Figure 3 illustrates the results of this analysis. The cumulative adoption rate in Figure 3 is calculated by dividing the number of cumulative movie viewers at week *t* by the total number of movie viewers in the case where social networks' WOM is not considered.
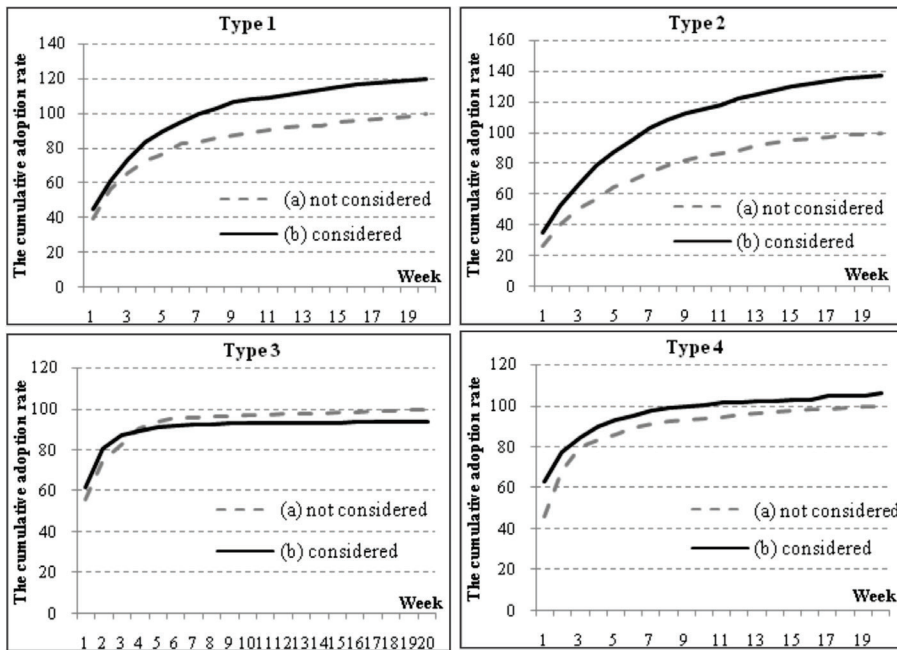
Figure 3: A comparison of simulation results (%)

Results show that for movies of genre Type 1, Type 2 and Type 4, the number of adopters increases when social networks' WOM is considered. In contrast, for movies of genre Type 3, the number of adopters decreases when social networks' WOM is considered.

For movies of genre Type 1 and Type 2, social networks positively influence the number of adopters because positive WOM spreads more readily through social networks for movies of these genres. However, for movies of Type 3 and Type 4, the number of adopters decrease, as negative WOM spreads more readily through social networks and prevents potential consumers from watching the movies. However, because movies that are classified as Type 4 are low with respect to consumers' expectations and not very well recognised, social networks have a more substantial role in allowing consumers to learn about the movies and subsequently watch them. As a result, for Type 4 movies, the positive effect of social networks exceeds the negating effect of negative WOM, and the total number of adopters increases.

Application to Diffusion Strategies

To clarify the effective method of weekly advertising budget allocation, we conducted simulations with our proposed model. Specifically, we set four patterns of advertising budget allocation: (i) focusing on the period around

Arai, Y.
Kajiyama, T.
Ouchi, N.

a release date (*standard*), (ii) focusing on the period before a release date (*before*), (iii) focusing on the period after a release date (*after*) and (iv) same weight during a period (*constant*). These strategies are outlined in **Figure 4**.
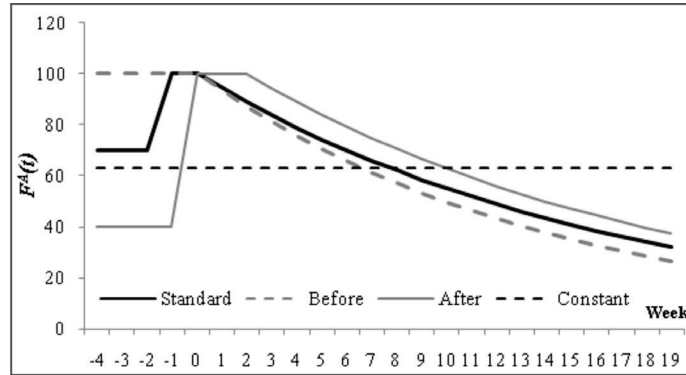
Figure 4: The four patterns of advertising budget allocation (%)

