

# Drivers of new product recommending and referral behaviour on social network sites

Patrali Chatterjee  
*Montclair State University*

Managers of new brands seek to leverage positive WOM and establish a critical mass of consumers who interact with their brands on social network sites (SNSs). Effective selection of 'seeds', or influencers, on SNSs, who will recommend the product and leverage the power of their social networks to influence other consumers is key to organic growth. This research examines the role of an influencer's activity on a social network website (network size, membership duration, share-of-posts), brand message source (marketer-generated versus member-generated), and recipient type (SNS member versus non-member) on an influencer's decision to recommend a new brand and the recipient's decision to make a referral visit. Empirical analyses of clickstream data from SNSs at a commercial website show that marketer- and consumer-generated brand ads differ in their impact on recommending propensity for high share-of-posts and long-term influencers, and for member and non-member recipients, which has implications for referral management.

## Introduction

Commercial reports documenting the benefits of social media websites in launching new products and brands have led many firms to incorporate social media in their integrated marketing communication plans, and to enhance visibility of brand profile pages on social network sites or SNSs (Tegler 2009). Prior research has investigated marketers' efforts to enhance new product adoption through social contagion or communication processes between consumers in target markets (Van den Bulte & Stremersch 2004). This research differs from others in examining social contagion through SNSs and recognising that contagion fosters adoption

of a new product through its impact on two stages of communication – awareness and evaluation. For new products in broad-based commonly purchased product categories, generating buzz or merely awareness of a new product's existence (e.g. Procter & Gamble's Gillette Fusion ProGlide launch, in Williamson 2010) may be enough to trigger quick message transmission through consumer-to-consumer interaction, thus ensuring success. However, for products with credence attributes or those that pose significant risks (like health products), merely generating awareness may not be enough; the influencer's ability to provide information that mitigates perceived risk and induce recipients to engage with the brand sponsor is critical to success in social media strategy. Hence examining the social value of influencers in a social network based on their eWOM or recommending behaviour, as well as their ability to generate referral visits (influence recipients to engage with and evaluate a new product or brand) warrants attention.

As firms leverage SNSs in their WOM-generation marketing campaigns, an important prerequisite for the success of such strategies is a better understanding of factors that are associated with an influencer's propensity to recommend a brand and generating a referral visit by the recipient. Hence, identifying measurable influencer and brand message characteristics that can increase recommending and referral visit propensity is critical to a brand manager's social media advertising strategy. This research aims to answer the following questions:

- Do differences in an influencer's activity at the SNS in terms of membership duration, share-of-posts and network size impact recommending and referral visit propensities?
- Do marketer-generated and customer-generated brand recommendation messages differ in their impact on recommending and referral propensities?
- Does referral visit propensity differ across SNS member and non-member recipients?
- Do member and non-member recipients differ in their referral response to marketer-generated versus customer-generated brand recommendation messages?

We use clickstream data of consumer activity on member and brand sponsor profile Pages (P capitalised to refer to profiles that can only be created

as a business account by a representative of a trademark owner) and membership information to examine recommending and referral behaviour associated with nine new product advertising campaigns over a 21-month period at a health and fitness social network website.

### **The SNS as social system and communication channel**

SNSs as web-based services allow individuals who sign up to be members to (i) construct a public or semi-public profile within a bounded system, (ii) articulate a list of other users or members with whom they share a connection, and (iii) view and traverse their list of connections and those made by others within the system. The nature and nomenclature of these connections may vary from site to site (Ellison *et al.* 2007). Most SNSs create visible differences and specify different rules between personal profile pages and brand or firm-owner profile Pages. Contrary to mass media advertisements, brand profile Pages on SNSs provide information and allow viewers to respond to the firm's communications or posts, forward them to their connections on SNS (on Facebook this happens through NewsFeed, on LinkedIn through Updates) or non-members of SNS by an email application similar to Webmail. During a purchase decision consumers visit brand profile Pages to gather information, ask for advice or to review the opinions of other users. After the purchase has been made, SNS members may communicate their own experiences on the brand profile Page. The result is an ongoing process of interpersonal influence and online word-of-mouth recommendation. Many brand sponsors make their brand profile Pages public and advertise SNSs they participate in in their print and mass media ads, so consumers who are not members of SNSs can also access and read information on their profile pages. However, these non-members cannot post any comments or communicate with SNS members on the Page.

Managers of new brands choose first-order *influencers* to receive information about their new product based on information provided to the SNS at registration, on their profile pages or group memberships on SNSs, or other criteria (Watts & Dodds 2007). The invitation to evaluate and recommend the brand may be provided through the messaging feature or display ads (e.g. social ads on Facebook, banner ads on MySpace, text ads on LinkedIn). Members can click on the ad invitation to visit the brand

profile page, view product information and sign up to receive free samples. After trying the product, some influencers may have no further interaction with the brand sponsor; others may choose to ‘connect’ or ‘follow’, or link their profile to the brand sponsor Page (similar to ‘Like’ on Facebook); yet others choose to ‘recommend’ by linking *and* posting a message on their profile page and brand sponsor Page. This message may be marketer generated (respond or copy the brand sponsor’s message) (marketer-generated message) or consumer generated (created by other consumers or self-created videos or ads, reviews, experiences or suggestions related to the brand). An influencer’s connections (or *recipients*) can view the brand sponsor link and recommendation on the influencer’s profile page as well as on their own profile page as updates.<sup>1</sup> *Influencers* can also forward (using email) their brand recommendation to friends and acquaintances who are not members of the SNS. *Recipients* (SNS members and non-members) can read the recommendation and click on the embedded hyperlink to generate a referral visit to the brand profile Page. On the brand profile Page they can view information provided by the brand sponsor and other customers, view videos, play games or sign up to receive communications from the brand sponsor. These recipients can become second-order influencers.

In this research we consider the actions of first-order influencers only and focus on two events: (i) when a member recommends a brand sponsor on her profile page or emails it to SNS non-members (*recommendation propensity*), and (ii) when a recipient clicks the link associated with recommendation to visit the brand sponsor profile Page (*referral visit propensity*). It is critical to examine both events individually, keeping in mind that the impact of source, message and recipient characteristics will differ across the two events. We propose hypotheses regarding the role of members’ participation in SNSs (network size, membership duration, share-of-posts), brand message source (marketer-generated versus consumer-generated) and recipient type (SNS member versus non-member), and propose an analytic model. Our approach relies on clickstream data collected unobtrusively by most SNS sites and their sponsor landing pages, which is broadly applicable.

