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Abstract

Purpose – The purpose of this paper is to explore customer engagement in Twitter via data mining.

Design/methodology/approach – This study's intended contributions are twofold: to find a clear connection among customer engagement, presumption, and Web 2.0 in a context of service-dominant (S-D) logic; and to identify social networks created by prosumers. To this end, the study employed data mining techniques. Tweets about IKEA were used as a sample. The resulting algorithm based on 300 tweets was applied to 4,000 tweets to identify the patterns of electronic word-of-mouth (eWOM).

Findings – Social networks created in IKEA's tweets consist of three forms of eWOM: objective statements, subjective statements, and knowledge sharing. Most objective statements are disseminated from satisfied or neutral customers, while subjective statements are disseminated from dissatisfied or neutral customers. Satisfied customers mainly carry out knowledge sharing, which seems to reflect presumption behavior.

Research limitations/implications – This study provides partial evidence of customer engagement and presumption in IKEA's tweets. The results indicate that there are three forms of eWOM in the networks: objective statements, subjective statements, and knowledge sharing. It seems that IKEA successfully engaged customers in knowledge sharing, while negative opinions were mainly disseminated in a limited circle.

Practical implications – Firms should make more of an effort to identify prosumers via data mining, since these networks are hidden behind "self-proclaimed" followers. Prosumers differ from opinion leaders, since they actively participate in product development. Thus, firms should seek prosumers in order to more closely fit their products to consumer needs. As a practical strategy, firms could employ celebrities for promotional purposes and use them as a platform to convert their followers to prosumers. In addition, firms are encouraged to make public how they resolve problematic customer complaints so that customers can feel they are a part of firms' service development.

Originality/value – Theoretically, the study makes unique contributions by offering a synergic framework of S-D logic and Web 2.0. The conceptual framework collectively relates customer engagement, presumption, and Web 2.0 to social networks. In addition, the idea of examining social networks based on different forms of eWOM has seldom been touched in the literature. Methodologically, the study employed seven algorithms to choose the most robust model, which was later applied to 4,000 tweets.

Keywords Algorithms, Data analysis, Marketing theory, Customer service management, Communications technology, Social networks

Paper type Research paper

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Introduction

Company-customer interactions have been considered as a key organizational capability to pursue service-dominant (S-D) logic, where service acts as "the core purpose of exchange and provides a theoretical understanding of how firms, customers, and other market actors 'co-create' value through their service interactions with each other" (Karpen *et al.*, 2012, p. 21). S-D logic has been extensively discussed as an emerging concept in a diverse range of disciplines, including e-commerce (Wu *et al.*, 2013). However, one of the criticisms of S-D logic is the lack of empirical evidence in its actual implementation (Karpen *et al.*, 2012; Brodie *et al.*, 2011). In this light, this study focusses on one of the factors driving S-D logic: customer engagement. Customer engagement is defined as "a psychological state that occurs by virtue of interactive, co-creative customer experiences with a focal agent/object (e.g. a brand) in focal service relationships" (Brodie *et al.*, 2011, p. 260). We view customer engagement as a catalyst of S-D logic.

According to Kumar *et al.* (2010), some customers may exhibit greater value to a firm, compared with others, due to transactional (e.g. purchase frequency or average spending) and non-transactional (e.g. word-of-mouth or knowledge sharing) engagement behaviors.

The purpose of the study is to explore non-transactional customer engagement on brands' social networking sites (SNS). More specifically, the study examines how knowledge sharing contributes to the creation of consumer networks on the internet and how customers are engaged in "prosumption." Prosumption is a behavioral aspect of S-D logic and can be defined as "value creation activities undertaken by the consumer that result in the production of products they eventually consume and that become their consumption experiences" (Xie *et al.*, 2008, p. 110). To this end, this study employs data mining techniques to analyze messages posted in Twitter or tweets. A tweet is short (up to 140 characters) and simple, which accelerates the speed and accuracy of message classification. In addition, since users can retweet information from others, message circulation and sharing can be directly related to community creation. An increasing number of global brands consider the content of tweets to be absolutely critical for their branding strategy (GlobalWebIndex, 2013), while little research explores community relationships on Twitter via data mining (Ikeda *et al.*, 2013). Our research design is summarized in Figure 1.

