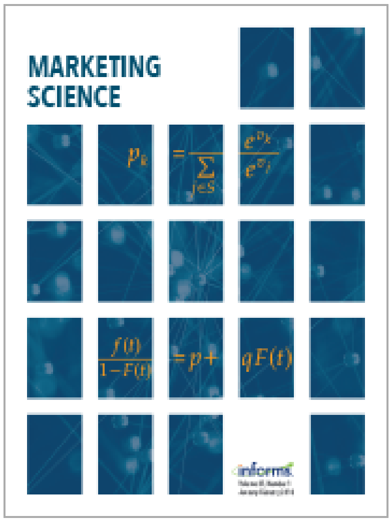

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Practice Prize Winner—Creating a Measurable Social Media Marketing Strategy: Increasing the Value and ROI of Intangibles and Tangibles for Hokey Pokey

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Practice Prize Winner

Creating a Measurable Social Media Marketing Strategy: Increasing the Value and ROI of Intangibles and Tangibles for Hokey Pokey

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Hokey Pokey, a popular "super premium" ice cream retailer, has over a dozen outlets based in India. Hokey Pokey offers "customized mix-in" flavors and realizes the importance of social media platforms to connect with its target consumers and create an engaging brand experience. However, with a limited marketing budget, the retailer needed to measure the success of its social media marketing efforts and create an optimized strategy. To accomplish this, we proposed and implemented a methodology to measure social media return on investment (ROI) and a customer's word-of-mouth (WOM) value by first creating a unique metric to measure the net influence wielded by a user in a social network, customer influence effect (CIE), and then predicting the user's ability to generate the spread of viral information. We then link WOM to the actual sales that it generates through a second metric, customer influence value (CIV), and we implement a strategy at Hokey Pokey to measure these metrics and identify their individual drivers. Finally, we refine our strategy to increase CIE and CIV, thereby impacting the profit. Our research shows that social media can be used to generate growth in sales, ROI, and positive word of mouth and can spread brand knowledge further.

Key words: social media marketing campaign; ROI; customer influence effect; customer influence value
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1. Introduction

With over 80% of global consumers across geodemographic barriers actively influencing preferences and purchase decisions through online social networks and word of mouth (WOM), social media such as blogs, forums, and user networks have taken a more primary role in the minds of the marketers. Organizations are increasingly investing in new marketing channels, leveraging technologies, and building their brand through social shopping, review marketing, social customer support, and viral marketing. Consumer brands, electronics, and automobiles are focusing an increasing portion of their marketing budgets on engaging customers through Facebook and Twitter.

However, despite the vast amount of individual and relationship data available through these types of media, organizations have been unable to directly and efficiently measure the effectiveness of their social media strategy using tangible metrics. The lack of robust methodologies to measure the impact of social media efforts in monetary terms forces organizations to employ suboptimal marketing strategies. Moreover, the fundamental nature of social media as a platform for consumers to interact with and influence each other has a more direct impact on brand communities, and it enjoys higher response rates and customer engagement compared with traditional marketing methodologies that focus only on the firm–consumer relationship (Trusov et al. 2009). Therefore, the need of the hour is to provide marketing practitioners and academia with a methodology to measure the monetary impact of social media and the effectiveness of WOM in generating sales.

In this research, we create a unique framework and a set of measures to capture the value of an individual's WOM in terms of both its viral impact and the net sales that it facilitates. We implement this framework by creating and deploying a social media strategy at ice cream retailer Hokey Pokey. Through this research, we measure and predict the individual impact of WOM of Hokey Pokey's customers, as well as accurately calculate the ROI of social media for this retailer.

2. Background

2.1. Study Objectives

The core objective of this research is to develop a framework to measure the monetary impact of WOM and test our methodology by implementing a scalable social media strategy at Hokey Pokey. Specifically, in this research, we have attempted to sufficiently answer the following questions:

1. How can an individual's influence be captured in monetary terms in a social network?
2. Can we quantify the intangible benefits to the brand, such as consumer perceptions and brand identity generated through the halo effect of influencers in the social media?
3. What is the net value of such an individual's influence to the bottom line, in terms of monetary impact (profit) and subsequent sales generated for the organization?
4. Can the intangible effect and monetary impact of a customer's influence be predicted ahead of time so that the firm can use these influencers to generate a profitable buzz in the future?

To answer these questions, we propose a unique metric, customer influence effect (CIE), that is defined as *the net influence wielded by a user* (*in a social network*) *in terms of his or her ability to spread positive or negative WOM through his or her direct and indirect connections*, to measure the influence of an individual in a social network. We then link the influence of an individual to the monetary value, customer influence value (CIV), that he or she accrues for the firm; we define CIV as the *monetary gain/loss realized by the firm that is attributable to a customer's influence effect.* Finally, we identify the drivers of influential behavior in a social network, i.e., network and WOM characteristics, and purchase characteristics.

2.2. About Hokey Pokey

Hokey Pokey is a chain of ice cream retailers that has a strong local presence in India. Hokey Pokey offers "customized mix-in" flavors, which are very popular with youngsters. The concept of customized food services was fairly new in the region, and the retailer felt the need to create a strong brand identity through its passionate customer base. Most of Hokey Pokey's existing brand advocates fell within the "millennial" demographic cohort. Given that over 50 million consumers in this segment in India actively spend over three hours, on average, in various online social networks,[1] Hokey Pokey realized the importance of social media marketing to engage its customers and drive a profitable strategy. The main business question then was "How do we measure the return of investment on social media marketing?"

With a blend of marketing strategy, social technology, and sophisticated modeling, we have been able to illustrate the success of marketing through social media at Hokey Pokey to (i) create and spread brand identity, (ii) stimulate a strong brand association among consumers and proactively identify brand advocates, and (iii) reach potential customers through existing ones.

2.3. Study Context

In this research, we first relate abstract social media measures such as "comments" and "conversations" to financial metrics by understanding the role and impact of influence in purchase decisions. The goal was to use these actions in social media to subsequently drive and increase sales for Hokey Pokey. We then demonstrate this increase in buzz and monetary gains by creating a framework (using CIE and CIV) that helps to identify the effect of influence through WOM and the corresponding influencers. This framework consequently measures the impact of WOM on sales and is described in §3. Most importantly, the framework provides marketers a first-of-its-kind methodology to measure the virality of WOM on social media, by measuring the influence effect of each customer in terms of his or her ability to spread WOM through his or her various connections (called the CIE). To implement this framework at Hokey Pokey, we created a social media strategy consisting of three stages: (a) a preliminary stage, which consisted of market research to understand the scope of social media penetration and to identify the ideal social platform; (b) a pretest stage, where the flow of WOM and influence were measured across different messaging formats to control for the effect of "tone" and "language" in our research; and (c) an implementation stage, consisting of two campaigns to stimulate WOM and track consequent lift in sales. Section 4 describes the implementation of each of these stages

[1] See India: Digital market overview (accessed August 27, 2012), http://www.digitalstrategyconsulting.com/india/2012/05/a_snapshot_of_digital_india_12.php.

in detail. Section 5 describes the methodology used to calculate CIE and CIV through an illustrated example. Following the measurement of CIE and CIV, in §6 we attempt to optimize the impact of WOM by understanding its antecedents and consequences and estimating the hypothesized effect of these drivers. Section 7 subsequently validates the estimated CIE and CIV against measured values. Finally, in §8 we analyze the results of this research, and in §9 we discuss its contributions to academia and practitioners.

3. Evaluating Social Influence: The Framework

3.1. Related Literature

Whereas net promoter score (Reichheld 2003) and customer referral value (Kumar et al. 2010) focus on the characteristics of the individuals (hosts) who propagate an instance of WOM (promoters, detractors, etc.), existing research explores the effect of an instance of WOM on the receiver (Christiansen and Tax 2000). However, most existing studies fail to capture the network effect in WOM propagation (with the exception of Gupta and Mela 2008). Trusov et al. (2009) discuss the concept of "influence" based on the effect that a user has on others' activities within a social networking site. The "influentials hypothesis" (Watts and Dodds 2007) briefly highlights the importance of the easily influenced members to the rapid spread of information. Simultaneous evaluation of influence from the perspective of both the influencing (host) and the influenced (receiver) individual is further complicated for two reasons: (i) the influence of every individual user is affected by the influence of every other user within the network to varying degrees (Marsden and Friedkin 1993), and (ii) each individual may play the role of both the host and the receiver.

In this study, we substantially extend upon the existing literature in three major ways: (1) we study influence in the context of WOM spread that is not limited to single-point site hits. Therefore, the core of our study is based on the direction of influence transfer. (2) We create a tangible measure of influence through CIE, which measures the "spread of buzz" and "eyes" that are affected by the information, and CIV, which measures the monetary value of a user's influence. (3) Because the WOM transmission is the primary focus of our research, conditional independence of influence with second-order and higher linkages cannot be assumed.

Trusov et al. (2009) studied WOM propagation in the context of online referrals. However, if their model is applied to our data, it would inadvertently miss the key factors including the measurement of the value of an individual's WOM beyond the first referee in our data. Moreover, the data used in their analysis only permit WOM referral after purchase (i.e., sign-up), not their model per se. Thus, their model may be appropriate for the aggregate data of the kind that they used, but for the individual-level data that we have, we needed a more detailed model that allows for deeper insights.