---

<sup>1</sup> On some SNS profiles owners can block some connections from viewing their profile page message (or Wall) or list of connections using a customisation feature. However, none of the SNS, to the author’s knowledge, allows profile owners to block certain messages.

## Conceptual background and hypotheses

Online word-of-mouth, or eWOM, information exchange is multi-directional (consumer-to-consumer, consumer-to-firm), involves multiple audiences, and consumers can post or simply lurk (passively review/read consumer-generated brand messages) (Schlosser 2005). It exists across multiple platforms like product review websites (e.g. consumerreview.com), retailers' websites (e.g. amazon.com), brands' websites (e.g. forums.us.dell.com), personal blogs, message boards and social networking sites (e.g. Facebook, MySpace, Friendster.com, Tribe.com) (Lee & Youn 2009). Lee and Youn (2009) demonstrate that different online platforms on which eWOM (personal blog versus independent review or brand website) is posted had an impact on likelihood of recommending the product, and attributions to product quality or circumstantial marketer intent. The strength of the ties between the communicators and the receivers of eWOM is usually considered weak because anyone can post their opinions about a product to various online platforms (Chatterjee 2001). Because the identity of the eWOM communicators is not constrained by the receivers' social circle, it is difficult for receivers to determine the quality and credibility of the product recommendations. eWOM communicators often do not feel much responsibility for the consequences of their recommendations because their postings will be read by complete strangers (Schindler & Bickart 2005) with greater possibility of misinformation or inaccurate information being passed on to consumers (Chatterjee 2001).

SNSs can be viewed as both social systems composed of members and communication channels through which information about new products is transmitted, hence they have the potential to alter members' adoption behaviour by selectively exposing them to information about new products. The most important difference between eWOM or posts at SNSs and other web-based WOM is the visible display of (i) connections ('Contacts', 'Fans' or 'Friends') who are also users of the SNS, (ii) information, opinions, reviews or ideas posted by the profile owner on the profile page, and (iii) groups or interest areas of which a profile owner is a member. eWOM on profile pages at SNSs is not anonymous, but is linked to the profile owner and can be viewed by the profile owner's connections if the profile is set for public display. The mutual and decontextualised nature of interpersonal links between connections and posts on profile

pages reduces the propensity of profile owners to distort information or present a self-idealised virtual identity. Since profile owners cannot selectively display a portion of their network or posts to a subset of connections, the visible display acts as a signal of the reliability of the profile owner identity and information on the profile page (Donath & Boyd 2004). Hence the potency of eWOM on SNSs is likely to depend not just on the characteristics of the message itself (marketer vs consumer generated) but also inferences the recipient makes about the profile owner's activity (i.e. posting activity and membership duration) and connections as displayed on the SNS profile page, and is likely to differ for SNS member and non-member recipients.

### ***Brand message source (marketer-generated vs consumer-generated)***

Unlike mass media where the advertising message is controlled by marketers, the internet has legitimised multiple sources of information. User- or consumer-generated content refers to media content created or produced by the general public rather than by paid professionals and primarily distributed on the internet. Examples of prominent websites that support the creation and consumption of consumer-generated content include YouTube, MySpace, Facebook, Wikipedia, Flickr and Blogger, among many others. Consumer-generated content as a form of WOM communication is perceived to be more reliable, credible and trustworthy by consumers compared to firm-initiated communications (Martin & Clark 1996; Muniz & Schau 2007). Consumer-generated recommendations provide access to consumption-related information that holds some 'informational value' and context-specific 'interpretive value' over and above the advertising messages provided by the marketer that can influence the recipient's compliance with the request (Shimp *et al.* 2007). Brand sponsors participate in SNSs to identify these informational and interpretive values specific to an SNS to add meaning to their ad messages that are consistent with those shared by members. Customer-generated brand messages are personalised to one's social network (Okazaki 2009) and more likely to communicate social norms (Muk 2007). Hence, we hypothesise:

**H1:** Consumer-generated brand messages will have higher (a) recommending and (b) referral propensity compared to marketer-generated brand messages.

### *Recipient relationship with SNS*

All WOM communication takes place within a social relationship categorised by tie strength, or the closeness, intimacy, support and association between the source and recipient (Frenzen & Davis 1990). Research suggests that consumers contribute more WOM to strong- than weak-tie relational partners, and strong ties have greater influence on the receiver's behaviour than weaker ties due to the frequency and perceived importance of social contact among strong-tie individuals (Brown & Reingen 1987). Online SNSs support both the maintenance of existing social ties and the formation of new connections (Ellison *et al.* 2007). Many participants on large SNSs are not necessarily 'networking' or looking to meet new people; instead, they are primarily communicating with people who are already a part of their extended social network and with whom they share some offline connection (Ellison *et al.* 2007).

Influencers differ in the extent to which they play a bridging role in an SNS (Sohn & Jee 2005; Ellison *et al.* 2007). Influencers can act as bridges between networks on SNSs, as well as between SNSs and the physical world. The former can result in connections between SNS members that would not otherwise be made (for example, 'Friends of Friends') and these are characterised by weak ties. An influencer can also have strong ties to consumers in the physical world (e.g. friends, relatives) who need or benefit from the product but are not members of the social network website. When an influencer posts a recommendation for a new brand on his or her SNS profile page it is automatically displayed to all SNS member recipients, irrespective of whether they are of interest or relevance to them (Boyd & Ellison 2007) since the linkages between connections on online SNSs are decontextualised (Donath & Boyd 2004).

In contrast, when the influencer recommends a new brand to non-members, the selection of recipients is made on a one-to-one basis and requires additional effort in terms of typing in each recipient's email address and attaching the recommendation. An influencer would not do it if she did not perceive the brand and recommendation message to be relevant and

of importance to the recipient. Extending findings from De Bruyn and Lilien (2008) to the context of SNS, we suggest that micro-targeting of non-member recipients can lead to a higher proportion (not necessarily the absolute number) of non-member recipients to generate a referral visit compared to automatic recommendation to all SNS member recipients. Please note that the absolute number of member recipients who make referral visits is likely to be higher than non-member recipients; even if a profile owner has more SNS connections than non-member recipients, proportionally our hypotheses should hold. Hence:

**H2:** Non-member recipients are more likely to make a referral visit than SNS member recipients for both marketer- and consumer-generated brand recommendations.

