

# Marketing Ecosystem: The Dynamics of Twitter, TV Advertising, and Customer Acquisition

**Hikaru Yamamoto**

Seikei University  
3-3-1 Kichijoji-kitamachi,  
Musashino-shi, Tokyo, Japan  
yamamoto@econ.seikei.ac.jp

**Naohiro Matsumura**

Osaka University  
1-7 Machikaneyama,  
Toyonaka, Osaka, Japan  
matumura@econ.osaka-u.ac.jp

## Abstract

Social media, especially the micro-blogging network Twitter, have gained much popularity among users and have thus attracted attention from firms. Social media can serve as advertising media and platforms of online word-of-mouth, because they enable consumers to share their consumption experiences with others easily. When firms advertise their products and services, they usually do not rely on one single medium. Instead, they combine various media to promote their products and services. Recently, they have started to include social media. The aim of this paper is to capture the dynamic relationships among TV advertising, tweets, offline word-of-mouth, and customer acquisition. We call these dynamics the “marketing ecosystem” and attempt to investigate this model. To achieve this goal, this paper employs a structural equation approach, which allows developing a more complete and accurate picture of the inter-relationships among constructs. We incorporate both the direct effects and the indirect effects of traditional marketing actions such as TV advertising, which in turn increase tweets and new customer acquisition. The results of our analysis show that TV advertising increases buzz on social media and offline word-of-mouth. The results also show that TV advertising, offline-word-of-mouth, and tweets have a strong impact on customer acquisition.

## Introduction

Recent developments on the Internet such as weblogs and social media enable consumers to share their consumption experiences with others. Social media, especially the micro-blogging network Twitter, have gained much popularity among users. Twitter enables users to share their consumption experiences with others easily with tweets that consist of 140 characters. The growing number

of users makes Twitter an attractive medium for firms, and thus Twitter has attracted lots of attention from firms.

Social media are useful tools to provide information on products and services, and to generate positive attitudes among consumers. They also serve as platforms on which to build customer relationships. Firms can build relationships with customers and potential customers. Social media also serve as fan communities, in which customers can connect and interact with each other. These interactions accelerate conversation about products and services, which in turn spread as word-of-mouth.

Social media content, such as tweets on Twitter, can be used to predict real world outcomes. For example, Asur and Huberman (2010) used the chatter from Twitter to forecast box-office revenues of movies in advance of their release. The result outperformed the accuracy of market-based predictors. Tumasjan et al. (2010) used the context of the German federal election to investigate if Twitter is used as a forum for political deliberation, and whether online messages on Twitter validly mirror offline political sentiment. They found that the mere number of messages mentioning a party reflects the election result. Jansen et al. (2009) analyzed Twitter as tool for electronic word-of-mouth, and found that an automated classification was able to extract statistically significant differences in customer sentiment (i.e. the attitude of a writer towards a brand).

The ultimate goal of a firm is to acquire new customers and increase sales revenues. To achieve this goal, firms employ various marketing tools, such as advertising and recently social media (blogs, Twitter, etc.). When firms advertise their products and services, they usually do not rely on a single medium. They combine various media to promote their products and services, include social media as advertising media.

The effects of media interact with each other. For example, Chang and Thorson (2004) found that television-web synergy leads to higher attention, increased message credibility, and more total and positive thoughts. Online media interact with offline media to influence marketing outcomes, such as brand sales. Naik and Peters (2009) proposed a new hierarchical model of online and offline advertising that incorporates within-media synergies and cross-media synergies, and allows higher-order interactions among various media. They analyzed the effects of offline media (e.g. television, radio, print), online (e.g. banner and search ad), and direct mail on both online and offline consideration metrics for a compact car brand. They showed that within- and cross-media synergies boosted the total media budget and online spending due to synergies between online media and various offline media.