Our intended contributions are twofold. First, there is an important lacuna in research on customer engagement in the context of Web 2.0. Web 2.0 can be characterized as interactive information sharing, interoperability, user-centered design, and collaboration (Campbell *et al.*, 2011). Since Web 2.0 enhances the openness and transparency of user-generated content (O'Reilly, 2007), global brands yearn for permanent, mutually beneficial interactions with their customers on the internet. Yet, in contrast with the rich source of literature on offline environments, customer engagement in online environments has been relatively understudied. In fact, our review of prior publications in *Internet Research* reveals that there are related topics, such as online brand community (Chang *et al.*, 2013), virtual communities (Lin and Huang, 2013), or global brands participation in SNS (Araujo and Neijens, 2012), but research on customer engagement or S-D logic as a main theme has been scarce (Chang *et al.*, 2013). Thus, our study serves as an important stepping-stone for our current knowledge. Second, more and more global brands adopt SNS in their customer relationship management. One of the reasons for this trend is the power of social media to foster customer engagement via active knowledge sharing. However, despite our social belief of the effects of SNS on customer engagement, little empirical evidence has been reported. Specifically, we strongly believe that the identification of engaged

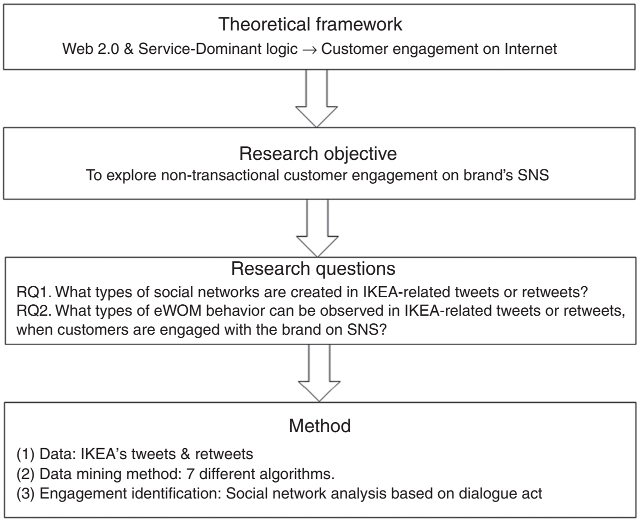


Figure 1.
Research procedure

customers who are willing to collaborate and participate in product development or service improvement is extremely useful for practitioners. Our study provides practical implications to marketers and advertisers as to what type of customer engagement they can achieve on Twitter.

In what follows, we first discuss the conceptual foundation that connects Web 2.0, S-D logic, and customer engagement in social media. Then, we explain our method, which is data mining, and discuss the results in detail. Finally, after recognizing important limitations, we draw research implications.

Conceptual background

Parallelism in the evolution of Web and marketing concepts

Advances in information and communication technology (ICT) have had a great impact on the evolution of marketing concepts. In Table I, we try to juxtapose the evolution of the Web and marketing concepts. In the past, with Web 1.0, firms used the Web only as an ICT tool, whose main advantage was the multimedia functionality that was uniquely different from traditional media. The interactive nature of Web 1.0 facilitated

	Internet		Marketing	
Timeline	Main concept	User tools	Main concept	Customer role
Mid-1990s	Birth and penetration of commercial Web	Static web sites e-brochures	Customer loyalty	Information receiver
Late 1990s	Web 1.0	Interactive environment	Relationship marketing	Information seeker
Mid-2000s	Web 2.0	Participative environment ↓	S-D logic/co-creation ↓	Value creator ↓
Late 2000s ↓ Present		Network creation/ engagement platforms	Social media marketing/customer engagement	Influential actor

Table I.
Parallelism between Web and marketing concept evolution

the development of fragmented relationships between producers and consumers, while allowing firms to increase the knowledge of their clients. However, it was not until Web 2.0 appeared that firms recognized the Web as a powerful tool in developing stable relationships with consumers. Web 2.0 emphasized the relational view of value creation and transformed this process by improving customer participation. Web 2.0 changed not only technical infrastructures, but also the power balance in the relationship between firms and their clients. Nowadays, consumers' empowerment through their participation in social networks facilitates co-creation activities. But the mere presence and establishment of friendships among users is not enough for successful Web 2.0 implementation. It is a participatory Web environment that enables firms to engage in a new form of interaction with their users.