Figure 5 compares the total number of movie viewers for each condition. In Figure 5, the y-axis is standardised by dividing the total number of movie viewers under each condition by the total number of movie viewers under the condition where movie type is Type 1, allocation pattern is *standard* and social networks' WOM is not considered.
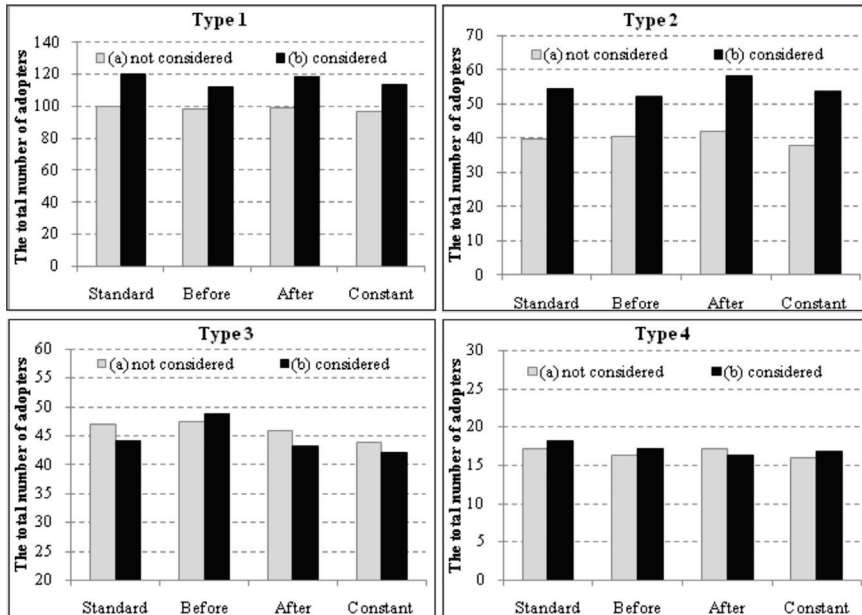

Figure 5: A comparison of the simulation results (%)

The results illustrated in Figure 5 provide a wide variety of valuable insights. For example, for Type 2 movies, the effective budget allocation strategy involves using the budget after the movie is released. In contrast, standard allocation strategies are best for movies of Type 1 and Type 4. This result may occur because a positive WOM is stimulated by the effects of post-release advertising, thereby drawing moviegoers to watch the film. In contrast, for Type 3 movies, allocating the budget prior to the movie's release represents the effective strategy. This result suggests that it is possible to successfully incite a number of individuals to see the movie before negative WOM spreads. In addition, differences in the number of movie viewers across budget allocation patterns become large when social networks' WOM is incorporated into the model.

These results have important implications, particularly for firms' public relations managers. When social networks are not developed, changes in weekly advertising budget allocation do not significantly affect the number of individuals that adopt products. However, when consumers receive information through social networking services, different budget allocation strategies can significantly impact the adoption rate. Therefore, it is of great importance to select the effective method of weekly advertising budget allocation when social networks are pervasive. In addition, this study suggests that the appropriate manner of this allocation depends on consumers' pre-release expectations regarding a movie. Therefore, sharing information between the creative department and the public relations department is more critical when determining how to allocate an advertising budget. These findings may apply to other contexts that are strongly influenced by the effects of advertising and WOM.

CONCLUSION

In this study, we constructed a model of consumer behaviour that accounts for social networks. The results of our simulations that utilise this model demonstrate the impact of social networks on consumer behaviour and product diffusion. Further, we applied our model to the diffusion strategies to determine effective weekly strategies concerning advertising budget allocation. As a result of these steps, we demonstrated that social networks tend to positively affect product diffusion, except for products for which consumers had high expectations but evaluated poorly. In addition, we identified effective weekly advertising budget allocation strategies corresponding to the characteristics of movies, and showed that the different allocation patterns of the weekly advertising budget have a greater impact on the number of adopters as social networks grow.

48

This study provides new insights on two fronts. First, it clarifies the impact of social networks on consumer behaviour and the diffusion process of products quantitatively, which had remained unclear in the past. Second, this study provides suggestions for effective diffusion strategies that account for the impact of social networks. As a result of these theoretical and practical contributions, this study is useful for firms to effectively diffuse their products, even with limited budgets. The results of this study are particularly useful for firms in emerging economies whose budgets are relatively small relative to large firms in developed economies.

Future researchers in this domain should seek to apply our model to other product markets. In addition, future research should evaluate multinational strategies with a consideration of social networks.

END NOTES

See appendix for the relationship among the equations in our model.

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APPENDIX

Relationships among equations in our model

(1) The condition where agent i decides to watch a movie:

$$a_i \cdot P_{i,t} + (1 - a_i) \cdot E_{i,t} > T_i$$

(2) Agent i's degree of preference for the movie:

$$P_{i,t} = (pb + adv + pre) \cdot F^P(t) \cdot I_i^P \cdot D_i^P$$

(3) Effects of advertising and WOM:

$$E_{i,t} = A_{i,t} + W_{i,t}$$

(7) Individual threshold:

$$T_i = \alpha + \beta \cdot r$$

(4) Effects of advertising:

$$A_{i,t} = adv \cdot R^A \cdot I_i^A \cdot G^A(t)$$

(5) Sum of effects of WOM:

$$W_{i,t} = \sum_{j=1}^{N_N} w_{i,j,t} + \sum_{k=1}^{N_I} w_{i,k,t} + \sum_{l=1}^{N_S} w_{i,l,t}$$

(6) Effects of WOM:

$$w_{i,j,t} = \begin{cases} (pb + adv + pre) \cdot R^W \cdot I_i^W \cdot O_j \cdot G^W(t) \ (before\ release) \\ RatingScore \cdot R^W \cdot I_i^W \cdot O_j \cdot G^W(t) \ (after\ release) \end{cases}$$