The concept of information feedback has been more elaborately discussed in sociology-based literature as an important driver for the consistent flow of information (Cross et al. 2001). The effect of feedback on propagation of WOM creates complications in creating linear propagation models (Reingen and Kernan 1986). Typically, the propagation model defines how WOM gets passed on from the source to the receiver to the next receiver. If the WOM flow were strictly acyclic and unidirectional, the propagation would roughly resemble a hub-and-spoke structure, which then reduces to integration over multiple hosts → receiver structures. Therefore, we account for the effect of information feedback (Dye 2000) on the influence of each user in this study.

Research on the dynamics of relational ties within networks can be classified based on the research focus (internal or external) and the representative set considered (group or individual level). For example, Burt (1992) and Gulati (1999) externally focused research at the individual level, whereas Putman's (1995) contributions to social capital took the internally focused approach to analyzing group-level behavior. In our research, we have considered the influence of individuals on the spreading of WOM.

Social network models of information flow enable an understanding of the effects of attributes such as the location of the host and the receiver within the network, path analysis of the information instance, and geography of the network as a whole, in addition to host-, receiver-, and network-specific characteristics (Granovetter 1983). Empirical models of social networks such as exponential random graphs (Robins et al. 2006) provide an understanding of how the network as a whole evolves with every consecutive instance of WOM. We have developed a new framework to understand the flow and influence of WOM and the financial gain that social media marketing can provide to an organization.

3.2. Measuring the Social Influence

To measure the impact of WOM in social media, we first extensively studied how information (or WOM) flows through the network, and we calculated the CIE of specific individuals accordingly. Sales data describing the purchase behavior of each individual are then combined with the CIE to obtain CIV. We approached this in three steps. First, we used the historical data to identify the influencers. This was done by studying the (social) network data and the information (WOM) flow. A match between the kind of information and the influence that each individual has on others was calculated. Based on that, the influencers were identified. Second, the influencers were encouraged to talk about Hokey Pokey by providing them with incentives such as free T-shirts, tote bags, coupons, discounts, and more, on a weekly basis. These incentives were presented to the winners who had the maximum CIE and/or CIV. Third and finally, the results were analyzed and the performance of the firm after implementing the metrics was measured. Figure 1 illustrates the detailed process that was adopted to compute the CIE, CIV, and the customer lifetime value (CLV).

3.2.1. Data. The first step for calculating CIV is to measure how WOM flows across a network of individuals. This flow of information is assessed from specific data about the individual concerned and metadata about the information itself, such as the category to which it belongs. Godin (2001) and Gladwell (2000) conceptually discussed characteristics of the message that make an instance of WOM worth spreading by each user in the network as the "virality" of the message itself and the "stickiness" of the message to an individual who receives it, respectively. Therefore, to accurately measure the impact of an individual's influence over another, specific characteristics of the WOM instance had to be controlled for.

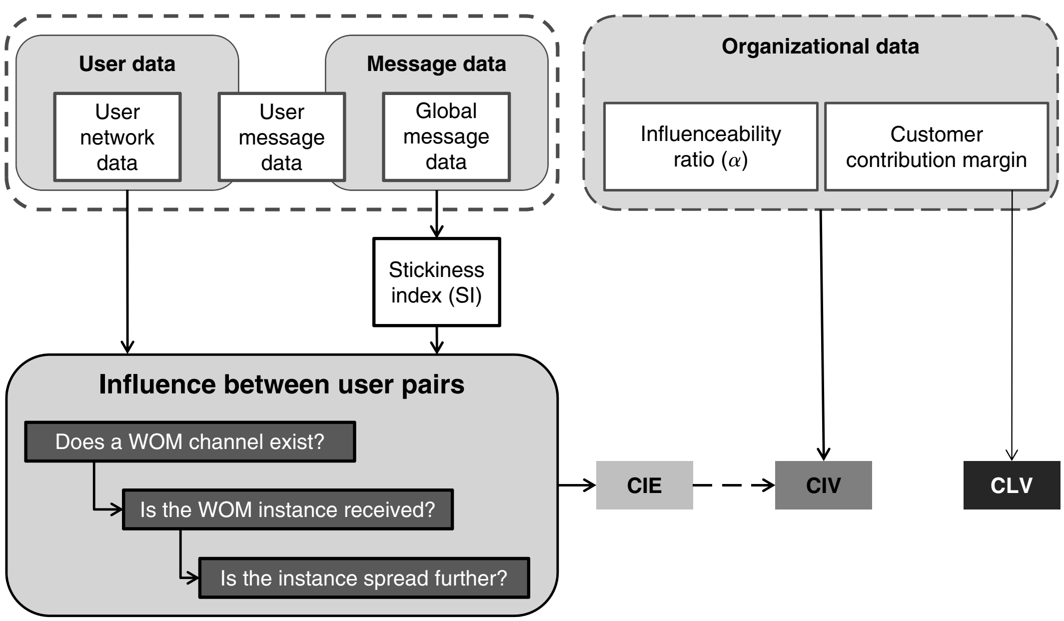
3.2.2. Stickiness Index. We measured the characteristics of each instance of WOM and the type of WOM each individual spreads by introducing a metric called the stickiness index (SI). The SI can be defined as an array of the degree to which a user or an instance of WOM is specific to each category of topics. In conceptual terms, the SI of a user refers to how specific the user is to a particular category of words, based on the association of the words between each other and with other words used by all users globally. For example, a user who profoundly discusses desserts, milkshakes, and floats is closely associated with discussions about ice creams.

The match between a user's SI and a WOM instance indicates the degree of stickiness of that WOM instance to that user. For example, if user A sends 50 tweets to user B and, if out of those 50 tweets 25 are about ice creams and related topics (milkshakes, desserts, etc.), then theoretically, the stickiness index of user A is 0.5. The details of the attributes of the stickiness of the message and the method of SI calculation used in this study are discussed in the appendix.

For example, between a pair of users, an SI is constructed for each of the two users to determine their "compatibility" with each other during the estimation of CIE and CIV. This is used to determine the "attractiveness" of the message to the user during the preliminary stage of our implementation strategy. The measurement of the SI during the preliminary phases of the strategy helped us to identify (1) the number of social media users in the region who actively discussed ice creams and (2) the type of topics that people who discussed ice creams frequently talked about. These analyses were instrumental in estimating the possible size of the target market and identifying the optimal incentives that these users would be interested in.

3.2.3. Influenceability Ratio. The subset social graph of customers who made a purchase at the store was used to calculate the influenceability ratio. The

Figure 1 **Process of Measuring the CIE, CIV, and CLV**



influenceability ratio is defined as the relative influence of multiple individuals in the network referring the product to a particular referral. For example, if a person has been influenced by many individuals, we need to determine how much influence each individual has on that person. The influence of each individual in the spread of WOM was calculated through the CIE metric. Off-line sales data were tied to WOM by obtaining the social media log-in IDs of customers at the store and were then used to calculate CIV.

3.2.4. Estimation. Following the calculation of CIV, our next step was to predict each of the nested stages and estimate future CIE and CIV. The estimation of the flow of WOM in the social network involved a three-stage nested process. The stages in this process verified whether the environment was conducive for one user to influence another by assessing whether (i) there was a connection between two users, (ii) an instance of WOM discussed by one user was received by the other, and (iii) the receiving user spread the message further. Factors affecting each of these stages were measured individually and used in the prediction of CIE using advanced statistical methods.

Given that all products are priced the same, if an individual *must* make a purchase to be able to spread WOM, the CIV model is simplified to a more robust version of the Trusov et al. (2009) model that accommodates for cyclic influence flows, and where we track multiple levels of referrals. Here, the CIV is just a scaled-up value of CIE (scaled by a constant purchase value). Multilevel marketing companies such as Amway can directly use such a model. If an individual may or may not make a purchase to spread WOM, the CIE and CIV may have the same drivers, but the parameter coefficients (effect of individual drivers on sales) might be different. This is a more realistic scenario where users may influence each other's purchase decisions without actually making a purchase themselves. Here, we may estimate the CIV by mixing the CIE drivers with a binary value that indicates whether or not a sale has occurred.

The third case is if products are differently priced, or if multiple values of a product may be purchased, it becomes necessary to jointly estimate the influence and purchase component in CIV. The CIE and CIV drivers may be very different here, as some of the factors affecting quantity and need (met by heterogeneity factors in the purchase component) may overshadow the social factors. In our case, we already control for the other heterogeneity factors by making the entire social media marketing campaign a social experience. It is therefore logical that the factors that drive people to share WOM about Hokey Pokey also drive them to make their own creations or try existing creations. CIE and CIV may be expected to be positively correlated, though this is not necessary. This is because the act of spreading WOM can cause an individual to also buy that product (Kumar et al. 2010).

3.3. Capturing Word-of-Mouth Data

Special tracking software was built to (i) track social connections in the network, such as who was connected to whom, and (ii) collect user-level data, such as the messages that each user discussed and responded to. Sales data at the store were captured through a software trapdoor that tied purchases to individual user information. The net purchases attributable to a user's influence effect were calculated iteratively through the CIV. The software collected real-time data that accounted for (a) the individual attributes of each user, such as the time, frequency, and level of activeness within the social network; (b) the social attributes between a pair of users, such as the number of common friends between them and how often they communicated; and (c) store-level information such as the purchase amount and frequency of each user. Additional (independent) software was built to collate all conversations in the social media, and identify how closely various keywords were associated, to measure the stickiness index.

The overall density of most social networks is not very high because of the existence of certain islands of subnetworks (called cliques) and inactive or ghost users. Therefore, our tracking methodology randomly identified users and snowballed their networks by iteratively tracking their connections until each clique was completely accounted for. This ensured that the depth of connections and network density around each individual was high and complete.