Participants in SNSs have shared experiences that resemble those usually realised by the traditional collection of special interest people in close proximity. SNS members share their knowledge, cooperate with each other to solve problems and feel responsibility for each other. This is especially true in the high-involvement healthcare sector, patients and care-givers increasingly giving and seeking online advice and information, social support and, on rare occasions, organising financial support for community members by participating in virtual communities (Misra *et al.* 2008). Members of an SNS share their own linguistic codes and protocols that have specific, shared meanings within the community hence consumer-generated comments are likely to be more effective than marketer-generated comments among SNS member recipients as discussed in the last section. However, brand message components with salient signals peculiar to SNS will not have any significance or influence to non-member recipients who are not members, thus limiting the effectiveness of consumer-generated brand messages among non-member recipients.

Further, in the context of highly regulated product categories like healthcare, consumers are aware that brand messages provided by marketers are subject to scrutiny by the FDA; hence marketers are less likely to exaggerate claims. However, claims made by consumers are not under FDA jurisdiction. Most healthcare SNS providers inform members at registration that commercial entities cannot obligate or provide incentives to individuals to comply with marketing requests, however non-members are



less likely to be aware of it. However, in low-involvement product categories like consumer packaged goods, consumers are likely to find consumer-generated messages more credible than marketer-generated messages and the following hypothesis will not apply. Hence:

**H3:** For high-involvement product categories, like healthcare SNSs, non-member recipients are more likely to make a referral visit when they receive a marketer-generated brand message compared to a consumer-generated brand message.

### *Extent of influencer's participation in social network site*

Prior research on consumer dissemination of word-of-mouth has examined the role of consumer personality characteristics like opinion leadership (Ellison & Fudenberg 1995), market mavenism (Feick & Price 1987) and motivations, altruism, product involvement, self-enhancement and desire to help the company (Balasubramanian & Mahajan, 2001; Henning-Therau *et al.* 2004) in propensity to engage in positive offline and online word-of-mouth. However, for a brand sponsor or SNS publisher these latent constructs are not easily available to identify first-order influencers for their brand messages and are difficult to measure on an ongoing basis for the hundreds of consumers who create profiles at social networking websites. Hence, managers need to identify measurable behavioural variables that predict influencers' propensity to recommend and generate referral visits.

Determining the quality of online posts is difficult since consumers are aware of the fact that marketers have attempted to influence eWOM by compensating consumers to review products and even going so far as to post their own reviews about their products (Chatterjee 2001). Because of this, consumers often look for a variety of cues when determining the quality of the online information (Greer 2003). In the context of SNSs, the profile page allows users to articulate their connections, post their activities, interests, opinions and any other information, as well as comments from connections that define their participation within the social network site. Profile viewers can use history of engagement within the SNS in terms of number of connections (or network size), number of posts and membership duration as cues or signals of quality. While it is difficult to

identify all variables that completely capture a profile owner's participation at an SNS, these three objective and measurable variables are available to researchers and social networks, and we examine their ability to predict recommending and referral behaviour.

#### *Relationship duration*

Members of an SNS differ in how often they interact with their connections as well as how long they have been members of the community. For example, highly social people may interact frequently with their connections, even though they have only recently joined. Conversely, some long-term members may prefer to read the posts of other members without directly participating themselves. Prior research has found that longer-duration membership in a group strengthens the social identification of members with the group (Bhattacharya, *et al.* 1995). Muniz and Schau (2007) found that long-term members tend to enjoy higher status within the brand community and that their claims to membership are regarded as more legitimate. In the context of eWOM in online communities, Schlosser (2005) found that senders are concerned that recipients will form undesirable judgements about them and make them appear indiscriminate. Hence, long-term members are less likely compared to a more recent member to jeopardise their enhanced status within a community by recommending a new product from a brand sponsor.

The mutual, public, unnuanced and decontextualised nature of interpersonal links between connections fosters cooperation through the structure of reputation maintenance (Donath & Boyd 2004). Since a profile owner's identity is persistent, and interactions are repeated, recipients can punish deceiving influencers through the social mechanism of reputation. Given the perception that long-term members are likely to have more domain-specific expertise (Petty 2000), the longer an influencer has been a member of an SNS, the more reliable the quality of information provided, as perceived by the recipient. Hence, we hypothesise:

- H4:** Duration of customer membership of an SNS will be (a) negatively associated with recommending propensity, but (b) positively associated with referral propensity.

*Relative share of posts (SOP)*

The relationship between share-of-post and propensity to generate word-of-mouth is less clear. There is growing recognition among managers of the importance of measuring the share of content a customer generates at an SNS (share-of-post) as opposed to simply reading other posts and participating in the SNS. Members who mostly participate by adding friends and brand sponsors to their profile pages, and confirm their own addition to friends' and brand sponsor profile pages, may not be committed to the community and are likely to be passive with very little information aside from increased friend count produced for other members to view. High share-of-post customers are likely to spend more time at the website, more likely to be attitudinally loyal to the firm, less exposed to competitive offerings compared to low share-of-post customers and more difficult to convert to brand ambassadors. High share-of-post members are more likely to have deeper product knowledge and are more likely to know and influence consumers with similar product requirements. Hence:

**H5:** Influencer's relative share of posts on SNSs will be positively associated with (a) recommending and (b) referral propensity.

*Network size*

Research on the effect of a member's network size on recommending and referral behaviour can validate the current practice of using number of 'Contacts', 'Fans' or 'Friends' to infer the network value of a member. The dual-party approval requirement (the inviter and invitee have to agree to be connected) limits the number of false or illusory connections (Donath & Boyd 2004). Intuitively, members with bigger network sizes have a higher chance of identifying recipients who might be interested in the new brand and generating referrals, hence one can expect network size to be positively associated with recommending and referral propensity. However, the visible display of connections and posts on a profile page has social implications, signalling honest self-presentation of one's identity claims in the digital space as well as a willingness to risk one's reputation (Donath & Boyd 2004). Recommending brands and products to others has an associated social risk since there could be potential negative repercussions if the recommendation later proves untrue. This is especially true of new health and fitness products, the empirical context of

this research, which may have higher perceived performance, psychological or physical risks.