Parallel to the development of Web 2.0, new marketing concepts emerged. Among them, S-D logic became particularly popular among academics and practitioners from the mid-2000s. Coincidentally, both terms, Web 2.0 and S-D logic, appeared in 2004 (O'Reilly, 2007; Vargo and Lusch, 2004). In S-D logic, prosumption-like behavior encompasses proactive and informed consumers who act as leading influencers, as well as market drivers. Prosumers are not mere opinion leaders – they not only ignite the chain of electronic word-of-mouth (eWOM), but also actively participate in value co-creation with firms. In other words, prosumers are those who "actively co-construct their own consumption experiences through personalized interaction, thereby co-creating unique value for themselves" (Prahalad and Ramaswamy, 2012, p. 12). They have grown more and more powerful in recent years, thanks to their skillful embrace of new technologies and, especially, social media. Through social media, prosumers tend to form a more complex social network, which reflects a higher degree of engagement with the firm. The creation of social networks should be viewed through the filter of value co-creation, as not all the ideas proposed by customers are equally interesting and not all customers are equally influential (Verhoef *et al.*, 2013).

In a more complex social network, prosumers may not only share information, but also criticize or question what the network members may be interested in or what the firm should be concerned about. In contrast, other customers may act as mere followers of those prosumers, which reflects a lower degree of engagement. Prior research corroborates that individuals differ in terms of psychological states and motivational levels for cognitive, emotional, and behavioral efforts, and thus exhibit different degrees of customer engagement (van Doorn *et al.*, 2010).

Customer engagement in social media

There is rich and interesting literature on Web 2.0 or S-D logic as separate topics, but only limited attention has been paid to their combined effects; in particular, on how S-D logic has been facilitated through the use of Web 2.0 (Karpen *et al.*, 2012). Using the evolutionary framework about the Web and marketing concepts in Table I, this study focusses on how firms are adopting social media in customer engagement.

Broadly defined, the term engagement refers to a psychological state and process that drives customer loyalty (Brodie *et al.*, 2013). In marketing, the underlying conceptual foundation of customer engagement lies in relationship marketing and S-D logic, which highlights the consumers' proactive contribution to value co-creation (Vargo and Lusch, 2008; Kasouf *et al.*, 2008; Brodie *et al.*, 2011). Brodie *et al.* (2011) argued that customer engagement reflects customers' interactive, co-creative experiences with other stakeholders in focal, networked service relationships. In other words, co-creation through customer engagement occurs when "the customer participates through spontaneous, discretionary behaviors that uniquely customize the customer-to-brand experience" (van Doorn *et al.*, 2010, p. 254). Since customer engagement is a form of social and interactive behavior, social networks serve as ideal platforms where consumers participate in prosumption – collaborative recommendations and development for specific products, services, and brands – through eWOM (Ramaswamy, 2009). For example, prior research suggests that Twitter directly impacts eWOM because it enables users to share brand-affecting thoughts with almost anyone who is online (Jansen *et al.*, 2009). Our conceptual framework is schematized in Figure 2.

In non-transactional customer engagement, eWOM offers value, since increased interpersonal influence on the brand reduces marketing costs and empowers the community to generate new ideas (Ramaswamy, 2009). This is especially relevant to SNS that facilitate not only interactive but also participatory consumer experiences. In the end, the effects of eWOM result in the creation of social networks.

The reason for eWOM being a value-creation behavior in non-transactional customer engagement may be drawn from social capital theory. Social capital theory proposes that "networks of relationships constitute a valuable resource for the conduct of social affairs" (Nahapiet and Ghoshal, 1998, p. 243). Social capital refers to a set of actual and potential resources embedded within, available through, and derived from the network of relationships possessed by an individual or social unit (Shanahan and Hopkins, 2007). There are structural, relational, and cognitive dimensions of social capital. The structural dimension covers the overall pattern of connections among individuals; the relational dimension means individuals' willingness to act together and build personal relationships; and the cognitive dimension refers to individuals' ability to act together and share meaning, understanding, and goals (Nahapiet and Ghoshal, 1998). Prior research suggests that eWOM involves all three dimensions and acts as a source of social capital (Hung and Li, 2007; José-Cabezudo and Camarero-Izquierdo, 2012). This means that eWOM indeed creates value.