Villanueva, Yoo, and Hanssens (2008) investigated the impact of marketing actions versus word-of-mouth customer acquisitions on the long-term firm value. They developed a statistical model capable of measuring the long-term impact of customer acquisitions through different channels on customer equity growth.

Similarly, Trusov, Bucklin, and Pauwels (2009) studied the effect of word-of-mouth marketing on membership growth on an Internet social networking site and compared it with traditional marketing vehicles (See Figure 1). In their model, traditional marketing led to WOM referrals and new sign-ups, and the new sign-ups led to more WOM referrals, thus indirectly leading to more new sign-ups. Traditional marketing stimulated WOM referrals, which led to another indirect effect on new sign-ups.

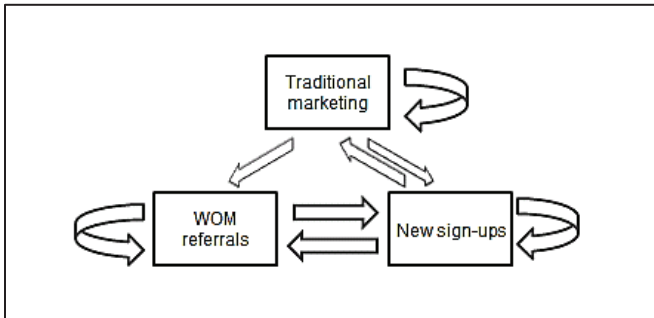


Figure 1. Trusov, Bucklin, and Pauwels' (2009) Model

Inspired by these works, our paper aims to capture the dynamics of TV advertising, word-of-mouth, and customer acquisition. Traditional marketing investments such as TV advertising increase tweets, which in turn accelerate new customer acquisition. In our approach, we include the buzz on Twitter, a new trend in social media marketing, and aim to understand its effect on revenue. Also, we break down WOM referrals to offline word-of-mouth and online word-of-mouth. Online word-of-mouth has a tendency to spread

easily via social networks, and the volume of propagation tends to be large. On the other hand, the volume of offline word-of-mouth is relatively small, but the communication has more reliability because the sender and the receiver tend to be more intimate.

To understand the dynamics of traditional advertising, Twitter, and customer acquisition, we incorporate both the direct effects and the indirect effects of traditional marketing actions such as TV advertising, which in turn increase tweets and new customer acquisition. To do so, this research employs a structural equation approach, which allows us to develop a more complete and accurate picture of the inter-relationships among constructs.

Our model and hypothesis are presented in the next section. We then explain the topic of analysis and the overview of the data. Finally, we show the results of the empirical analysis and conclusions.

## Model

Figure 2 represents the proposed model of the paper, which we call the “marketing ecosystem.” The model indicates that TV advertising influences tweets (online word-of-mouth) and offline word-of-mouth, and tweets influence conversion.

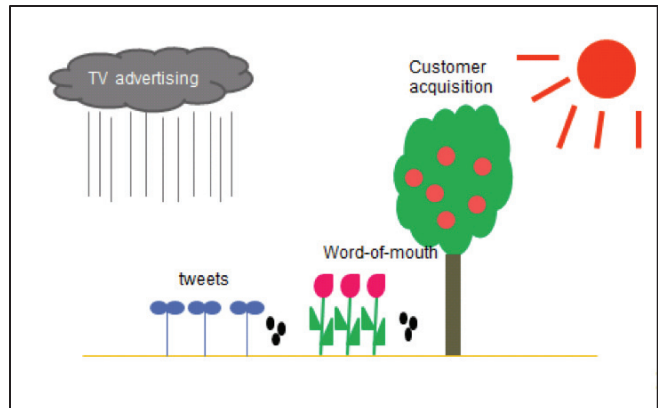


Figure 2. Proposed model of the marketing ecosystem

In an ecosystem, rainfall provides water to the ground, which supports sprouting. These sprouts grow large and bear fruit. The seeds fall off, which will grow into new sprouts. In the marketing ecosystem in Figure 2, the rain of TV advertising falls to the ground, which helps sprouts from the tweets to come out. These sprouts grow into a large tree and bear fruit in the form of customers. Also, the rain of TV advertising helps to grow the flowers of offline word-of-mouth, which leads to the fruit of customers.