The drivers of CIE were calibrated through observations tracked in the natural spread of WOM over a six-month period; 825,091 conversations involving 1,736 individuals in the social networking sites were used to estimate the factors affecting each of the nested phases. To estimate CIV, 10 seed customers of Hokey Pokey were chosen from a pool of 203 existing customers who actively used the social media. The seed customers were selected based on their estimated CIE and loyalty to Hokey Pokey, measured by the number of positive instances of WOM they had generated on Facebook and Twitter. There were two campaigns that were initiated for Hokey Pokey—the "Creations on the Wall" and the "Share Your Brownies" campaigns. The Creations on the Wall campaign focused on getting the customers to create their own flavors and initiate WOM for their creations. The Share Your Brownies campaign was initiated to further encourage the customers to propagate their creations by giving them award points called "brownie points." Each seed user and subsequent users who were selected based on the Creations on the Wall campaign initiated WOM about a specific creation and were responsible for marketing these creations to their friends using social media during the Share Your Brownies campaign. Customers were rewarded with brownie points for the store purchases that they influenced, based on their scaled CIV. Additional bonus points were awarded to customers based on their CIE, for the degree to which they marketed creations through their WOM.

Finally, using the store-level behavioral data, the expected contribution margin from each customer during the estimation time frame was jointly estimated along with the nested stages in the estimation of CIE to compute CIV.

4. Implementation at Hokey Pokey

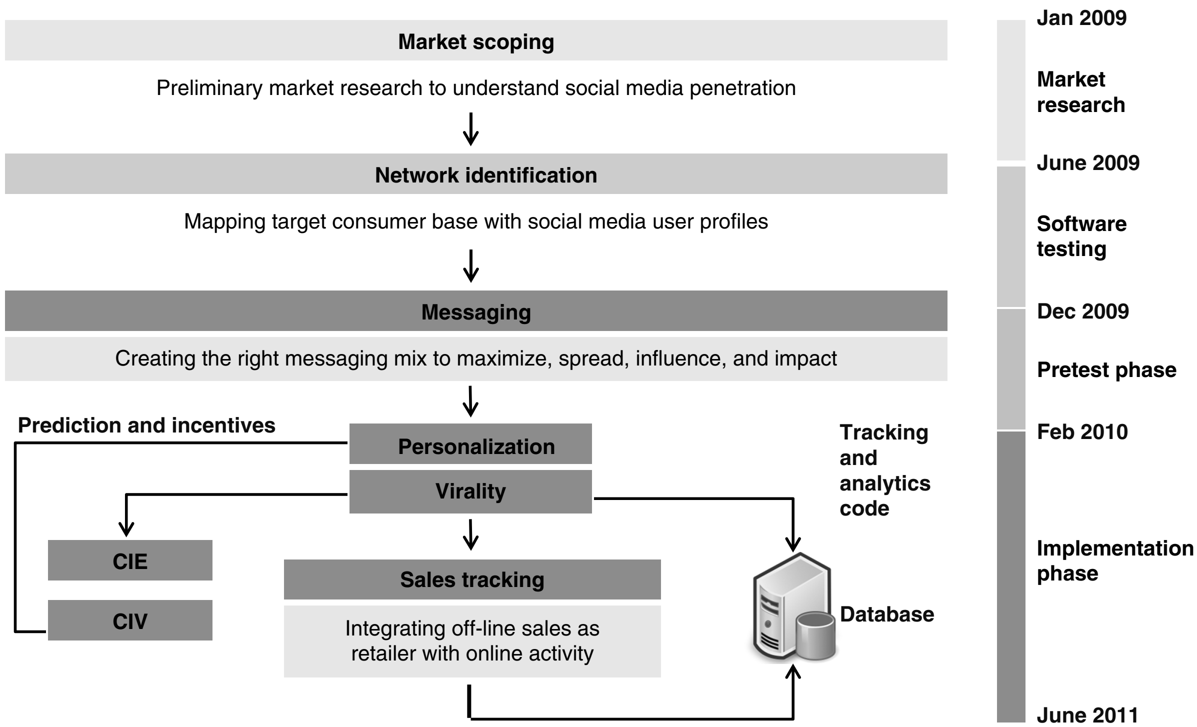
Figure 2 describes an overview of the stages involved in the implementation of the CIV framework at Hokey Pokey.

The first six months of the campaign were devoted to understanding the social media market and the potential for generating and influencing purchase decisions in the region. The social media penetration in India was studied across various social networks (Orkut, Twitter, Facebook, Foursquare, Gowalla, etc.) to identify an ideal social network in which this field study could be conducted. The software (in PHP language) was built to track user networks in social media and the strength of their influence, as well as collect and archive conversations (positive or negative word of mouth), at the time of the study, on the social network related to Hokey Pokey.

To control for the actual message being shared by consumers in the social media, the effectiveness of four messaging formats—(i) *personal*, (ii) *conversational*, (iii) *referral*, and (iv) *generic*—were measured across 76 randomly selected users who (a) did not have direct association among each other and (b) were reachable within four degrees of separation to ensure that WOM was not confined to groups within the network. Personal messages included individual experiences and customizations, conversational messages included questions and polls, and referral messages explicitly recommended a specific creation. Generic messages were included as a control category for the pretest. Effectiveness for the purpose of WOM spread was measured using the following three parameters: (i) the degree of spread, or the number of times the message was forwarded (or modified and forwarded); (ii) the depth of influence, or the number of connections that the message jumped; and (iii) the engagement impact, or the number of comments and replies received for each message. Mixed messaging formats of personal and referral messages were shown to maximize spread as well as to traverse across more levels of connections than other formats, as described in §4.2. Therefore, the social media marketing strategy was crafted to include elements from the personal format to the influencers and the referral format to specific products and offerings in a store.

Finally, the strategy was implemented through two overlapping campaigns that ran for a period of 19 months. Off-line purchases at each store were

Figure 2 **Overview of the Research Study**



collected and tied to social media conversations to identify the monetary value of online influence. In total, this campaign included 1,963 conversations (discounting forwarded, shared, and retweeted instances of conversations) from 351 users. The CIE and CIV of all customers were calculated and used to reward loyal and influential customers. Web Appendix 1 (available at http://dx.doi.org/10.1287/mksc.1120.0768) shows the timeline for the complete campaign (June 2009 to June 2011), as well as the activities carried out during the study period. The performance of the campaign was monitored from March 2010 to June 2011.

4.1. Preliminary Phase: Identifying the Ideal Online Social Network

The choice of a social media platform was limited by the following conditions.

1. *Large number of primary users.* Because of the competitiveness in the market, and as most customers would not habitually travel a long distance to reach an ice cream parlor, the primary number of users of the selected social media platform in the region must be greater than 1,000. Because of the relatively lower adoption of platforms in the region, Foursquare and Second Life were eliminated from the choice set.

2. *Regional concentration of users.* To ensure that the spread of information about Hokey Pokey was meaningful to the recipient, an additional condition required the users in the social media platform to have at least 20% of their social contacts also be from the same region.

3. *Barriers that prevent the spread of WOM.* To attain a critical mass at an early stage, the platform must offer minimum barriers for users to actively engage. Media such as blogs were eliminated from the set as they required a great deal of conscious processing.

4. *Ease of social ties.* Consumers had to be able to form social connections between each other to spread the message about the brand. Therefore, media such as Twitter and Facebook, where forming new ties is relatively easy, were chosen over others such as Orkut.

Table 1 examines these parameters across the various social media. Custom tracking programs were written to measure the parameters for conditions 1 and 2. Conditions 3 and 4 were evaluated qualitatively by studying each platform. Based on these measures, Facebook and Twitter were selected to conduct the social media campaign.

4.2. Pretest Phase: Identifying Spread, Influence, and Social Impact

During the pretest phase, a select group of consumers were encouraged to discuss Hokey Pokey on the chosen social networks. The degrees of spread, depth of influence, and engagement impact of these discussions were then measured through software that plugged into the application program interface of these networks that are open to the public such as the fan pages in Facebook. The degree of spread was measured based on the number of times the message was forwarded (or modified and forwarded) by receivers. For example, a message that was received and forwarded 50 times had a degree of spread equal to 50. The depth of influence was measured as the number of connections (nodes) that the message jumped (such as friends of friends). For instance, a message originating from user A that was received and forwarded by user B to user C has jumped two connections and has a depth of influence equal to 2. The engagement impact was measured by the number of comments and replies received for each message. A Facebook message with 15 comments on Facebook and 12 replies on Twitter, for instance, has an engagement impact of 27. Tracking software was built using PHP to measure and analyze these metrics. The message contents were uniformly distributed across both the pretest consumers and platforms. Table 2 describes the average spread, influence, and impact across Twitter and Facebook for 76 pretest participants over a period of one month. In the table, the mean values of personal, referral, and conversational messages are compared with that of the generic messages to obtain the value of the t-statistic.