On this basis, we argue that three forms of eWOM through social networks may reflect the creation of social capital: objective statements, subjective statements, and knowledge sharing. Objective statements are fact based, including information, questions, and replies/answers, which have frequently been employed in the analysis of tweets (de Maertelaere *et al.*, 2012; Kwon and Sung, 2011). Subjective statements are judgmental in nature, such as criticism or praise; in other words, positive or negative opinions (Kaiser and Bodendorf, 2012). Knowledge sharing is not a mere statement; the

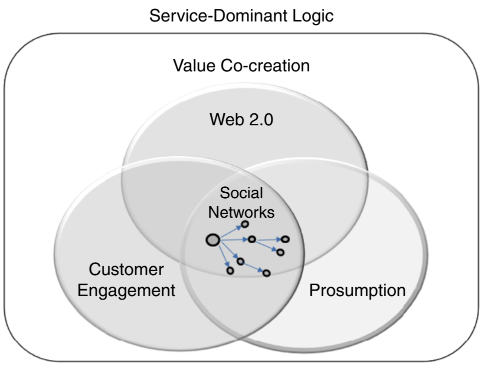


Figure 2. Conceptual framework

message is expected to be shared and circulated in public (Shu and Chuang, 2011), thus serving as a driver of social capital (Shanahan and Hopkins, 2007). We believe that the presence of knowledge sharing serves as an indicator of prosumers.

IKEA as the prosumer organization

This study chooses IKEA as an illustrative case for two reasons. The first reason is related to IKEA's customer-centric, value co-creation culture (Möller, 2006). IKEA requires consumers to transport and assemble furniture by themselves, because the company wants to reduce operational costs and pass on these savings to consumers by lowering prices (Kambil *et al.*, 1999). In doing so, IKEA has "reframed furniture manufacturing to involve the customer doing part of the production at a time after purchase versus the manufacturer doing it in a factory" (Lusch *et al.*, 2010, p. 25). In other words, IKEA has challenged the logic in the furniture business not only by re-allocating existent activities in the traditional value chain, but also by "constructing a new, coordinated set of activities resulting in a new kind of output – not just a more efficiently produced traditional output" (Normann, 2001, p. 107). Furthermore, IKEA offers total customer solutions by an "all under one roof" concept, in which the customers create, improve, and complete their living spaces (IKEA, 2005). In this way, IKEA tries to be the prosumer organization that enables customers to co-create value and act as co-producers (Edvardsson *et al.*, 2007). This is exactly what S-D logic proposes to serve.

The second reason why we envisage IKEA as ideal for our study is that it actively utilizes SNS as a value co-creation tool. IKEA seeks more and more virtual collaboration throughout its value network, in which their customers meet via the internet to work on projects. For example, IKEA Hong Kong uses Facebook to allow customers to customize the design of their own furniture pieces and puts their name on its products. Personalized items are then shared with their friends through their social networks. Such social experience ignites extensive eWOM: more than 27,000 pieces of furniture have been shared from more than 6,000 unique users delivering 3,640,000 stories in their fans' and friends of their fans' news feeds on Facebook (Spikes Asia, 2013).

Similarly, IKEA Spain organized a campaign where five celebrities designed five unique spaces with a limited budget using furniture featured in the new 2014 catalogue. These spaces were displayed in all IKEA stores throughout Spain. The objective of this campaign was to exemplify IKEA's value co-creation strategy – each celebrity tried to define his or her living environment with help from IKEA's experts, taking into account their preferences, needs, and lifestyles. On Facebook, IKEA's followers could send photos of the spaces proposed by the celebrities, which were shared with fans and friends of their fans. The campaign also had a hashtag (#empiezaalgonuevo), which served as a seed of eWOM and retweeted or mentioned the launch of the new catalogue. In fact, #empiezaalgonuevo has been one of the topics most talked about on Twitter in Spain (Trending Topic, 2013).

The above evidence illustrates that IKEA has adopted Web 2.0 to allow information to be exchanged for supporting social interaction and participation through SNS and thus can make a strong case for our data mining attempt. On this basis, we posit the following research questions:

RQ1. What types of social networks are created in IKEA-related tweets or retweets?

RQ2. What types of eWOM behavior can be observed in IKEA-related tweets or retweets, when customers are engaged with the brand on SNS?

Method

Data set collection

We collected 300 tweets for the data analysis. This was a non-probabilistic sample for the sake of simplicity, since our objective here was not a generalization of the results. These initial tweets were then preprocessed and normalized. In this process, we simplified or "cleaned up" the data through three main steps. In the first step, outliers, misclassifications, and missing values were eliminated. In the second step, the dimensionality of the data set was reduced through projections or feature selection techniques. Finally, in the third step, the range of all inputs was normalized.