Twitter is used for various purposes. It can be used for personal status updates, and also for sharing information. When users tweet personal status updates, they do not

require an information source. However, when they tweet about information, whether it is about politics or about their purchase behavior, they are likely to rely on information sources.

The source of information could be news provided by mass media, marketing information that is created and sent by firms, and content created by others on other social media. Obviously, users cannot tweet about or follow something they do not know, and advertising plays an important role in raising the awareness level. In that sense, traditional advertising is the entrance point of the customer funnel, leading to interests in products and services, and thus leading to conversation. Advertising is information created and sent by firms, and could be one of the important sources of word-of-mouth. This leads to our first hypothesis:

H1: TV advertising stimulates postings on social media, such as tweets on Twitter

In the field of marketing, the effect of TV advertising has been analyzed extensively (Tellis and Ambler 2008). The bottom line is that advertising creates and increases brand awareness, establishes a positive attitude, and leads to purchases. Our second hypothesis is regarding the effect of advertising:

H2: TV advertising increases customer acquisition

When users tweet about a product or a service, they are obviously aware of it. Moreover, the tweet, positive or negative, can be considered as evidence of interest in the product or service. If a user follows a corporate account on Twitter, it could be considered that the user is willing to commit to a long-term relationship with the brand. As Jansen et al. (2009) point out, electronic word-of-mouth on Twitter could be evidence of a positive attitude toward the brand, and a positive attitude leads to purchases. Thus, it makes sense to assume that conversation about specific products on Twitter increases customer acquisition.

H3: Twitter has a positive impact on customer acquisition

Just as users need sources of information when they tweet about products or services, offline word-of-mouth in our daily lives also requires information sources on the products or services provided by firms. It could be a news release, event, or product usage experience. Among the firm-created information, one of the most important factors is advertising. Therefore, we can assume the following:

H4: TV advertising increases offline WOM

Trusov et al. (2009) found that WOM referrals have a strong impact on new customer acquisition. Godes and Mayzlin (2009) showed that in some cases, purely exogenous word-of-mouth is associated with higher week-to-week sales. Wangenheim and Bayon (2007) examined the links between customer satisfaction, WOM referrals, and new customer acquisition. Based on these related works, we build the following hypothesis:

H5: Offline WOM increases customer acquisition

In the following section, we examine our proposed model and the hypotheses using the data provided by mobile service provider.

## Data Description

Data were provided by MTI Ltd., which is one of the largest and oldest mobile SNS providers in Japan. MTI offers a service called Luna Luna (Lnln.jp), which calls itself a “mobile site for women.” Figure 3 is a screen shot of the English version.



Figure 3. Screen shot of the member's page

It is a mobile phone application that takes information many women needs, such as menstruation and contraception care, with a lot of guides and Q&A columns around women's physiology. The service has more than 1.8 million registered users, i.e. paid subscribers, who pay 180-189 yen (US\$ 2.21-2.32 as of February 1, 2011) each month, depending on carrier. The monthly fee is 230 yen (US\$ 2.82) for smartphones such as the iPhone.

MTI released the English version in October 2010, which charges a one-time US\$1.99 download fee and does not require a monthly maintenance charge, as in Japan.

The data provided were acquired from July 2010 to January 2011, which included daily subscription data of this service. In the model, we have two types of conversions: *Conversion* indicates the number of new subscribers with traditional mobile phones, and *Smartphone conversion*, the number of new subscribers

with smartphones such as an iPhone. We treated these two conversions separately because they attract different types of users, with different hardware and different prices.