4.3. Implementation Phase: Campaigns

4.3.1. Creations on the Wall. The Creations on the Wall campaign was aimed at increasing the number of custom ice cream creations made at each parlor,

Table 1 Preliminary Phase: Identifying the Most Viable Social Media Platforms

Media	Example	Regional adoption (number)	Proportion of local connections (%)	Effort for sharing	Cost of tie formation
Blogs	WordPress	37,000	13	Resource intensive	Moderate
Location sharing	Foursquare	2,700	43	Minimal	Low
Personal network	Facebook	64,000	57	Minimal	Moderate
Video blog	YouTube	3,760	12	Moderate	Low
Micro blog	Twitter	5,620	29	Minimal	Low
Virtual world	Second Life	800	31	Moderate	Low
Social coupons	Groupon	—	85	Minimal	Moderate

Table 2 Identifying Spread, Influence, and Social Impact (t-Test Results)

	Personal	Referral	Conversational	Generic
Spread				
Mean	42.07692	**103**	59.23077	69.23077
Std. dev.	556.4103	999.5	553.5256	516.5256
t-stat	−2.98893	3.127084	−1.10222	
P-value	0.003185	0.002452	0.140648	
Influence				
Mean	3.307692	**10.84615**	1.230769	4.692308
Std. dev.	6.730769	47.80769	0.525641	1.397436
t-stat	0.048978	3.163101	−9	
P-value	1.739607	0.00374	9.02E−09	
Impact				
Mean	**188.6923**	134.8462	150.3846	121.5385
Std. dev.	998.8974	1035.308	1226.923	822.7692
t-stat	5.672939	1.113122	2.297287	
P-value	3.83E−06	0.138341	0.015519	

Note. Highest values are in bold.

and it allowed customers to identify themselves with their creation. Parlor employees were trained to educate customers about custom creations and distribute a form in which customers could enter their creations. Customers could name their creations and post these on one wall in the parlor that was dedicated for this purpose. Other customers could browse this wall and purchase these creations. The creators of the most popular creations were then motivated to enter the second campaign with customized T-shirts and emotional incentives such as the ability to seed and initiate WOM about their creations. More details about all the incentive are provided in Web Appendix 1.

4.3.2. Share Your Brownies. Share Your Brownies was aimed at generating a viral spread of creations by fostering a sense of personal identity. Combinations for winning creations from the first campaign were shared with all Hokey Pokey parlors, and winners were encouraged to discuss their creations on Facebook and Twitter. All relevant discussions were tracked, and influencers were incentivized with brownie points when their followers or friends made a purchase or discussed the creation online.

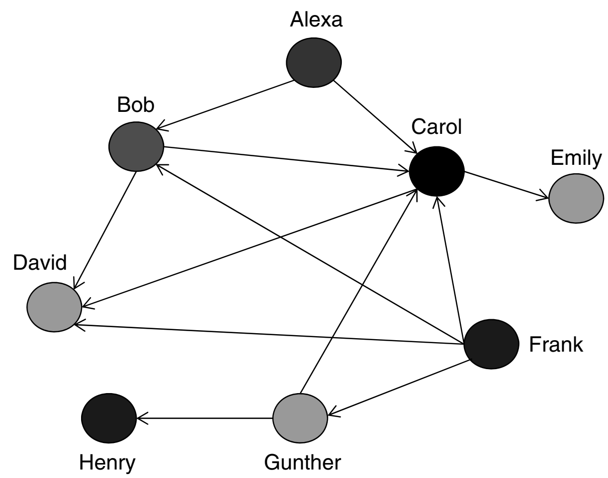
The campaign plan and execution are described in Web Appendix 1. The figures in the Web Appendix 1 illustrate the details of the operation carried out by Hokey Pokey as well as the snapshot of how the influence of the individuals is measured. It also provides the link to the training video, which showcases the entire campaign.

5. The Impact of Influence: Measures and Calculations

5.1. Identifying Influencers—An Illustration

The CIE of an individual measures the net spread and influence of the instance of WOM from that individual. To understand the construction of CIE, let us consider a subset of the social graph of media users[2] discussing a specific creation, Mango Monster. This is shown in Figure 3.

Figure 3 Identifying Influencers—An Illustration



Alexa talks about Mango Monster in Facebook or Twitter and influences Bob and Carol to further spread this message. Existing literature in the social network and influence theory suggest that the influence of a user progressively attenuates as the distance of the message increases (Bonacich 1972, Hubbell 1965, Katz 1953). In other words, Alexa wields a greater influence on Bob and Carol than on David or Emily. Hubbell (1965) described a measure of network centrality in which the influence of Alexa is a function of the influence of the people that she is connected with, plus a factor attributable to her own decision to spread the message. We therefore extend Hubbell's influence measure to calculate the CIE of a user as

$$CIE_j = \omega_j + \sum_i k_{j\to i} \times CIE_i, \qquad (1)$$

where CIE_j is the CIE of a user j, ω is the degree of spread (number of messages posted), and $k_{j\to i}$ is the Hubbell's influence of j on i.

The calculation of CIE is an iterative process, calculated upwards from the last influence (more details are provided in Web Appendix 2). In the example, Emily and Henry do not influence anybody directly. However, they still indulge in WOM and therefore might be of value to the firm. For example, networks such as Digg.com and Twitter tend to showcase the most heavily discussed topics, adding to the virality of the discussion. Therefore, we only include the direct WOM component in Emily's and Henry's CIE. Tables 3(a) and 3(b) show Hubbell's influence. A high value of this influence measure lends itself to the

[2] User names have been changed.

Table 3(a) Hubbell's Influence of Each User

	Alexa	Bob	Carol	David	Emily	Frank	Gunther	Henry
Alexa	1.000	0.067	0.071	0.009	0.005	0.000	0.001	0.000
Bob	0.000	1.000	0.067	0.071	0.004	0.000	0.005	0.000
Carol	0.000	0.000	1.000	0.067	0.067	0.000	0.004	0.000
David	0.000	0.000	0.005	1.001	0.000	0.004	0.067	0.004
Emily	0.000	0.000	0.000	0.000	1.000	0.000	0.000	0.000
Frank	0.067	0.071	0.081	0.077	0.005	1.005	0.072	0.005
Gunther	0.004	0.005	0.072	0.010	0.005	0.067	1.005	0.067
Henry	0.000	0.000	0.000	0.000	0.000	0.000	0.000	1.000

Table 3(b) Computed CIE for Network

User	Spread (scaled)	CIE
Alexa	0.19	0.22183
Bob	0.24	0.26723
Carol	0.18	0.20811
David	0.19	0.20285
Emily	0.22	0.22
Frank	0.12	0.1929
Gunther	0.16	0.19614
Henry	0.14	0.14

interpretation that a user who has a high eigenvector score must be one who is socially connected to others who have a high eigenvector score and is one who is adjacent to users who are themselves high scorers (Borgatti and Cross 2003). Therefore, even if a user effectively influences only one other user, but this user is instrumental in influencing many others, then the first user is considered highly influential. For example, though David only influences Gunther, Gunther actively spreads the information to his network, so David's influence in the network is high.

The CIV and CIE calculations can be understood via the following example described in Figure 4, wherein the calculations are done for Alexa, Bob, Carol, David, and Emily. For ease of understanding, we have assumed that the influencer has an equal effect on each of the individuals he influences and that CLV is observed.

In the Figure 3, Alexa influences Bob and Carol. Bob influences Carol and David. While calculating the CIV for Alexa, we need to consider the CLV and CIV of both Bob and Carol. Now, because Carol is influenced by both Alexa and Bob, the CLV as well as the CIV of Carol will be equally divided between Alexa and Bob. Thus, the CIV of Alexa is the same as the complete CLV and CIV of Bob and half the CLV and CIV of Carol.

The CIE metric alone can be used to quantify the degree to which information would spread from a specific consumer. Such a metric is particularly useful in the context of viral marketing. For example, marketers can strategically publish a YouTube video to a select class of high CIE consumers and maximize the spread of content in a given time. In the case of Hokey Pokey, the CIE metric was useful to continuously identify the set of consumers to initially evangelize each creation to maximize spread.

Once we identified the influencers and induced viral spread of information, our next step was to measure the monetary value of influence. The next section describes the missing link between information spread and monetary effect through individual purchases and, consequently, CIV.

5.2. Valuation of Influence: Measuring the Monetary Value of WOM

To measure the monetary effect of an individual's influence, we first consider the value that each individual brings to the firm through his or her purchase. The measurement and calculation of CLV has been widely used in the academic literature and practice (Venkatesan and Kumar 2004, Kumar 2008).

Figure 4 Computation of CIV

$CIV_\theta = \sum_i k_{\theta\to i} \times CLV_i + \sum_i k_{\theta\to i} \times CIV_i$,

$k_{\theta\to i}$: Hubbell's influence of θ on i,

CLV: customer lifetime value, and

CIV_θ: CIV of user θ.

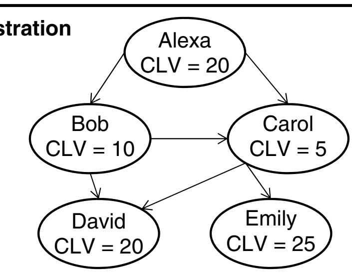
For example,

For each individual in a multihost network,

$$\begin{aligned} CIV_{\text{Alexa}} &= [CLV_{\text{Bob}} + 0.5CLV_{\text{Carol}}] \\ &\quad [10 + 0.5 \times 5] \\ &\quad + [CIV_{\text{Bob}} + 0.5CIV_{\text{Carol}}] \\ &\quad [30 + 0.5 \times 35] \\ &= 60, \end{aligned}$$

where $CIV_{\text{Bob}} = 12.5 + 17.5 = 30$ and $CIV_{\text{Carol}} = 25 + 10 = 35$.

Illustration



Customer	Alexa	Bob	Carol	David	Emily
CLV	20	10	5	20	25
CIV	60	30	35	0	0

(Allowing CLV to vary across customer results in different CIV for each customer)

Table 4 **Computed CIV for the Network**

User	CLV (scaled)	CIV
Alexa	75	88.65
Bob	75	88.335
Carol	100	115.01
David	75	85.91
Emily	140	140
Frank	0	36.08
Gunther	150	164.77
Henry	70	70

In this research, CLV_i refers to the value brought to Hokey Pokey by a customer i through her direct purchases. Using the CIE and CLV of an influencer on each influencee, we can calculate the value that the influencer brings to the firm by his or her spread of WOM.