Classification schemes

Our coding involved two sets of classification schemes. The first set of classification schemes was based on customers' emotional states: Satisfaction, Dissatisfaction, Neutral, and Exclude. Satisfaction has long been considered one of the most influential factors of customer loyalty and WOM (Brown *et al.*, 2007). Classifying satisfied and dissatisfied IKEA customers helped us to understand the content of tweets from the perspective of loyalty formation. We viewed Satisfaction-Dissatisfaction as a trichotomous scale, and anything unclear (the "gray zone") between the two extremes was classified as Neutral.

The second set of classification schemes was based on the dialogue acts: Sharing, Information, Opinion, Question, Reply, and Exclude. As discussed in our conceptual framework, we are mainly interested in three forms of eWOM, namely objective statements (Information, Question, and Reply), subjective statements (Opinion), and knowledge sharing (Sharing). In both classification schemes, Exclude encompassed anything irrelevant to our analysis – pointless jokes, ill-natured communications, or any commercial messages by the company itself or a third party.

Two human coders classified the tweets in two phases according to the pre-established classification schemes. In the first phase, each coder coded 30 tweets separately according to the emotional states. The results matched for all tweets. Then, the coders classified 100 tweets. After completing all coding, we measured inter-coder agreement. We then checked the discrepancies between the coders. They discussed their interpretations of conflicting results until a consensus was reached. If a consensus could not be reached, one of the researchers acted as a judge to arbitrate the conflicts. Cohen's κ coefficient was 0.96, which can be considered as almost perfect agreement. On this basis, the coders evaluated an additional 200 tweets.

In the second phase, each coder classified 30 tweets separately according to the dialogue act classes. The results matched for 28 tweets. The coders were asked to discuss the reasons for the discrepancies and resolve the conflicting results. Since the coders reached consensus, they were then asked to classify 70 additional tweets. There were several coding results that did not match between the coders. Employing the same procedure as in the first phase, we measured inter-coder agreement using Cohen's κ, which produced 0.95 on average. The coders discussed their interpretations of conflicting results and a consensus was reached. Thus, the coders were asked to assess 200 additional tweets.

Table II shows a cross-tabulation between the two classification schemes to draw a preliminary map. As the results clearly show, the percentage of Sharing is notably high, regardless of whether the customers' emotional state was Neutral, Satisfaction, or Dissatisfaction (16.7, 16.7, and 20.7 percent, respectively), while the next highest percentage is the combination between Information and Neutral (9.3 percent).

Algorithms

Based on this data set, the model was created to find patterns with machine learning techniques (Larose, 2005). In this study, we employed seven methods for our model generation. Naïve Bayes (NB) is based on Bayes Probability Laws and considers each feature independently of the rest (Domingos and Pazzani, 1997). Each feature contributes to the model information. K-nearest neighbor (KNN) classifies the element according to its neighbors. Depending on the K value, it considers the KNN and estimates the value of the data instance that is not classified (Cover and Hart, 1967). Decision trees C4.5 (C4.5) divides the data linearly using limits in the attributes and generates a decision tree. The division is chosen using a metric, such as the data entropy (Quinlan, 1993). Compared with its predecessor, the Iterative Dichotomiser 3, C4.5 avoids data over fitting and missing applicable data, while improving its efficiency of calculation (Chiang, 2012). Support vector machine (SVM) supervises learning the parameters of a function that allows the automatic classification of objects. This method usually changes the dimension of the search space through different kernel functions, while trying to improve the classification through a hyperplane separation of the data instances in the expanded space (Cortes and Vapnik, 1995). These four algorithms, NB, KNN, C4.5, and SVM, have been widely used in prior research on social media data mining (Kaiser and Bodendorf, 2012).

In addition, this study employs three more algorithms. Artificial neural networks (NN) are inspired by the process of natural neurons within the central nervous system. They define a neurons network divided in layers. There are three main kinds of layers – input (where the data is introduced), output (where the final class assignation is made), and hidden (where different calculus are made in order to improve the neural network results) (Bhadeshia, 1999). The uRules classification (R) is based on logic rules that generate a set of rules to classify the information according to them (Qin *et al.*, 2009). The Forest classification (F) is a hybrid method that incorporates the advantages of different tree classifiers (such as C4.5). This methodology trains the classifier and assigns a confidence value to each tree. This confidence value is used to reach an agreement between the different tree classifiers (Ho, 1995).