The company airs TV commercials to promote the service. For TV advertising, we were provided daily data on household reach and ad expenditure for TV. In our “marketing ecosystem” model, household reach is included as a variable and named *TV advertising*. The site conducted a self-reporting survey of new subscribers, asking them which of the media was the trigger for subscription. The users who answered TV advertising as the trigger were used and named *TV conversion*.

For Twitter, the tweets containing the term “Luna” were collected. A total of 15,144 tweets were collected, and these postings were manually investigated by the staff of MTI to classify them by sentiment. We used a number of positive tweets in our analysis. Here are some examples of positive tweets:

Started using Luna Luna! Great tool for diet, especially since my weight hit the record...

Luna Luna really works! It’s amazing.

We also use the number of followers and followees for each user who tweets. We named these measures *Followers* and *Followees* respectively and included them in the model.

All tweets are not equal. Some tweets have a large influence, while some tweets do not. Using the number of followers and followees, we created an index called *Celebrity Tweet Index* and named the variable *Celebrity Tweet*. It is defined as  $\sqrt{\text{(number of followers/number of followees)}}$ . This is a variable that captures the importance of a tweet. A simple example is provided.

Suppose there is a user who just started using Twitter, who has 10 followers and is following 10 users; his *Celebrity Tweet Index* will be 1. Similarly, there is an intermediate user who actively uses Twitter, follows 100 users, and is followed by 100 users. His *Celebrity Tweet Index* will also be 1, as in the first example. Now, suppose there is a celebrity who has 1000 followers and follows 10 users. His *Celebrity Tweet Index* will be 10. In contrast, a user who follows 1000 users and has 10 followees would have celebrity tweet index of 0.1.

Our study aims to understand the effect of offline word-of-mouth simultaneously with other factors, such as buzz on Twitter, electric referrals, and TV advertising. Unlike other data, the offline word-of-mouth behavior is difficult to measure. For this reason, we employed the self-report survey to count offline word-of-mouth. The number of new users whose main trigger was offline word-of-mouth is included in our study and is named *Offline WOM*.

The customers spread word-of-mouth and they invite new customers. These invitations (electronic referrals) have been one of the driving forces for service providers to acquire new users. The site offers an electronic referral program, and we used this as an evidence of offline word-of-mouth. The reason why we treat an electronic referral as offline, not online word-of-mouth, is because users usually send this to their friends in an offline environment, and not to a stranger in an online environment.

The number of successful electronic referrals, meaning the friend sends an invitation and the receiver subscribes to the service because of the invitation, is included in the model and named *Referral*.

## Analysis

### Marketing Ecosystem

To test the model, as explained in the previous section, a structural equation modeling approach was employed. It allows confirmatory modeling and exploratory modeling. The former modeling is used for theory testing, and the latter is suitable for theory development. In this paper, we conducted the exploratory modeling to investigate the marketing ecosystem presented in the previous section.

Figure 4 represents our operational model. This is the model that reflects our hypothesis and best fits the data we collected.

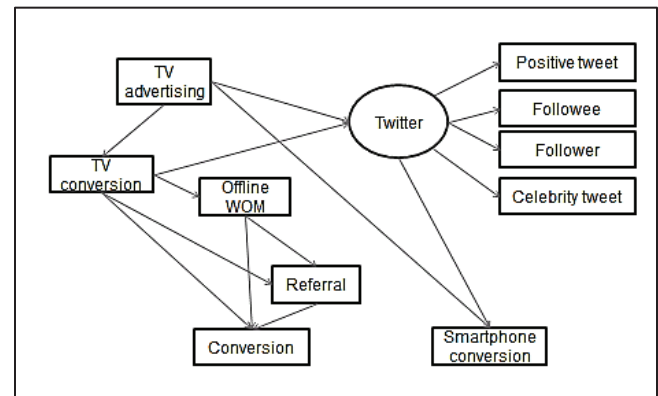


Figure 4. Operational model

In the model, *TV advertising* stimulates *TV conversion*. *TV conversion* stimulates *Offline WOM* and *Referral*. *TV conversion*, *Offline WOM*, and *Referral* stimulate *Conversion*. In the right hand side of the model, *TV advertising* stimulates the latent constructs *Twitter*.