The CIV of an individual is calculated by iteratively summing the CLV of all the people influenced by the individual, and the proportional CIV of each of his or her influencee's that is attributable to the individual's influence, as

$$CIV_j = \sum_i k_{j\to i} CLV_i + \sum_i k_{j\to i} CIV_i, \tag{2}$$

where CIV_j is the CIV of a user j, CLV is the customer lifetime value, and $k_{j\to i}$ is the Hubbell's influence of j on i.

The monetary value of each consumer was calculated using Equation (2). Table 4 provides a summary of the measured CIV for the sample network in Figure 3. At any time, a screenshot of the real-time CIV of customers can be seen in the administration dashboard of the software (Web Appendix 1).

Frank provides an interesting example of the value of the CIV metric. Based on the CLV value alone, Frank has never made a purchase from Hokey Pokey. Therefore, traditional customer management techniques would not consider him to be a customer. However, he has directly influenced Alexa, Carol, and Bob to make a purchase and therefore still brings a certain value to the firm. Such observations were common during the Share Your Brownies campaign, where a number of customers brought in significant sales through their influence, although their direct contribution margins were below average. This finding is corroborated by Kumar et al. (2010), where the highest referral value was provided by a medium lifetime value customer. Following the measurement of CIV, our next step was to predict the value that the customers were likely to bring in through their influence.

6. Optimizing WOM

To further optimize the marketing strategy, the CIV across all current customers and future prospects had to be predicted. The prediction of CIV was broken into a hierarchical model consisting of the antecedents and consequences of WOM, as shown in Figure 5. Following this conceptual framework of how individuals were influenced through WOM, specific drivers at each stage of the hierarchical model were hypothesized and subsequently tested. Finally, these drivers were used to predict and optimize CIV.

6.1. Drivers, Hypotheses, and Rationale

The hypothesized drivers of customer influence effect and customer influencer value, as described in the nested three-stage model, are shown in Web Appendix 1. The drivers are broadly categorized as (i) network and WOM characteristics measured in the social media and (ii) purchase characteristics measured at the store. The network characteristics were further categorized as characteristics specific to (i) the host or user spreading the WOM; (ii) the receiver, or user receiving the WOM; and (iii) the actual message itself. The detailed description of the hypotheses and the rationale is provided in Web Appendix 3.

Table 5 describes the hypothesized effect of each social media driver on each nested stage and the rationale behind the hypothesis.

All three stages are estimated using an actor-driven model. The reason for using a stochastic model using time-series network data lies in the fact that, for an actor, changes in network dynamics such as new ties being created or destroyed and WOM being spread occur at most once during a micro step.

The first stage in the prediction of CIV was estimating whether a tie would form (or break) between a prospective influencer and an influencee. Second, the influencee must see the information posted, or be available, to be influenced. Third, once influenced, the influencee must act on this influence by either sharing this information further (spread) or acting on this information (purchase).

The probability of a user "choosing" to forge a tie with another, conditional upon these current characteristics (relative to the choice of not forging this tie), is described using a logit model as

$$P(\text{tie}_{\text{host}\to\text{receiver}} = 1) = \frac{1}{1 + e^{-\sum_i \beta_i W_{\text{host}\to\text{receiver}}(i) + \varepsilon_1}}, \tag{3}$$

where $W_{\text{host}\to\text{receiver}}(i)$ is the current value of characteristic i, β_i is the corresponding parameter estimate, and $\varepsilon_1 \sim \text{iid } \mathrm{N}(0, \sigma_1^2)$.

Here, ε_1 is the error term when predicting the probability of a tie existing, based on $W_{\text{host}\to\text{receiver}}$ characteristics; σ_1^2 is the standard deviation of the error terms.

Existing research shows that interactions and WOM affect network structure, and vice versa (Granovetter 1983, Gupta and Mela 2008). If the effect of WOM on

Figure 5 Antecedents and Consequences of WOM

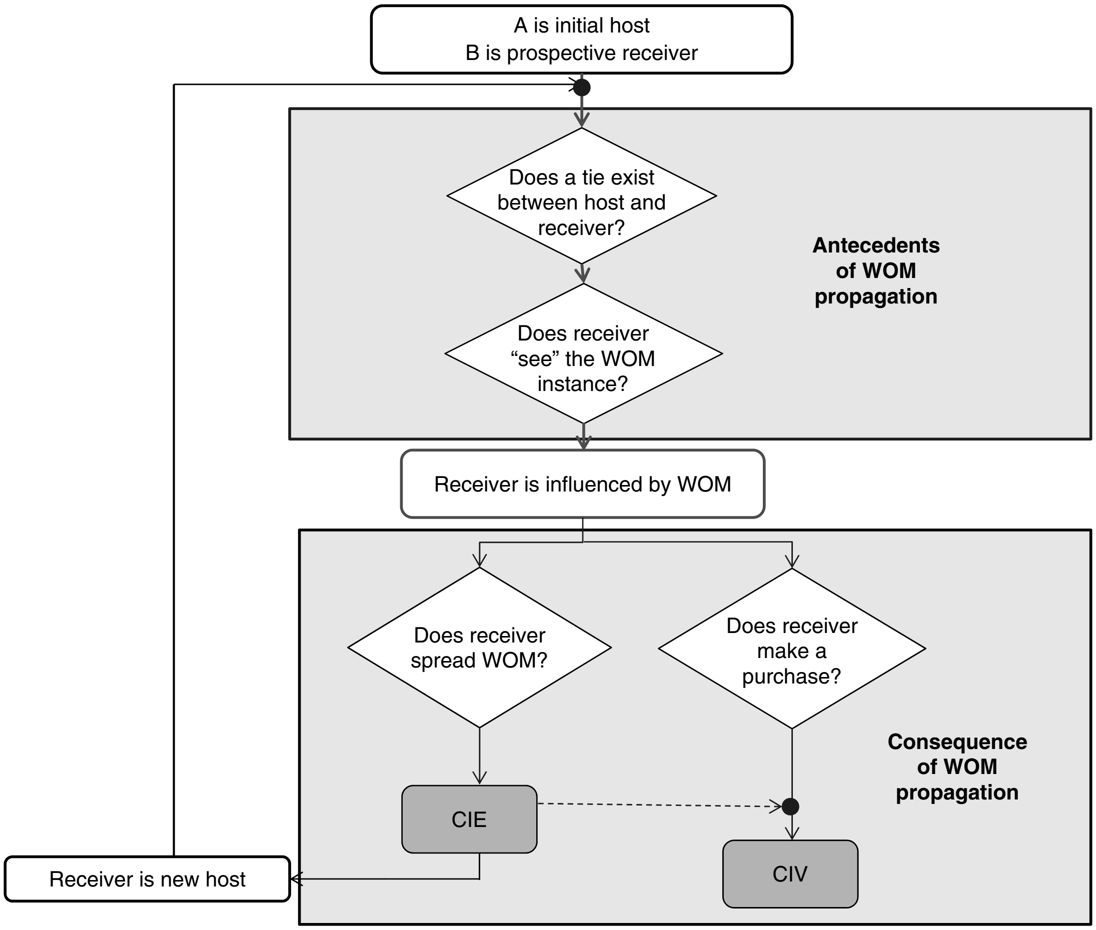


Table 5 Hypotheses and Rationale

Dependent variable	Factor	Independent variable	Hypothesized effect	Rationale
Tie existence	Generosity	*Reciprocity*	+	People respond to each other similarly (Gouldner 1960).
		Same hashtags	+	People who discuss the same kind of topics both share a common interest and are more visible to each other.
		Same lists	+	Members in the same list are more visible to each other and also display a common interest through their membership.
	Host clout	*Number of followers*	+	Hosts with more followers are perceived as being more popular.
		Degree of transitive triangulation	+	Receivers perceive a host as more popular when a considerable number of people they follow also follow the host.
Reception of WOM	Activeness compatibility	*Activeness match* × *Share of WOM*	+	Receivers are more likely to "see" a WOM instance from a host if the host and receiver are active in the network during the same time period and the host has a high share in the total messages the receiver gets.
Spread of WOM	Receiver talkativeness	*Spreading (retweet) frequency*	+	Receivers who usually spread a message are more likely to spread this WOM instance than others.
		Hashtag references	+	Receivers who discuss a variety of topics (hashtags) are more likely to add their thoughts and content to the spread of WOM.
		External host clout	+	A receiver is more likely to spread WOM from a host if the host is considered a "celebrity."
		Degree of transitive triangulation	+	Receivers are more likely to spread WOM from a host who is followed by a number of other people that the receiver is following.

network structure is not accounted for, it would imply that existing network structure determines WOM flow, but not vice versa. This, in turn, would imply that people are born with friends and social ties and do not choose to be influenced by people based on what they say.

Ties between users on Facebook (called "friendships") form a symmetric relationship, unlike those on Twitter (called "follows"). In other words, a tie existing between a pair of users implies that either user may influence the other on Facebook, whereas the direction of the relationship (who follows whom) becomes important on Twitter. Therefore, tie formation on Facebook is considered a special case of Equation (3), where a user's role as host and receiver are interchangeable.