Members with a bigger network size face greater reputational risks that those with a smaller network size, and are likely to be more cautious or selective in recommending brand sponsors, in order to protect their social standing in the network. If a brand recommendation is deemed to be unworthy or erroneous, or motivated by monetary gain, the influencer may be categorised as a 'sell-out' or 'spammer', reducing his/her social standing. Research suggests that better connected adopters exert more influence than less connected ones (Dholakia *et al.* 2004). The visible display of members of one's social network at SNSs plays a signalling role in enhancing a recipients' decision to comply with an influencer's new product recommendation. More people linking to an influencer's profile may lead recipients to infer that more people have vetted the information and implicitly have sanctioned it. Hence, we hypothesise:

**H6:** The size of an influencer's network will be (a) negatively associated with brand recommending, but (b) positively associated with referral propensity.

Intuitively, network size should grow over time; hence longer-duration members are likely to have larger network sizes relative to recent members. However, research shows that participatory duration (duration based on activity at the site rather than time-based duration) has a weak relationship to network size (Thompson & Sinha 2008).

### *Model of brand recommending and referral behaviour*

Our analytical approach considers two events: (i) the probability that a brand is recommended with the influencer liking the brand sponsor and posting a brand message on her profile; and (ii) the probability that a recommended brand message generates a referral visit by the recipient. An influencer  $i$  ( $i = 1 \dots I$ ) at a website enters the sample when s/he first accesses an ad invite (i.e. ad message with clickable hyperlink to brand sponsor Page) at the site, and remains in the sample until the last page prior to session exit. We assume influencer  $i$  is exposed to a qualified ad invite  $w$  ( $w = 1, \dots, W$ ) at page view occasions  $o = 1, \dots, O_s$  in session  $s$  at the site.

*Recommending propensity*

The recommendation event corresponds to the influencer liking the brand sponsor and posting to the Wall/emailing to non-members. An influencer  $i$  will recommend the brand corresponding to  $w$  on page view  $o$  in session  $s$  if his latent utility  $U_{i\{o,w\}}^c$  from recommending the ad message is greater than a threshold value (without loss of generality, this threshold is normalised to zero) otherwise ad message  $w$  is not recommended. The relation between the observed response (recommends or not) and the latent utility of recommending is:

$$Recommend_{i\{o,w\}} = \begin{cases} 1 & \text{if } U_{i\{o,w\}}^e > 0, \text{ consumer } i \text{ recommends } w \text{ at pageview } o \\ 0 & \text{if } U_{i\{o,w\}}^e \leq 0, \text{ consumer } i \text{ does not recommend brand } w. \end{cases} \quad (1)$$

The latent utility of recommending brand  $w$  can be conceptualised as a function of the influencer's latent intrinsic propensity to recommend brands to others ( $\alpha_{i0}$ ) (Okazaki and Hirose (2009) propose that enduring involvement, a stable personality trait, may predispose some individuals more than others), the influencer's perceived value of the brand message, and the influencer's projection of brand message relevance to recipient.<sup>2</sup> Thus  $U_{i\{o,w\}}^c$  is specified as:

$$\begin{aligned} U_{i\{o,w\}}^e &= \alpha_{i0} + \beta_i' BrandMessageSource_{i\{o,w\}} + \alpha_{ik} BrandMessageSource_{i\{o,w\}} \\ &\quad * Duration_i + \varphi_{ii} BrandMessageSource_{i\{o,w\}} * SOP_i \\ &\quad + \lambda_{ii} BrandMessageSource_{i\{o,w\}} * NwkSize_i + \delta RecipientType_{i\{o,w\}} + \epsilon_{i\{o,w\}}^e \\ \alpha_{i0} &= \alpha_{00} + \alpha_{01} Duration_i + \alpha_{02} SOP_i + \alpha_{03} NwkSize \end{aligned} \quad (2)$$

$\alpha_{00}$  represents brand dummies and  $\beta_i'$  is the associated vector of parameter coefficients of brand message source impacting recommending outcomes at each page view.  $\alpha_{ik}$ ,  $\varphi_{ik}$  and  $\lambda_{ik}$  are the corresponding vector of parameter coefficients capturing interaction between brand message source ( $k$  = consumer generated) and SNS duration, SOP and network

<sup>2</sup> Not considering the impact of covariates is equivalent to assuming that all brands have the same probability of being recommended and generating referrals, and this is no managerial control of the process. This model is applicable when the manager has information on recommendations sent and referrals generated but no other information from server logs or internal databases.

size variables respectively. Prior research suggests that influencers have imperfect information about recipients' preferences, hence the influencer's projection of relevance of brand message  $w$  to the recipient may be imperfect. This information is unavailable to most website operators and captured through  $\varepsilon_{i\{o,w\}}^e \sim N(0,1)$  is the random error term. Members vary in their (unobserved) intrinsic propensity to recommend ad messages ( $\alpha_{i0}$ ) based on their participation in an SNS, hence in a hierarchical framework, we specify  $\alpha_{i0}$  as a function of relationship duration, SOP and network size. The recommending equation is estimated as binary probit, with the utility of not recommending the ad message normalised to zero and the covariates defined with respect to it.