In structural equation modeling, the key variables of interest are usually "latent constructs," which are displayed as an ellipse. The observed variables depend on the unobserved, or latent, variables. In our model, the variables *Positive Tweet*, *Followers*, *Followees*, and *Celebrity Tweet*

are hypothesized to depend on the single underlying, but not directly observed variable, or latent variable named *Twitter*. In other words, *Positive Tweet*, *Followers*, *Followees*, and *Celebrity Tweet Index* are indicators of the latent variable *Twitter*.

Since *Twitter* is easily accessed via smartphones, we draw the path from *Twitter* to *Smartphone conversion*. *TV advertising* also stimulates *Smartphone conversion*.

The statistical significance of the parameters was determined by using a maximum likelihood estimation technique. In structural equation modeling, measurement and theoretical parameters are estimated simultaneously.

The model is tested against the obtained data to determine how well the model fits the data. The goodness of fit index shows decent fit to the data (CFI=.953, NFI=0.946, RFI=0.906, IFI=0.953). The R-square of the variables are shown in Table 1.

The R-square for *Conversion* and *Smartphone conversion* was .968 and .880 respectively, showing that the variables and constructs used in the model explain these marketing outcomes fairly.

Structural equation models are most often represented graphically. Figure 5 represents the result of the fitted model. In the figure, only the paths that were significant are displayed. Each single-headed arrow represents a regression weight, and the values displayed near the arrow represent the standardized coefficient. The standardized estimate, standard error, t-value, and probabilities are shown in Table 2.

Since *TV advertising* increase *Twitter* construct (0.354), Hypothesis 1 is supported. It shows that marketing activity such as *TV advertising* increase buzz on social media. *TV advertising* increases *TV conversion* (.308), and that increases *Conversion* (.371). This indicates the power of

*TV advertising* on customer acquisition, and supports our Hypothesis 2. Hypothesis 3 is supported, since *Twitter* has a strong and positive effect on *Smartphone Conversion* (.927). *TV advertising* also has a direct effect on *Smartphone conversion* (.077), but the effect is small compared to *Twitter*.

	R-square
TV conversion	0.095
Offline WOM	0.855
Twitter	0.581
Referral	0.811
Celebrity Tweet	0.500
Followers	0.093
Followees	0.339
Positive Tweet	0.243
Conversion	0.968
Smartphone CV	0.880