Classification evaluation

The classification evaluation requires the definition of the following concepts related to how an instance has been correctly or incorrectly classified (Esuli and Sebastiani, 2010). The following indexes are generally employed:

- True positive (tp): the instance has been correctly classified as part of the category.

Categories	Exclude	Information	Opinion	Question	Reply	Sharing	Total
Exclude	6.0	0.0	0.0	0.0	0.0	0.0	6.0
Neutral	0.0	9.3	5.0	3.0	0.3	16.7	34.3
Satisfaction	0.0	2.3	7.7	0.3	0.0	16.7	27.0
Dissatisfaction	0.0	1.3	6.7	3.7	0.3	20.7	32.7
Total	6.0	13.0	19.3	7.0	0.7	54.0	100.0

Note: In percentage of 300 tweets

Table II. Cross-tabulation between two classification schemes (percent)

- False positive (*fp*): the instance has been incorrectly classified as part of the category.
- True negative (*tn*): the instance has been correctly classified as not part of the category.
- False negative (*fn*): the instance has been incorrectly classified as not part of the category.

The measures of Precision, Recall, and F-Measure are defined as follows:

$$Precision = \frac{tp}{tp+fp} \tag{1}$$

$$Recall = \frac{tp}{tp+fn} \tag{2}$$

$$\mathrm{F}-Measure = 2\cdot\frac{Precision\cdot Recall}{Precision+Recall} \tag{3}$$

Precision is used to measure the situation when an instance that does not belong to the category set is classified as part of the category set. Recall measures the situation when an instance is correctly classified according to its category. The F-Measure is a metric that balances these measures.

Results

Model validation

In order to determine the best classification results, we compared various model validation strategies. For each classification scheme, we applied five different models with the seven algorithms. In each model, we calculated the F-Measures for each classification scheme for a comparative purpose. Model 1 was generated by 200 tweets with the cross-fold validation. The cross-fold validation avoids over fitting during modeling. Model 2 used the same procedure with 300 tweets. In Model 3, a model was first created and trained with 100 tweets and then tested with 200 tweets. Similarly, in Model 4, a 100-tweet model was first generated and trained, then applied to 300 tweets. Finally, in Model 5, a 200-tweet model was created and tested with 300 tweets. The results indicate that the 300-tweet model (Model 2) produced the best classification results.

Cross-validation

Table III summarizes the results of the first classification scheme (customers' emotional states: Satisfaction, Dissatisfaction, Neutral, and Exclude) via the seven methods with 300 tweets using a fivefold cross-validation. The cross-validation was used in an attempt to avoid over fitting of the model. Overall, the best classification method was NB, which achieved good results for all the categories. The F-Measures ranged from 0.33 to 0.53, indicating reasonable learning. As for Satisfaction, KNN, NN, and F obtained better results (F-Measures = 0.55, 0.55, and 0.56, respectively), but the classification of Neutral and Dissatisfaction were worse in these methods.

Technique	Class	Precision	Recall	F-measure
NB	Exclude	0.385	0.294	0.333
	Neutral	0.44	0.463	0.451
	Satisfaction	0.513	0.551	0.532
	Dissatisfaction	0.424	0.391	0.407
KNN	Exclude	0.8	0.118	0.205
	Neutral	0.414	0.379	0.396
	Satisfaction	0.435	0.757	0.553
	Dissatisfaction	0.636	0.219	0.326
C4.5	Exclude	0.346	0.265	0.3
	Neutral	0.382	0.442	0.41
	Satisfaction	0.402	0.458	0.428
	Dissatisfaction	0.286	0.188	0.226
SVM	Exclude	0	0	0
	Neutral	0.323	0.747	0.451
	Satisfaction	0.443	0.252	0.321
	Dissatisfaction	0.263	0.078	0.12
NN	Exclude	0.929	0.382	0.542
	Neutral	0.4	0.316	0.353
	Satisfaction	0.421	0.794	0.55
	Dissatisfaction	0.889	0.125	0.219
R	Exclude	0	0	0
	Neutral	0.407	0.347	0.375
	Satisfaction	0.405	0.813	0.54
	Dissatisfaction	0	0	0
F	Exclude	0.846	0.324	0.468
	Neutral	0.42	0.442	0.431
	Satisfaction	0.445	0.757	0.561
	Dissatisfaction	0.8	0.063	0.116