### *Referral propensity*

After a brand is recommended, it appears on the SNS member recipient's profile Updates or in the non-member recipient's email inbox. The recipient decides whether and when to view the recommendation and click on the hyperlink to visit the brand profile Page. Let  $RV_{i\{o,w\}}^*$  denote the latent propensity that ad message URL  $w$  recommended by sender  $i$  on page view occasion  $o$  leads to a referral visit by the recipient:

$$RV_{i\{o,w\}} = \begin{cases} 1 & \text{if } RV_{i\{o,w\}}^* > 0 \text{ and } U_{i\{o,w\}}^e > 0, w \text{ recommended by } i \\ & \text{at occasion } o \text{ generates referral visit} \\ 0 & \text{if } RV_{i\{o,w\}}^* \leq 0 \text{ and } U_{i\{o,w\}}^e > 0, w \text{ recommended by } i \\ & \text{at occasion } o \text{ does not generate referral undefined, if } U_{i\{o,w\}}^e \leq 0. \end{cases} \quad (3)$$

In probit framework a referral is observed conditional on recommend ( $Recommend_{i\{o,w\}}$ ) if the latent index specified below is positive:

$$\begin{aligned} RV_{i\{o,w\}}^* | (Recommend_{i\{o,w\}} = 1) &= \alpha_{i0} + \beta_{ki}' BrandMessageSource_{i\{o,w\}} \\ &+ \beta_{ki}' BrandMessageSource_{i\{o,w\}} * Duration_i + \varphi_{ki} BrandMessageSource_{i\{o,w\}} * SOP_i \\ &+ \varphi_{ki} BrandMessageSource_{i\{o,w\}} * NwkSize_i + \varepsilon_{i\{o,w\}}^r \\ \alpha_{i0} &= \alpha_{00} + \alpha_{01} Duration_i + \alpha_{02} SOP_i + \alpha_{03} NwkSize_i \end{aligned}$$

Other parameter coefficients are interpreted in a similar way to the recommending equation, except that they refer to the referral visit probability. The influencer's influence on the recipient (i.e. perceptual affinity) in generating referral is a recipient's private information, not available to a website manager or sender, hence we specify an influencer-specific random effect  $\varepsilon_{i\{o,w\}}^r \sim N(0, \sigma_r^2)$ , which induces correlation between multiple recommendations by the influencer  $i$ . We use a censored probit specification with sample selection for the splitting mechanism, since a brand recommendation must occur first ( $Recommend_{i\{o,w\}} = 1$ ) in order to generate a referral. We perform full Bayesian inference using Markov Chain Monte Carlo algorithms to estimate our model, following Chib and Greenberg's (1998) analysis of hierarchical Seemingly Unrelated Regression models with correlated errors.

## Methodology

This study uses clickstream data from the SNS of a commercial health and fitness website during a 21-month period, and membership data. The consumer activity file had information on consumer ID, the browser and system used, the page code of the ad invite viewed, action on the page (read, print or recommend/email), the time and day of request, and the referring page or site. The ad message data file contained information on the brand message source and the URL. Nine ad campaigns for new product trials, seven over-the-counter therapeutics and two supplements, and extensive data on campaign features were available for analysis. All of these campaigns ran for the same, fixed, duration and were offered only at this website, making them good candidates for this quasi-experiment. The identity of brand sponsors of health and fitness products cannot be disclosed, at the request of the data sponsor.

### *Selection of consumers*

Consumer activity was tracked using consumers' numeric IDs. Hence, we are reasonably sure that each cookie corresponds to a subscribing unit – individual or household – making up 85% of the full data set. There were 198,193 unique subscribers at the website in January 2007; they generated 262,830 sessions and 766,425 page view occasions. SNS relationship data

were calculated from membership subscription and profile data. We use logarithms of SNS relationship variables to control for large variances in duration, network size and posting activity. For this research, we randomly selected 2173 members. Clickstream activity for the 2173 consumers shows that the average number of sessions at the site was 3.8 during the observation period. Senders selectively recommend brands in only 15% (7131) of page views. Approximately 57% of the recommendations (4111) lead to a referral visit by the recipient within the observation period. Information on variables was constructed from the server clickstream logs and internal firm databases. Table 1 describes the model variables and their specifications.

**Table 1: Variable description and operationalisation**

Variable name	Values	How variable was created
<b>Influencer's participation in social network site</b>		
$DURATION_i$	0.01–2.014	Logarithm of number of days signed in to SNS, Ln(Days)
$SOP_i$	(–0.9)–0.89	$(SOP_i - SOP_{mean})/sd$ Relative (normalised) influencer share of all posts at the SNS.
$NwkSize_i$	0.01–1.2	Logarithm of number of friends on member's profile page at the time
<b>Brand message source</b>		
$CUSTOMER-GENERATED$	1/0	1: if influencer's recommendation message is customer-generated created by clicking on new message on the message editor; 0: if marketer-generated when influencer copies or modifies or responds to existing message.
<b>Recipient's SNS relationship</b>		
$NMEMBER$	1/0	1: if recipient is not a member of the SNS; 0 otherwise

## Data analyses

### Descriptive statistics

Long-term customers (11% of customer base) and high-SOP customers (24% of customer base) spend relatively less time in each session and have significantly fewer page views (account for 2.6% and 7.1% of total page views, see Table 2) compared to newer and low-SOP customers. Our proposed model was fit to the 49,074 page view observations for 2173 customers (who viewed 5528 unique ad messages) at the website. Table 2 reports summary statistics of variables used in our model, broken down



**Table 2: Summary statistics**

Variable	Ad message pageview outcomes			
	Overall	<i>Recommend</i> = 0, <i>RV</i> = 0	<i>Recommend</i> = 1, <i>RV</i> = 0	<i>Recommend</i> = 1, <i>RV</i> = 1
No. observations/pageviews	49,074	41,943	3020	4111
Unique ad message views	5528	4245	476	807
<b>Influencer's SNS relationship</b>				
<i>DURATION<sub>i</sub></i> (0/1)	0.026	0.014	0.010	0.004
<i>SOP<sub>i</sub></i> (0/1)	0.071	0.029	0.319	0.107
<i>NwkSize<sub>i</sub></i>	0.019	0.122	0.918	0.189
<b>Brand message source</b>				
<i>CUSTOMER-GENERATED</i>	0.301	0.109	0.249	0.466
<b>Recipient type</b>				
<i>NMEMBER</i> (0/1)	0.274	0.265	0.381	0.291

by two outcome measures, whether a recommendation was made and, if recommended, whether it generated a referral. A total of 23.2% (1283) recommendations occurred (out of 5528 ad messages belonging to brands considered in this study, which is 1.5% of total ad messages at the website), and 14.6% (807) generated referral visits.

### *Estimation results*

Table 3 presents a summary of the parameter estimates for our models, the probability that the brand message being viewed is recommended,  $P(\textit{Recommend} = 1)$  and, conditional on being recommended, if it generated a referral visit  $P(\textit{RV} = 1 | \textit{Recommend} = 1)$ . Tolerance values and variance inflation factors did not indicate multicollinearity between variables or their linear combinations.