Table 1. R-square of variables

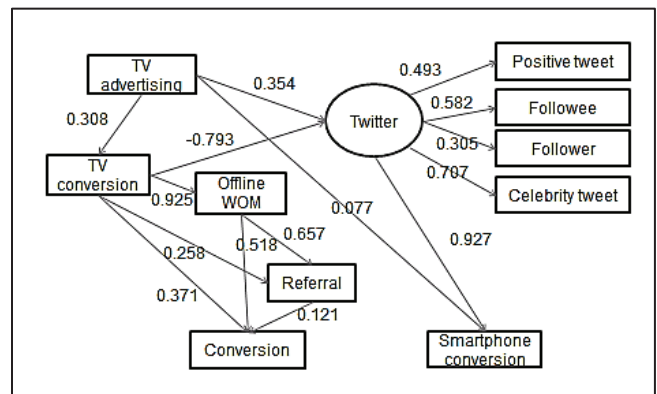


Figure 5. Fitted operational model

			standardized estimate	standard error	t-value	p-value
TV conversion	<---	TV advertising	0.308	0	5.786	***
Offline WOM	<---	TV conversion	0.925	0.01	43.432	***
Referral	<---	TV conversion	0.258	0.002	4.033	***
Referral	<---	Offline WOM	0.657	0.004	10.277	***
Twitter	<---	TV conversion	-0.793	0	-12.434	***
Twitter	<---	TV advertising	0.354	0	6.561	***
Conversion	<---	TV conversion	0.371	0.088	13.662	***
Conversion	<---	Referral	0.121	2.931	5.232	***
Conversion	<---	Offline WOM	0.518	0.218	16.952	***
Smartphone CV	<---	TV advertising	0.077	0	2.131	0.033
Positive Tweet	<---	Twitter	0.493	1.151	7.938	***
Followees	<---	Twitter	0.582	1175.49	11.189	***
Followers	<---	Twitter	0.305	3425.232	6.839	***
Celebrity Tweet	<---	Twitter	0.707			
Smartphone CV	<---	Twitter	0.927	3.785	14.282	***

Table 2. Parameter estimates

\*\*\*p<.01

Twitter is gaining users via smartphone, and positive tweets and celebrity endorsement drive customer acquisition on a smartphone. Twitter is a powerful tool for firms that provide mobile services on smartphones to use to acquire customers.

The results also show that *TV advertising* is a source of electronic word-of-mouth, supporting Hypothesis 4. *TV advertising* increases *TV conversion*, and *TV conversion* increases *Offline WOM* (.925). This indicates that TV advertising serves as an information source for offline word-of-mouth. As mentioned earlier, the users need something to talk about. Information introduced in TV advertising serves as “conversation piece” for users.

The results show that *Offline WOM* is a strong factor to increase *Conversion* (.518), supporting Hypothesis 5. This effect has the largest impact on *Conversion*, indicating the power of offline word-of-mouth.

In our model, *TV conversion* has a negative effect on Twitter. This requires careful consideration for interpretation, but we can assume that consumers who rely on TV as the most important information source have a tendency not to use novel media like Twitter. The users who rely on traditional media do not seem to fit well with Twitter.

The results of structural equation modeling support our hypotheses. As depicted in the marketing ecosystem model in Figure 2, the rain of TV advertising makes the land flourish, tweets and offline WOM begin to come out, and results in a harvest in the fruit of conversion, i.e. customer acquisition.

### Effect of TV advertising

One of the most common uses of structural equation modeling is the simultaneous estimation of direct and indirect effects. For example, *TV advertising* increases *Twitter*, and *Twitter* increases *Smartphone conversion*. This means *TV advertising* has an indirect effect on *Smartphone conversion* through *Twitter*.

The standardized indirect effect is defined as the product of two standardized direct effects, and the total effect is the sum of direct effects and indirect effects. Table 3 represents the total effect of *TV advertising*, which incorporates both direct and indirect effects. As shown in the table, *TV advertising* has a positive total effect on *TV conversion* and *Offline WOM*. It also increases *Referral*. This is because TV advertising provides consumers with something to talk about. It also increases positive tweets about the service and stimulates celebrities to tweet on the subject. *TV advertising* also stimulates Twitter users to follow other users. *TV advertising* has the effect to increase *Conversion* and *Smartphone conversion*, with are the most important factors for the firm.

	Standardized coefficient of TV advertising	Non-standardized coefficient of TV advertising
TV conversion	0.308	2.87863E-05
Offline WOM	0.285	1.06316E-05
Referral	0.267	6.29199E-07
Celebrity Tweet	0.078	6.61262E-09
Followers	0.033	0.00015219
Followees	0.064	8.66896E-05
Positive Tweet	0.054	5.98427E-08
Conversion	0.294	7.88494E-05
Smartphone CV	0.179	4.40569E-07

Table 3. Total effect of TV advertising

As explained, the variable *TV advertising* is household reach of the TV advertising, and is linked to the ad expenditure for TV advertising. Using this relationship, the firm can predict marketing ROI. The key questions for management are: How much do we need to spend to acquire new customer? Or to generate a positive tweet about a product? To answer these questions, we conducted a simple regression to explain the *ad expenditure* with *TV advertising*, i.e. household reach. The following is the result (R-square=0.46).

$$ad\ expenditure = 0.219 * TV\ advertising + 784613.036$$

Since the R-square is not high, we need to be careful with the conclusion, but using the formula above we can link *TV advertising* and *ad expenditure*, and other variables of interest like tweets and more importantly, customer acquisition. This will give a firm a starting point to consider marketing ROI. Table 4 is the result of a cost analysis simulation using the regression coefficient.