The probability of an influenced user seeing information about the creation is predicted through an *exposure function* that is dependent on the specific characteristics of the two users and the characteristics of the Twitter network. This exposure function is described as

$$v_{\text{host}\to\text{receiver}} = \sum_j \beta_j X_{\text{host}\to\text{receiver}}(j) + \varepsilon_2, \qquad (4)$$

where $X_{\text{host}\to\text{receiver}}(j)$ is the value of characteristic j, β_j is the the corresponding parameter estimate, and $\varepsilon_2 \sim \text{iid } \mathrm{N}(0, \sigma_2^2)$.

The probability equation for the exposure function is given by

$$\Pr(\textit{receiver seeing host WOM} = 1) = 1/(1+\exp(-v)).$$

In (4), ε_2 is the error term when predicting the probability of a tie existing, based on $v_{\text{host}\to\text{receiver}}$ characteristics; σ_2^2 is the standard deviation of the error terms. The specific user and network characteristics that drive a receiver to see the host's information are explained in detail in §6.2.

The probability of an influencee spreading a WOM instance is predicted relative to a baseline probability of that user spreading any information at all. The receiver's preferences toward the influencer and the specific creation itself may further depress or elevate the probability of the receiver spreading this WOM. The probability of a receiver spreading the WOM instance m is therefore expressed as

$$h_{m,\,\text{host}}(\text{receiver}) = h_0(\text{receiver})[e^{\sum_k \beta_k Y_{m,\,\text{host}}(k)+\varepsilon_3}], \qquad (5)$$

where $h_{m,\,\text{host}}(\text{receiver})$ is the spread of message m from the host to the receiver, $h_0(\text{receiver})$ is the baseline probability of the receiver sending a tweet, $Y_{m,\,\text{host}}(k)$ is the specific host and message characteristic variable k for the host and m, β_k is the corresponding parameter estimate, and $\varepsilon_3 \sim \text{iid } \mathrm{N}(0, \sigma_3^2)$.

The final consequence of influencing a user about a creation is the influencee making a purchase. Literature already exists to predict the probability (Rossi et al. 1996) and quantity (Gupta 1988, Tellis and Zufryden 1995) of purchase for a given customer profile. Customer lifetime value accounts for the value that a customer brings to a firm through his or her direct contributions (Venkatesan and Kumar 2004). In addition to the other factors traditionally used to predict CLV, the role of influence in the purchase decision is accounted for by including variables such as characteristics of the influencer, his or her expertise, and clout on the influencee, as

$$CLV_{\text{receiver}} = \sum_l \beta_l Z_{\text{receiver}}(l) + \varepsilon_4, \qquad (6)$$

where $Z_{\text{receiver}}(l)$ is the dependent variable l for that receiver, β_l is the corresponding parameter estimate, and $\varepsilon_4 \sim \text{iid } \mathrm{N}(0, \sigma_4^2)$.

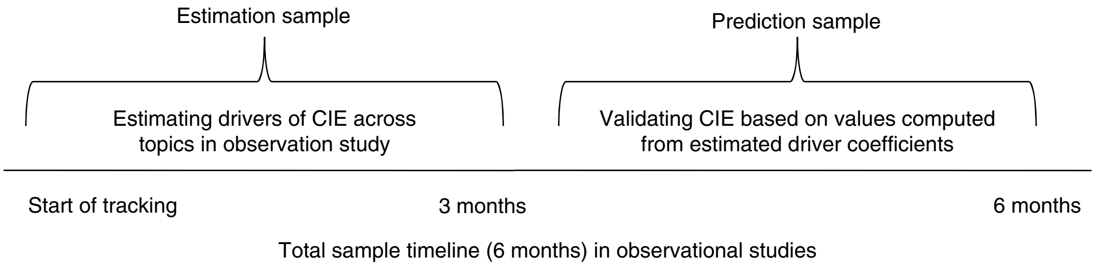
The CLV accounts for the purchase component in Equation (2) to estimate CIV. At the end of the first six months of the study, three months of the timeline were used as the window to estimate the parameters in Equations (3)–(6). These parameters were then used in Equation (2) to predict the CIV for the next three months, as shown in Figure 6.

6.2. Convergence Statistics and Parameter Estimates

The techniques considered to estimate the model parameters in each stage of the nested process started with a direct approach using a nonstochastic model procedure such as a simple logistic regression. The advantage of such a technique is the consistency of the parameter estimates as well as the ability to scale across large sample spaces. The efficiency of linear models in a networked setting is limited because of its lack of precision in analyzing nonlinear state spaces as a linear structure (e.g., network interactions). For example, given n users within the network, $[n(n-1)]$ directed relationships may occur with $[n!]$ possible network topologies. Therefore, the permissible number of network configurations in our sample is extremely large.

Because the choices of each individual must be estimated simultaneously in each nested stage, stochastic models are used to estimate the probabilities of tie formation, reception, and spread of WOM. The parameter estimates for each stage were therefore obtained through a three-phase iterative stochastic algorithm in the SIENA (simulation investigation for empirical network analysis) stochastic network modeling software. Snijders et al. (2007) provided deep information on actor- or agent-based stochastic models (using SIENA). In essence, SIENA is a statistical program built for the analysis of social networks.

Figure 6 Estimation and Prediction Windows



SIENA simulates a social network model across various parameters to find a best-fit stochastic model. However, the trouble with the SIENA program is that it is limited in the number of simultaneous nodes and simulations it can perform. Because of the size, complexity, and real-time nature of information in this study, we built a modeling engine based on SIENA to analyze over a thousand stochastic simulations simultaneously. Some key influences, ideas, and uses of SIENA are as follows.

a. *The use of network- and actor-level parameters*: In our model, we used network-level, user-level, and message-level attributes.

b. *The drive of an actor-based model*: Both users and their messages were considered actors in each model.

Table 6 Phasewise Convergence Statistics for Simulation

Phase	Factor	Statistic	Average	Std. dev.	T-Ratios
1.1: *Tie existence* (Pr(*tie* = 1))	Generosity	*Reciprocity*	0.002	2.281	0.001
		Same lists	3.295	110.951	0.03
		Same hashtags	−0.352	6.715	−0.052
	Host clout	*Degree of transitive triangulation*	0.008	2.663	0.003
		Number of followers	0.532	11.139	0.048
1.2: *Reception of WOM* (Pr(*see* = 1))	Activeness compatibility	*Share of WOM*	0.292	4.871	0.06
		Ln(*Activeness match*)	−0.027	1.818	−0.015
		Share of WOM × Ln(*Activeness match*)	−0.084	2.464	−0.034
	Receiver talkativeness	*Spreading frequency*	0.231	12.813	0.018
		Hashtag references	0.231	12.813	0.018
		External host clout	0.227	9.827	0.023
		Degree of transitive triangulation	−0.171	2.2	−0.078

Table 7 Phasewise Parameter Estimates

Phase	Factor	Statistic	Estimates	Std. error	P-Value
1.1: *Tie existence* (Pr(*tie* = 1))	Generosity	*Reciprocity*	4.2845	1.2810	< 0.001
	Network compatibility	*SI match*	−1.1846	0.5463	< 0.001
		Same hashtags	−1.551	2.6001	0.274
		Same lists	−0.7923	1.1799	0.251
	Host clout	*Number of followers*	6.0142	2.4059	0.006
		Degree of transitive triangulation	1.0299	0.6218	< 0.001
1.2: *Reception of WOM* (Pr(*see* = 1))	Activeness compatibility	*Share of WOM*	0.4159	0.1002	< 0.001
		Ln(*Activeness match*)	0.0533	0.0261	0.021
		Share of WOM × Ln(*Activeness match*)	0.1063	0.0388	< 0.001
2.1: *Spread of WOM* (Pr(*spread* = 1))	Message stickiness	*SI match of message to receiver*	4.105	0.841	< 0.001
	Receiver talkativeness	*Spreading frequency*	0.53	0.306	0.42
		Hashtag references	1.049	0.314	< 0.001
	Host expertise	*SI match of message to host*	3.5662	0.807	< 0.001
		External host clout	2.299	3.622	0.26
		Degree of transitive triangulation	0.1054	0.0334	< 0.001

c. *The use of cross-sectional and time-series data*: We used the SIENA model of driving exponential random graph models for behavior across customers over time.

The first phase in this algorithm ran 400 iterations to estimate the derivative matrix of the target variables with respect to the dependent parameter vectors. The second phase was used to estimate the parameters and ran for 2,560 iterations. The third phase ran a simulation using these parameters to estimate the standard errors and check for model convergence. The phasewise convergence statistics is described in Table 6. The probability of purchase of each influenced customer in the study also followed a Gamma distribution with random effects that accounted for customer heterogeneity, as discussed by Allenby et al. (1999). The parameter estimates and significance are shown in Table 7. Based on these estimates, the CIV was calculated for all the Twitter users in the region and their first degree of followers. Customers who promised high future CIV were contacted both directly and through their friend networks and were incentivized as described in the next subsection.

7. Validating CIE and CIV

The most important impact of this research to the field of marketing is the identification and prediction of key influencers. Therefore, the predicted CIE and CIV of each influencer were subsequently validated against the actual WOM and sales that they generated.

The administration dashboard in the software included visual displays of both predicted and actual CIE and CIV, as well as aggregate CIE and CIV across each creation. When we compared the deciles from high CIE to low CIE, we found that 85% of the WOM spread could be attributed to the top two deciles. Using this information, Hokey Pokey can target marketing messages accordingly and maximize the WOM spread. This result also has implications on cost savings, because the firm does not have to go after a customer who belongs to the lower CIE deciles. The predicted CIV and sales generated through a customer in the subsequent time period had a correlation of 0.87, thereby affirming that CIV has the ability to explain future sales of Hokey Pokey.