An overview of the results shows that decomposing the recommendation and referral process yields insights that would be unavailable from a single-stage approach, which would simply predict overall referral visit propensity. Table 3 shows that many model covariates have different effect signs for recommending and referral generation, or they are predictive of one but not the other. For example, the variable *NMEMBER* is negatively signed for recommending but positively signed for referral generation, which suggests that influencers are significantly less likely to recommend to friends who are not SNS members, however the non-

members who receive the recommendation are more likely to generate a referral visit, highlighting the benefits of leveraging the social networks of participants that extend beyond the SNS. This diagnostic capability is a key advantage, which would not be revealed if we merely estimated referral propensity. Substantive results from our estimation are discussed next.

*Brand message source (marketer-generated vs consumer-generated)*

We find that consumer-generated recommendations are significantly more likely to be recommended (H1a is supported at  $p < 0.01$ ), but are not more likely to generate a referral (H1b is not supported,  $p > 0.05$ ) compared to marketer-generated ad messages.

*Recipient relationship with SNS*

SNS non-members who receive the recommendation are significantly more likely to generate a referral visit (H2 is supported at  $p < 0.05$ ), highlighting incremental benefits from leveraging SNS participants as discussed earlier. One explanation for these findings lies in the fact that all SNS connections, which include a mixture of strong and weak ties, are automatically recommended. Since emailing non-members involves more effort, influencers are more likely to be selective. Contrary to our expectations, H3 is not supported at a significant level, non-member recipients do not differ in their likelihood of generating a referral visit for customer-generated or marketer-generated brand messages.

*Extent of members' participation in SNS*

As we hypothesised, long-term members of the SNS are significantly less likely to recommend but significantly more likely to induce referral visits compared to casual subscribers, thus supporting H4a,b at  $p < 0.01$ . Further analyses from our analytical model show that the referral ability of long-term members is further enhanced when these members take the time to personalise the recommended messages, as indicated by the referral coefficient for *CONSUMER-GENERATED \* DURATION*. The referral probability of long-term members (number of sign-up days higher than the median) who recommend marketer-generated ad messages is higher by 0.094, or 9.4% ( $\text{prob}(\text{Recommend} = 1) \cdot \text{prob}(\text{RV} = 1 / \text{Recommend} = 1)$ ), compared to short-term members. On occasions when long-term members recommend consumer-generated ad messages, this increases further

to 23.8%  $\{0.094 + (1 - \Phi(0.385))\}$ . In contrast, high-*SOP* members are not significantly more likely to recommend brand messages (H5a is not supported,  $p > 0.05$ ) but are more likely to generate referral visits compared to low-*SOP* senders (H5b is supported,  $p < 0.01$ ). Further analyses indicate that, though high-*SOP* members are less likely to recommend in general, they are more likely to recommend customer-generated content, but it is not more likely to induce referral visits relative to marketer-generated content.

Network size does not have a significant association with recommending propensity. Members with a bigger network size (more connections listed on profile page) are not significantly less likely to recommend brand

**Table 3: Brand message recommending and referral probability – MCMC posterior estimates (standard deviation is in parentheses)**

Covariates	P (Recommend = 1)	P (RV = 1   Recommend = 1)
INTERCEPT (OTC brands)	<b>0.872</b> (0.014)	<b>0.249</b> (0.015)
INTERCEPT (Supplement brands)	<b>0.612</b> (0.211)	<b>0.178</b> (0.069)
CUSTOMER-GENERATED (0/1)	<b>2.682</b> (0.094) <i>H1a sig.</i>	0.091 (0.061) <i>H1b not sig.</i>
CUSTOMER-GENERATED * DURATION	0.118 (0.106)	<b>0.385</b> (0.131)
NMEMBER (0/1)	-0.349 (0.106)	<b>0.448</b> (0.165) <i>H2 sig.</i>
NMEMBER * CUSTOMER-GENERATED	0.179 (0.452)	0.169 (0.09) <i>H3 not sig.</i>
DURATION <sub>i</sub>	-1.094 (0.076) <i>H4a sig.</i>	<b>0.293</b> (0.086) <i>H4b sig.</i>
SOP <sub>i</sub>	0.118 (0.073) <i>H5a not sig.</i>	<b>0.247</b> (0.026) <i>H5b sig.</i>
CUSTOMER-GENERATED * SOP	<b>0.483</b> (0.031)	0.227 (0.291)
NwkSize <sub>i</sub>	0.108 (0.162) <i>H6a not sig.</i>	<b>0.205</b> (0.089) <i>H6b sig.</i>
CUSTOMER-GENERATED * NwkSize	<b>0.278</b> (0.097)	-0.618 (0.171)
<b>Control variables</b>		
VIDEO (0/1)	0.126 (0.116)	<b>0.221</b> (0.102)
WEEKEND (0/1)	-0.487 (0.921)	<b>0.283</b> (0.104)
<b>Recommend-referral correlation coefficient</b>		
$\sigma^2_{\epsilon,r}$		<b>0.173</b> (0.078)
N	49,074	7131

Note: \*Estimates in bold indicates coefficients are significant at 95% posterior probability interval.

messages than those with smaller network size, thus providing no support for H6a ( $p > 0.05$ ). However they are significantly more likely to generate referral visits compared to those with smaller network size (H6b is supported,  $p < 0.01$ ). Since we consider logarithm of *network size*, this coefficient can be interpreted as elasticity.

### *Control variables*

We find that if a recommended brand message has a video link it is more likely to generate a referral visit. Though influencers are not more likely to send recommendation messages on weekends, recipients are more likely to generate referral visits if they receive recommended brand messages at weekends.

## **Conclusions and recommendations**

This research examines customer-to-customer brand recommending and referral behaviour at an SNS. The intended contribution to the literature is threefold. First and foremost, this study extends research on recommending and referral behaviour to social media and incorporates the role of underlying covariates that earlier published research suggests (see Brown & Reingen 1987; Feick & Price 1987; Martin & Clark 1996), but could not examine because data were not available to researchers or firms on network activity (network size, membership duration, share-of-posts), message source (marketer vs consumer generated), and recipient-specific covariates.