The first column in Table 4 suggests what a firm can buy with 1000 yen (US\$12.19 as of February 1, 2011). The table shows that it will buy the firm 0.36 *Conversion* and 0.002 *Smartphone conversion*. The second column suggests the cost necessary to increase one unit. For example, to acquire one customer, it requires 2,777 yen. Similarly, it requires 20,599 yen to acquire one offline word-of-mouth. This can be understood as cost per offline WOM. The cost per positive tweet is high at 3,659,596 yen. Positive tweets are not just tweets. They are positive, online word-of-mouth, which increases conversion. Positive tweets are difficult to generate, since they will not occur unless the user has a positive attitude or experience with the service and is satisfied. This makes the positive tweet rare and valuable. The third column represents frequently used index, cost per mil, i.e. cost to acquire 1000.

	Effect per 1000 yen	Cost per one unit increase (yen)	Cost per mil(yen)
TV conversion	0.131	7,608	7,607,794
Offline WOM	0.049	20,599	20,598,880
Referral	0.003	348,062	348,061,547
Celebrity Tweet	0.000	33,118,479	33,118,479,248
Followers	0.695	1,439	1,438,986
Followees	0.396	2,526	2,526,256
Positive tweet	0.000	3,659,596	3,659,596,103
Conversion	0.360	2,777	2,777,447
Smartphone CV	0.002	497,084	497,084,292

Table 4. Simulation of cost analysis for marketing ecosystem

The customers spread word-of-mouth and they invite new customers. These invitations have been one of the driving forces for service providers to acquire new users. Some papers focus on these special customers, i.e. customers who contribute to the company's revenue by acquiring new customers. For example, Hogan, Lemon, and Libai (2005) incorporated word-of-mouth effects into a model of customer lifetime value and quantified the advertising ripple effect. Matsumura and Yamamoto (2009) calculated the monetary value of each customer and his or her network on the mobile SNS by incorporating the social factor to customer purchase analysis. Trusov et al. (2009) also calculated the monetary value of a WOM referral.

By combining the monetary value of a customer and the acquisition cost, we can gain an understanding of rich managerial implications from social media marketing.

## Conclusion

In this paper, we focused on Twitter as a marketing tool and built a model to capture the dynamic relationships among TV advertising, tweets, offline word-of-mouth, and customer acquisition. We employed a structural equation approach to incorporate both the direct effects and the indirect effects of traditional marketing actions, such as TV commercials, which in turn increase tweets and new customer acquisition.

The results of our analysis show that TV advertising increases buzz on social media and offline word-of-mouth. The results also show that TV advertising, offline-word-of-mouth and tweets have strong impacts on customer acquisition. The results of structural equation modeling support our hypothesis, i.e. the rain of TV advertising makes the land flourish, and tweets and offline WOM begin to come out and end up harvesting the fruit of conversion, i.e. customer acquisition.

In our model, TV advertising has an indirect effect on conversion. It has a positive and direct effect on smartphone conversion, but the effect is rather small. Due to the emergence of social media, it is said that the traditional forms of communication appear to be losing their effectiveness. Our results show that TV advertising may not have the strong positive direct effect on customer acquisition, but it has an indirect effect via online and offline word-of-mouth.

Our paper has a number of limitations. First, TV advertising has carry-over or delayed effects on consumer behavior. Past research on advertising has solved the effect precisely (Clarke 1976; Tellis, Chandy, and Thaivanich 2000). As current consumers use mobile phones and watch TV simultaneously, our model does not incorporate such effects. However, there is a possibility of such an effect and that would be promising extension.