Metrics such as CLV tend to be reliable over a three-year prediction period in traditional settings. However, we discovered that because of the rapid inflow of WOM in the social media, the influence that an individual has over another tends to decay almost in real time. However, after a 90-day burn-in period to allow a new user to develop steady relationships and conversations, the estimated parameters could consistently predict CIE and CIV up to 60 days ahead, as described in Table 8.

Table 8 Rank-Ordered Correlation Between Predicted and Actual CIE and CIV

	Day 15 prediction	Day 30 prediction	Day 45 prediction	Day 60 prediction
CIE across all customers	0.86	0.80	0.72	0.69
CIE for top 2 deciles	0.91	0.87	0.79	0.77
CIV across all customers	0.83	0.82	0.78	0.76
CIV for top 2 deciles	0.85	0.85	0.80	0.78

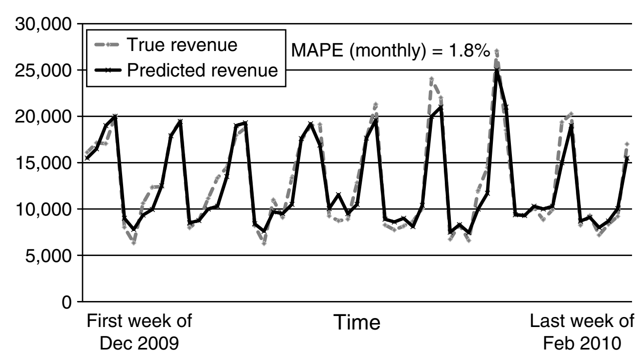
The rank-ordered correlation between predicted and actual CIV across all customers over a two-month time frame was 0.76 and over a 15-day time frame was 0.83. Similarly, the correlation between predicted and actual CIE was 0.69 during the two-month time frame and 0.86 over the 15-day time frame. Table 8 also includes the rank-ordered correlations between the predicted and actual CIE and CIV for only the customers who were in the top two deciles of the actual ranks. Although the correlations during each prediction time frame between the whole population of users and only the top two deciles seem consistent for CIV, the accuracy of CIE over the time frame significantly improves if only the top influencers are considered, indicating that (a) there are more rapid changes in the rank of an individual's influence effect when the effect is low, and (b) by not considering the low CIE individuals, firms can significantly improve the prediction of CIE and, consequently, the virality of the message they are marketing.

8. Results and Research Impact

8.1. Assessing the Sales Lift at Hokey Pokey

The sales lift was calculated as per the actual sales and the projected sales generated using the model estimated to predict sales. Figure 7 shows the projected sales and the actual sales for Hokey Pokey for the two months prior to the start of the campaign. From the historical data on sales for Hokey Pokey, we have projected the future sales under the prevailing scenario.

Figure 7 Fitting Actual vs. Predicted Sales Revenue (Weekly Data)



After implementing the social media marketing campaign, the actual sales of each parlor is added up to obtain the total sales for Hokey Pokey. Hokey Pokey has experienced a positive sales lift in almost all the months during the campaign.

8.1.1. Model Specification and Interpretation. We estimated the daily revenue using the following model and with the data over a two-year period prior to the start of the campaign:

$$\begin{aligned}\log Revenue_t &= 9.267 - 0.177 Monday - 0.156 Tuesday + 0.139 Friday \\ &\quad + 0.520 Saturday + 0.600 Sunday + 0.520 Xmas \\ &\quad + 0.860 NewYear + \frac{1}{1 - 0.371B - 0.161B^2}\alpha_t. \end{aligned} \tag{7}$$

Here, $B = Y_t$ lagged by one time period (in this case, one day), $B^2 = Y_t$ lagged by two time periods (in this case, two days), $Y_t = \log \text{Revenue}_t -$ (sum of Monday, Tuesday, Friday, weekends, Christmas and New Year's effects), and a_t is the error term.

We note the following:

- The MAPE for the fitted model was 3%.
- Log transformation was implemented to smooth the data for better performance.
- Promotions for Christmas and New Year's eve have a significant effect on sales (both P-values are less than 0.001).
- Holiday promotions (New Year's eve) are more competent than event promotions (Radio One contest) for the purpose of revenue generation.

8.2. WOM Spread Over Time

Figure 8 shows the positive WOM generated for various creations (e.g., Sudden Death, Chocbronilla) during four time points in the study (May 2010, September 2010, January 2011, and June 2011), measured as 100 instances of WOM. For example, the creation Sahara Surprise was only mildly popular during the initial phases, and it was almost not discussed at all between March and September 2010, but it became one of the most discussed creations after influencing a few high CIE users around November 2010.

8.3. Tangible and Intangible Impact

The implementation of the above phases enabled Hokey Pokey to identify the drivers of CIE (intangible contributions) and CIV (tangible contributions). The most valuable of the customers were further incentivized to maximize spread and consecutive sales. The "seeding" of these customers to maximize information spread yielded Hokey Pokey an increase of 49% in brand awareness, 83% in ROI, and 40% in sales. The impact of this research can be classified broadly at the firm and customer levels as described in Figure 9.

At the firm level, the main contribution of this study was in the realm of *social media accountability.* Whereas most firms are still grappling with social media accountability, the use of the CIE and CIV metrics gave Hokey Pokey a competitive edge in the social media space. The critical impact factors at the firm level are (i) measuring the ROI of a social media marketing effort and (ii) assessing the increase in the firm's revenue and profit. Similarly, at the customer level, the impact factors are (iii) calculating the value of an individual's influence in a network (CIE) and (iv) measuring the CIV in monetary terms.

Using the estimated drivers of CIE and CIV, the marketing strategies were continuously fine-tuned. For example, regular meetings (Tweetups) were sponsored in the parlors for active customers in the social media. These activities provided high-value influencers with the opportunity to connect with others, thereby boosting the overall spread of WOM. Similarly, high CIV customers were highlighted through in-store promotions showcasing their pictures and

Figure 8 Boost in Positive WOM Across Campaign Timeline (Scaled Values)

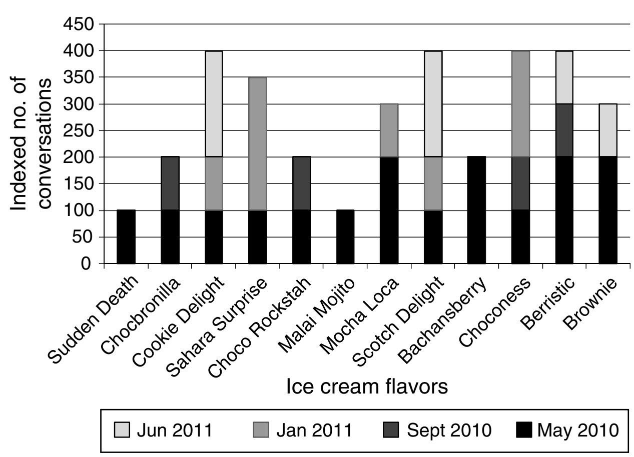


Figure 9 Overall Impact of the Research Study

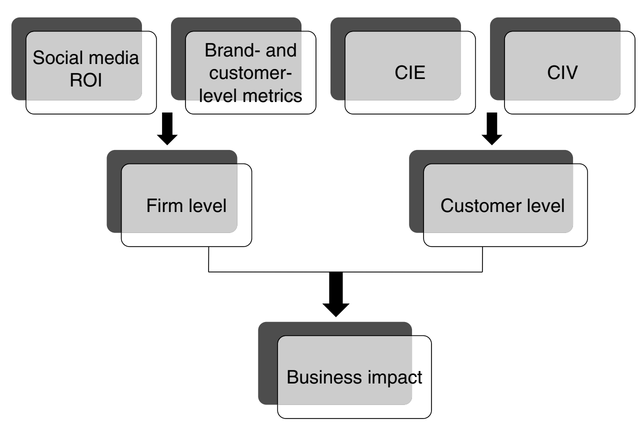
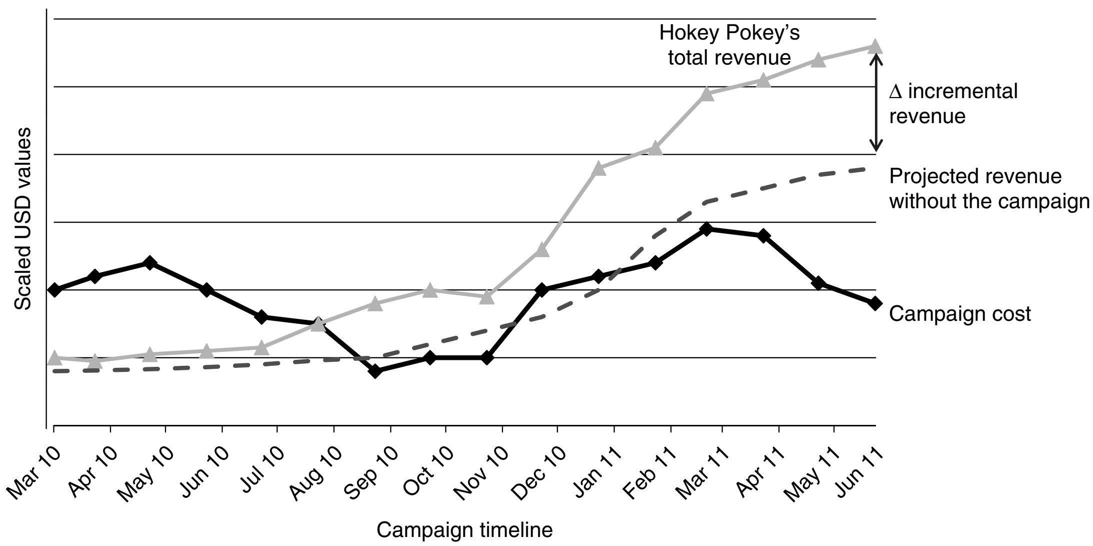


Figure 10 Performance Metrics at Hokey Pokey vs. Campaign Cost



through store-initiated social media conversations in an effort to increase their clout within the social networks. Finally, customers were incentivized for their CIV through discount coupons for creations that they could share with their friends in an effort to boost their popularity. The details of all the incentives given are provided in the handbook of campaigns, the link to which is provided in Web Appendix 1.