Second, most research to date, with the exception of that of De Bruyn and Lilien (2008), considers aggregate impact on either recommending or referrals but not on both. This study isolates the impact of network, message source and recipient covariates on both outcomes, and clearly demonstrates that impacts differ for recommending and referral visit outcomes. For example, consumer-generated messages increase recommendation propensity but have no impact on referral visit propensities. Theoretically, this implies that information criteria that enhance awareness may not be equally effective in product evaluation. Managerially, it means that managers can use estimates for their own data to optimise the performance of each outcome and thus to maximise overall campaign performance.

Third, prior research on word-of-mouth and referral behaviour has been based on self-reported or intention data. This research uses actual behaviour in the form of clickstream data, and hence is free of reporting or researcher bias (Robinson *et al.* 2007). The recommendation event represents a conscious decision by the influencer to disseminate positive word-of-mouth to recipients and is a more active endorsement of a brand sponsor's product than self-reported intentions (Lee & Youn 2009). The referral event is a behavioural measure of the effectiveness of an influencer's recommendation and completes a feedback loop in the communication process. Managerially, it can help brand sponsors identify and reach potential consumers in the SNS with latent need for the product, as well as those in the general population who are not members of the SNS.

Our empirical analysis shows that consumer-generated brand messages are significantly more likely to be recommended but are not significantly more likely to generate referrals. The former supports earlier findings (Martin & Clark 1996; Muniz & Schau 2007), but the latter is contrary to findings in the context of customer testimonials (Shimp *et al.* 2007). In fact, contrary to our expectations for H3, even non-members do not differ in their referral visit propensity for consumer- versus marketer-generated messages. Together these findings suggest that neither SNS members nor non-members perceive any differences between marketer and consumer motivations to exaggerate claims for high-involvement and regulated products. Future research should investigate if this is due to lack of consumer knowledge or the efficacy of FDA regulatory practices in the online space. We expect that consumer-generated messages will be more effective in generating referrals for non-regulated and low-involvement products, similar to Shimp *et al.* (2007), but future research needs to validate it for SNSs. This finding highlights the importance of examining both recommending and referral behaviour. Brand managers that tout number of videos shared or sent, but not referrals, may have over-inflated the effectiveness of their campaigns.

As hypothesised, non-member recipients are more likely to generate referral visits than SNS members, thus supporting De Bruyn and Lilien's (2008) finding that selectivity of recipients enhances referral probability. While SNS managers can provide features that make it easier to recommend brand messages to non-members, thus leading to more recommendations and referral visits, the benefit of doing so may backfire, as senders

become less selective in recommending non-members who may not be interested in the product, and may thus lead to lower referral probabilities.

Long-term SNS members are less likely to recommend brand messages but more likely to generate referrals, thus replicating findings by Schlosser (2005) for WOM generation, and Muniz and Schau (2007) for effectiveness of WOM or referral. As websites mature, there will be more long-term members at successful SNSs. SNS managers who track only recommendations may despair when the aggregate number of recommendations declines. However, managers who also track referrals will take comfort in the fact that 'less is more' since long-term members have higher conversion rates, i.e. percentage of recommendations from long-term members that generate referral visits is higher than those of newer members. This suggests that SNS managers can increase advertising revenues by pegging their CPC rates to the proportion of long-term members, and charge higher CPC rates for their social ads or sponsor invites than those with a higher proportion of newer members.

Differences in share-of-posts or network size do not lead to differences in brand message recommending probability, contrary to findings in the market maven literature (Feick & Price 1987). However, high-SOP and big-network-size members are more likely to generate referral visits. This suggests that the visible display of network connections and activity increases recipients' compliance with the request to make a referral visit. This suggests that the current practice among brand sponsors of using network size as a proxy for recommending value of a SNS member is ineffective, it can be used to identify members with higher referral visit generation capabilities at high involvement SNS.

Existing research on online advertising has documented the role of design elements in internet advertising effectiveness (Robinson *et al.* 2007). This study does not consider design elements, however future research should consider the impact of recommendation message characteristics on referral probabilities. The proposed model formulation can be extended to accommodate different brand message variables along with the covariates considered in this research. Brand managers are also interested in examining whether recipients who make a referral visit purchase at the brand sponsor's website. A hierarchy of effects in terms of ad messages that encourage recipients to visit and also purchase will help managers monetise content at the site. De Bruyn and Lilien (2008) found that

viral email messages are more effective in making recipients aware of an offer or website, but they had no influence on higher-order outcomes like purchases. Availability of a history of recommending and referral data on senders themselves would make it possible to segment the consumer base in terms of their 'network value' and develop CRM initiatives to retain and encourage word-of-mouth behaviour among influencers.

## Acknowledgement

The author thanks Tina Duggal, graduate assistant in the Department of Marketing, for her help in pre-processing the data used in this research.

## References

- Balasubramanian, S. & Mahajan, V. (2001) The economic leverage of the virtual community. *International Journal of Electronic Commerce*, **5**(3) (Spring), pp. 103–138.
- Bhattacharya, C.B., Rao, H. & Glynn, M.A. (1995) Understanding the bond of identification: an investigation of its correlates among art museum members. *Journal of Marketing*, **59** (October), pp. 46–57.
- Boyd, D.M. & Ellison, N.B. (2007). Social network sites: definition, history, and scholarship. *Journal of Computer-Mediated Communication*, **13**(1), article 11. Available online at: <http://jcmc.indiana.edu/vol13/issue1/boyd.ellison.html> (accessed on 12 January 2011).
- Brown, J.J. & Reingen, P.H. (1987) Social ties and word-of-mouth referral behavior. *Journal of Consumer Research*, **14**(3), pp. 350–362.
- Chatterjee, P. (2001) Online review: do consumers use them? *Advances in Consumer Research*, **28**, pp. 129–133.
- Chib, S. & Greenberg, E. (1998) Analysis of multivariate probit models. *Biometrika*, **85**(2), pp. 347–361.
- De Bruyn, A. & Lilien, G.L. (2008) A multi-stage model of word of mouth through viral marketing. *International Journal of Research in Marketing*, **25**(3), pp.143–225.
- Dholakia, U., Bagozzi, R. & Pearo, L. (2004) A social influence model of consumer participation in network- and small-group-based virtual communities. *International Journal of Research in Marketing*, **21**(3), pp. 241–263.
- Donath, J. & Boyd, D. (2004) Public displays of connection. *BT Technology Journal*, **22**(4), pp. 71–82.
- Ellison, G. & Fudenberg, D. (1995) Word-of-mouth communication and social learning. *Quarterly Journal of Economics*, **110**(1), pp. 93–125.
- Ellison, N.B., Steinfield, C. & Lampe, C. (2007) The benefits of Facebook 'friends': social capital and college students' use of online social network sites. *Journal of Computer-Mediated Communication*, **12**(4), article 1. Available online at: <http://jcmc.indiana.edu/vol12/issue4/ellison.html> (accessed on 12 January 2011).