Also, as modeled in Trusov et al. (2009), lagged effects within the variables should be considered, e.g. past tweets produce more tweets. Inclusion of the "temporal causality" is needed in future research.

## Acknowledgments

The authors would like to thank MTI Ltd. for providing valuable data and support.

## References

- Asur, S. and Huberman, B.A. 2010. Predicting the Future with Social Media. arXiv:1003.5699v1 [cs.CY]
- Chang, Y. and Thorson, E. 2004. Television and Web Advertising Synergies. *Journal of Advertising* 33(2): 75-81.
- Clarke, D.G. 1976. Econometric Measurement of the Duration of Advertising Effect on Sales. *Journal of Marketing Research* 13(4): 345-357.
- Godes, D. and Mayzlin, D. 2009. Firm-Created Word-of-Mouth Communication: Evidence from a Field Test. *Marketing Science* 28(4): 721-739.
- Hogan, J.E.; Lemon, K.N.; and Libai, B. 2005. Quantifying the Ripple: Word-of-Mouth and Advertising Effectiveness. *Journal of Advertising Research* 44(3): 271-280.
- Jansen, B.; Zhang, M.; Sobel, K.; and Chowdury, A. 2009. Twitter power: Tweets as Electronic Word of Mouth. *Journal of the American Society for Information Science and Technology* 60(11): 2169-2188.
- Java, A.; Song, X.; Finin, T.; and Tseng, B. 2007. Why We Twitter: Understanding Microblogging Usage and Communities. In *Proceedings of the 9th WebKDD and 1st SNA-KDD 2007 Workshop on Web Mining and Social Network Analysis*, 56-65.
- Matsumura, N. and Yamamoto, H. 2010. Monetary Value of Customer Networks in Mobile Social Networking Services. In *Proceedings of the International Conference on Weblogs and Social Media (ICWSM2010)*: 287-290.

- Naik, P.A. and Peters, K. 2009. A Hierarchical Marketing Communications Model of Online and Offline Media Synergies. *Journal of Interactive Marketing* 23(4): 288-299.
- Tellis, G.J. and Ambler, T. eds. 2007. *The Sage Handbook of Advertising*. London: Sage Publications.
- Tellis, G.J.; Chandy, R.K.; and Thaivanich, P. 2000. Which Ad Works, When, Where, and How Often? Modeling the Effects of Direct Television Advertising. *Journal of Marketing Research* 37(1): 32-46.
- Trusov, M.; Bucklin, R. E.; and Pauwels, K. 2009. Effects of Word-of-Mouth Versus Traditional Marketing: Findings from an Internet Social Networking Site. *Journal of Marketing* 73: 91-102.
- Tumasjan, A.; Sprenger, T.O.; Sandner, P.G.; and Welpe, I.M. 2010. Predicting Elections with Twitter: What 140 Characters Reveal about Political Sentiment. In *Proceedings of the International Conference on Weblogs and Social Media (ICWSM2010)*: 178-185.
- Villanueva, J.; Yoo, S.; and Hanssens, D.M. 2008. The Impact of Marketing-Induced Versus Word-of-Mouth Customer Acquisition on Customer Equity Growth. *Journal of Marketing Research* 45: 48-59.
- Wall Street Journal 2010. Luna Luna, Rabbits and You: Japanese Women's Health Comes to the iPhone. October 26, 2010. <http://blogs.wsj.com/japanrealtime/2010/10/26/luna-luna-rabbits-and-you-japanese-womens-health-comes-to-the-iphone/>
- Wangenheim, F.V. and Bayon, T. 2007. The Chain from New Customer Satisfaction via Word-of-mouth Referrals to New Customer Acquisition. *Journal of Academy of Marketing Science* 35: 233-249.