8.4. Social Media Performance vs. Cost of Investing

The performance metrics based on our strategy at Hokey Pokey are shown in Figure 10. The figure shows the difference in the projected revenue in the absence of the campaign and the actual revenue that was seen after implementing the campaign. The same comparsion is made for the costs that are incurred in the process. The incremental sales, profit, and ROI can be calculated as the change in profit divided by the campaign cost. The actual sales numbers are not displayed for privacy reasons.

The cost of our strategy included the cost of leasing the software to track the buzz in the social media, promotional material such as in-store posters, and printing and development costs in the creation of customer forms and training materials. The net revenue, after accounting for other factors, saw a lift of more than 10% during the initial implementation between March and June 2010. What we learned from this phase was instrumental in creating and implementing the above-mentioned subsequent strategy with the appropriate messaging structure between January and June 2011. This strategy has been instrumental in generating a sales lift exceeding 40% between January and June 2011. Because of lower recurring costs in our strategy, and the tendency of WOM to spread exponentially (Trusov et al. 2009), we see the increase in the ROI of social media strategy at Hokey Pokey to be 83% as of June 2011 and expect it to exceed even more by December 2011.

8.5. Social Media Campaign Results

The revenue obtained (in terms of ice cream sales) from Facebook and Twitter was benchmarked against the previous three years' metrics. Store-level sales were tied back to the corresponding social network, message, and influencer social graph through tracking tags and dynamically generated coupon codes. Of the total revenue from the second campaign, about 23% was attributable to conversations on Twitter, whereas about 80% was attributed to Facebook (with a 3%–8% overlap between the two social networks). Table 9 provides an overview of the metrics used

Table 9 Pre- and Post-Performance Metrics

	Nov 2008–Feb 2010	Mar 2010–Jun 2011	
	Pre-campaign	Post-campaign	Lift
Sales revenue growth rate (%)	X	$1.4X$	40%
Social media ROI	Y	$1.83Y$	83%
Growth in brand awareness	Z	$1.49Z$	49%
Number of positive WOM instances (per week)	8	276	33.5 times
Proportional sale of custom creations	5%	60%	11 times
Number of customers making more than two purchases per week	36	173	3.8 times

as key success indicators in our strategy, along with the recorded values before the start of the campaign (till February 2010) and post-campaign (March 2010–June 2011).

Increasing customer adoption of custom creations was critical for the viral spread of WOM as well as the Hokey Pokey brand. Through our campaign, the sales of "custom creations," as a proportion of total sales, increased from 5% to more than 60% following the second campaign, because positive WOM increased by 33.5 times, thereby proving that the campaign was a success.

In addition to sales, a few more key metrics were measured to gauge the progress of the campaign. Before the beginning of the campaign, ready-made creations dominated the number of creations made in each store in terms of the sales volume. Therefore, the proportion of sales of custom creations, as opposed to prebuilt ones, was used to measure the impact of the social media strategy on shaping consumer perceptions. To measure the off-line ripple effect of the campaign on the behavioral loyalty of customers, the number of customers, both on and outside the social media, who visited a Hokey Pokey store more often than twice a week was measured. The choice of two purchases per week was chosen because a smaller time frame could not sufficiently capture a significant number of repeat customers in the preliminary tests run before the campaign. Measuring a larger time frame would have required the use of special off-line loyalty instruments that could bias the social media research strategy.

Loyalty was also measured based on the consumer attitudes online. The number of instances of both positive and negative WOM was measured because Hokey Pokey did not have a focused online presence before the launch of the campaign. WOM instances were classified as positive or negative by the observers as well as by advanced natural language processing software that measured the sentiment of each WOM instance. The success rate in terms of all the different performance metrics can be seen in Table 9.

The proportion of sales of custom creations witnessed a significant transformation following the social media strategy, indicating that the customer perception was more closely aligned with the Hokey Pokey brand message. In terms of loyalty, the number of repeat customers significantly increased as a result of the campaign. With regard to the sentiment of WOM, our campaign shows a large volume of positive WOM being generated across almost all the campaign creations following the initial launch in March 2010 and being progressively consolidated to fewer creations being marketed by more influential customers.

9. Contributions to Academia and Practitioners

From a practitioner's point of view, the CIE and CIV metrics have many applications for a wide variety of firms. The current study describes the application of these metrics in the case of an off-line retailer, but online retailers can also utilize these metrics directly. For example, online retailers can allow their customers to sign in at their stores with their social network IDs from Twitter, Facebook, Google+, etc., and directly tie online customer influence to sales.

The current study also describes the application in a localized setting for a small business chain. The models can be directly extended to a larger global setting. Companies such as Dell and Zappos already have strong customer relationship management and ticketing systems tied to social networks. Therefore, measuring the impact of influence at the point of sale in such organizations is relatively easy. The contributions of this study to marketing academia and practitioners are summarized below.

1. *Simultaneous measurement of tangible and intangible value of social media*: The methodology proposed in this study to simultaneously measure *spread*, *influence*, and *impact* of social media conversations in terms of monetary gain is the first of its kind in the area of social media marketing and would equip marketers with knowledge of marketing in the social space. Marketers need to concentrate on both CIE and CIV to maximize their impact. CIE is the first step to identify the influencers, but the CIV metrics can be used to further optimize the campaign by allowing funneling of the most influencing customers.

2. *Market sensing*: For the first time, social media marketers have a tool that can be readily implemented as social platforms evolve toward openness. Between the beginning of this research and now, Facebook has already started opening user social graphs and currently provides sophisticated analytics to marketers at the aggregate level. The framework used in this study could be directly and easily applied in various social networks as it is scalable to most social networks.

3. *Accountability in social media marketing*: By measuring the value of social media in monetary terms, chief marketing officers can compare the ROI through social media with other traditional marketing vehicles and provide the boardroom with financial projections instead of abstract metrics such as engagement and hits. In the digital world, the accountability of social media spend would go a long way in strengthening marketing within the boardroom.

4. *Generalizable and scalable evaluation framework*: Though the analysis was done for Facebook and Twitter, we have ensured that our models are scalable and can be directly applied across any other online

social network. Furthermore, the proposed framework can be applied to any other retailer, whether the products and services are cocreated by the customer or merely spreading the word about movies or new products/services in any market globally, thereby providing the most generalizability. In conclusion, this study has armed marketing academia and practitioners with a robust methodology to measure the effectiveness of social media marketing expenditures and maximize the ROI of social media campaigns.

We also acknowledge that the goal of this paper is to implement a generalizable process for marketing strategy and not to consistently identify the specific underlying relationships.

10. Future Research Directions

Because the CIV model is relatively new, a significant stream of research is now open for academic understanding of WOM flow, as well as various application studies and field experiments useful to the industry. Subsequent studies in this domain may be directed toward the following: (a) Applications of social influences to the various industrial settings (business to business and business to consumer) and evaluation of variations in the degree of influence across domains. (b) How user characteristics such as the lifetime value of a customer affect the degree of influence, accounting for user-level heterogeneity, may open up a new research area. (c) Study related to the "memory" and "retention" of an instance of WOM. For example, how long does an instance of WOM continue to influence a receiver? (d) Modeling the degree of influence and the probability of reception from a host in to account for host-level heterogeneity effects. (e) Applying a game-theoretic framework to identify an optimal allocation of the degree of influence in both host–receiver and multihost scenarios in order to estimate optimal influence allocation strategies. (f) Whether the comments about the opinion leader and comments of the opinion leader are influential across different categories. (g) Analysis of the CIE and CIV metrics across different sectors and the determination of common drivers and natural impacts of WOM and social media marketing on the ROI.

Electronic Companion

An electronic companion to this paper is available as part of the online version at http://dx.doi.org/10.1287/mksc.1120.0768.

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Appendix. Measuring the Stickiness Index

We measure the SI between two vectors of words as the corresponding strengths of association between all possible pairs of keywords across two arrays. Specifically, the SI of a user refers to how specific the user is to a particular category of words, based on the association of the words between each other and with other words used by all users globally. For example, a user who has discussions about desserts, milkshakes, and floats is closely associated with discussions about ice creams.

SI is calculated based on semantic linkages of word-level interactions using natural language programming to understand the "context" of words. SI is calculated based on the probable association between an array of words, given a global association across word clouds as

$$\rho_{i,j} = \frac{M_{i \cap j}}{M_{i \cup j}},$$

where $\rho_{i,j}$ is the strength of association between keywords i and j, and M_σ is the global volume of occurrence of any keyword σ.

Therefore, we can use SI to identify how closely other keywords such as "dessert," "sundae," and "food" are associated with a focal keyword (in our case, ice creams). We evaluate stickiness for all possible word associations in the social network to obtain a vector of "concepts" or "categories," based on a real-time natural conversation:

$$\varphi_j = \sum_{i=1}^{n} \rho_{ji}\omega_i \quad \forall j \in [0, n],$$

where φ_j is the relative topical specificity about keyword j, and ω_i is the relative weight of keyword i.

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