- Feick, L.F. & Price, L.L. (1987) The market maven: a diffuser of marketplace information. *Journal of Marketing*, **51**(1), pp. 83–98.
- Frenzen, J.K. & Davis, H.L. (1990) Purchasing behavior in embedded markets. *Journal of Consumer Research*, **17**(1), pp. 1–12.
- Greer, J.D. (2003) Evaluating the credibility of online information: a test of source and advertising influence. *Mass Communication & Society*, **6**(1), pp. 11–28.
- Henning-Therau, T., Gwinner, K.P., Walsh, G. & Gremler, D.D. (2004) Electronic word-of-mouth via consumer-opinion platforms: what motivates consumers to articulate themselves on the internet? *Journal of Interactive Marketing*, **18**(1), pp. 38–52.
- Lee, M. & Youn, S. (2009) Electronic word of mouth (eWOM): how eWOM platforms influence consumer product judgment. *International Journal of Advertising*, **28**(3), pp. 473–499.
- Martin, C. & Clark, T. (1996) Networks of customer-to-customer relationships in marketing, in Iacobucci, D. (ed.) *Networks in Marketing*. London: Sage, pp. 342–366.
- Misra, R., Mukherjee, A. & Peterson, R. (2008) Value creation in virtual communities: the case of a healthcare website. *International Journal of Pharmaceutical and Healthcare Marketing*, **2**(3), pp. 321–337.
- Muk, A. (2007) Consumers' intentions to opt in to SMS advertising: a cross-national study of young Americans and Koreans. *International Journal of Advertising*, **26**(2), pp. 177–198.
- Muniz, A. & Schau, H. (2007) Vigilante marketing and consumer-created communications. *Journal of Advertising*, **36**(3), pp. 187–202.
- Okazaki, S. (2009) Social influence model and electronic word-of-mouth: PC versus mobile internet. *International Journal of Advertising*, **28**(3), pp. 439–472.
- Okazaki, S. & Hirose, M. (2009) Effects of displacement-reinforcement between traditional media, PC internet and mobile internet: a quasi-experiment in Japan. *International Journal of Advertising*, **28**(1) pp. 77–104.
- Petty, R. (2000) Marketing without consent: consumer choice and costs, privacy, and public policy. *Journal of Public Policy and Marketing*, **19**(1), pp. 42–53.
- Robinson, H., Wysocka, A. & Hand, C. (2007) Internet advertising effectiveness – the effect of design on click-through rates for banner ads. *International Journal of Advertising*, **26**(4), pp. 527–541.
- Schindler, R.M. & Bickart, B. (2005) Published 'word of mouth': referable, consumer generated information on the internet, in Haugtvedt, C.P., Machleit, K.A. & Yalch, R. (eds) *Online Consumer Psychology: Understanding and Influencing Consumer Behavior*. NJ: Lawrence Erlbaum Associates, pp. 35–61.
- Schlosser, A. (2005) Posting versus lurking: communicating in a multiple audience context. *Journal of Consumer Research*, **32**, pp. 260–265.
- Shimp, T.A., Wood, S.L. & Smarandescu, L. (2007) Self-generated advertisements: testimonials and the perils of consumer exaggeration. *Journal of Advertising Research*, **47**, pp. 453–461.
- Sohn, D. & Jee, J. (2005) Network structures of commercial portal sites: implications for web advertising planning. *International Journal of Advertising*, **24**(4), pp. 425–440.



- Tegler, E. (2009) Ford is counting on army of 100 bloggers to launch new fiesta. *Advertising Age*, September 14, pp.20.
- Thompson, S.A. & Sinha, R.K. (2008) Brand communities and new product adoption: the influence and limits of oppositional loyalty. *Journal of Marketing*, **72**, pp. 65–80.
- Van den Bulte, C. & Stremersch, S. (2004) Social contagion and income heterogeneity in new product diffusion: a meta-analytic test. *Marketing Science*, **23**(4), pp. 530–544.
- Watts, D.J. & Dodds, P.S. (2007) Influentials, networks, and public opinion formation. *Journal of Consumer Research*, **34**(4), pp. 441–458.
- Williamson, D.A. (2010) Brand Interactions on Social Networks. E-Marketer Report. Available online at: [http://www.emarketer.com/Report.aspx?code=emarketer\\_2000694](http://www.emarketer.com/Report.aspx?code=emarketer_2000694) (accessed on 12 January 2011).

## About the author

Patrali Chatterjee is Associate Professor of Marketing at the School of Business, Montclair State University. Prior to joining Montclair State University, Dr Chatterjee was Vice Chair and Assistant Professor, Department of Marketing at Rutgers Business School, Rutgers University. She holds a PhD in Marketing from Owen School of Management, Vanderbilt University. Prof. Chatterjee's research interests include online advertising research, clickstream data modeling, customer equity management and the leveraging technology in sustaining online businesses and nonprofits. Dr Chatterjee's research has appeared in several books and academic journals including *Advances in Consumer Research*, *Journal of Business Research*, *Journal of Computer-Mediated Communication*, *Journal of Electronic Commerce Research*, *Journal of Product and Brand Management*, *Marketing Science* and the *Review of Economics and Statistics*. Her research has been reported in news and business media outlets like *The Wall Street Journal*, *Stanford Innovation Review* and *The Star Ledger* among others.

Address correspondence to: Patrali Chatterjee, School of Business, Montclair State University, Upper Montclair, New Jersey 07043.

Email: [chatterjeep@mail.montclair.edu](mailto:chatterjeep@mail.montclair.edu)

Copyright of International Journal of Advertising is the property of World Advertising Research Center Limited and its content may not be copied or emailed to multiple sites or posted to a listserv without the copyright holder's express written permission. However, users may print, download, or email articles for individual use.