Notes: NB, Naïve Bayes; KNN, K-nearest neighbor; C4.5, decision trees C4.5; SVM, support vector machine; NN, artificial neural networks; R, uRules; F, Forest. Based on 300 tweets with cross-fold validation

Table III.
Model generation results of the first classification scheme

Table IV shows the results of the second classification scheme (dialogue acts: Sharing, Information, Opinion, Question, Reply, and Exclude) with the same procedure as the one used for the first classification scheme. Again, the classification method NB achieved the best results in terms of Information, Sharing, and Opinion, while NN better classified Exclude than the other methods. For all classifications, the F-Measure was zero for Reply, since no instance was found in the data set. For the similar reason, the F-Measure for Question was also low.

Social network analysis

The best classifier based on NB was applied to a similar data set containing 4,000 tweets. Using this information, we performed social network analysis. An increasing number of behavioral and social scientists have applied social network analysis to detect interaction patterns among users (Kaiser and Bodendorf, 2012). The networks were created using the users as nodes and the retweets and mentions as their relationships. The analysis of the networks focussed on the identification of influential actors. These actors were those users whose opinions were easily propagated through the networks.

Technique	Class	Precision	Recall	F-measure
NB	Exclude	0.526	0.303	0.385
	Information	0.387	0.375	0.381
	Sharing	0.677	0.813	0.739
	Opinion	0.444	0.444	0.444
	Question	1	0.143	0.25
	Reply	0	0	0
KNN	Exclude	0.167	0.03	0.051
	Information	0	0	0
	Sharing	0.479	0.899	0.625
	Opinion	0.414	0.148	0.218
	Question	1	0.143	0.25
	Reply	0	0	0
C4.5	Exclude	0.44	0.333	0.379
	Information	0.387	0.375	0.381
	Sharing	0.667	0.82	0.735
	Opinion	0.5	0.444	0.471
	Question	0	0	0
	Reply	0	0	0
SVM	Exclude	0.5	0.333	0.4
	Information	0.37	0.313	0.339
	Sharing	0.611	0.77	0.682
	Opinion	0.452	0.407	0.429
	Question	0.667	0.143	0.235
	Reply	0	0	0
NN	Exclude	0.48	0.364	0.414
	Information	0.333	0.094	0.146
	Sharing	0.6	0.928	0.729
	Opinion	0.319	0.185	0.234
	Question	0.75	0.214	0.333
	Reply	0	0	0
R	Exclude	0.2	0.121	0.151
	Information	0.243	0.281	0.261
	Sharing	0.581	0.906	0.708
	Opinion	0.269	0.086	0.131
	Question	0	0	0
	Reply	0	0	0
F	Exclude	0.364	0.242	0.291
	Information	0.273	0.094	0.14
	Sharing	0.594	0.935	0.726
	Opinion	0.37	0.21	0.268
	Question	1	0.143	0.25
	Reply	0	0	0

Notes: NB, Naïve Bayes; KNN, K-nearest neighbor; C4.5, decision trees C4.5; SVM, support vector machine; NN, artificial neural networks; R, uRules; F, Forest. Based on 300 tweets with cross-fold validation

Table IV.
Model generation results of the second classification scheme

The algorithm PageRank was used for this analysis (Brin and Page, 1998). PageRank is a link analysis algorithm initially used by the Google Web search engine. By assigning a numerical weight to each element of a linked set of nodes (which in the original implementation was thought of as a hyperlinked set of Web pages, such as the World Wide Web), PageRank measures the importance of each node within the graph in terms of the extent to which a node contributes to the flow of information exchange with the other nodes. The numerical weight assigned to each node, n_i, is referred to as the PageRank value of n_i, denoted by $PR(n_i)$.

The PageRank algorithm is an iterative algorithm, which recurrently calculates the following values:

$$PR(n_i) = \frac{1-d}{N} + d \sum_{n_j \in M(n_i)} \frac{PR(n_j)}{L(n_j)}$$

$PR(n_j)$ is the PageRank value of node n_j, d is the damping factor used to adjust the algorithm, N is the number of nodes, $L(n_j)$ is the number of out-bound links to node n_j, and $M(n_i)$ is the set of nodes with in-bound links to n_i. This algorithm is usually solved using an algebraic process or an iterative process. In addition, when the iterative process is used, the PageRank values are usually normalized.

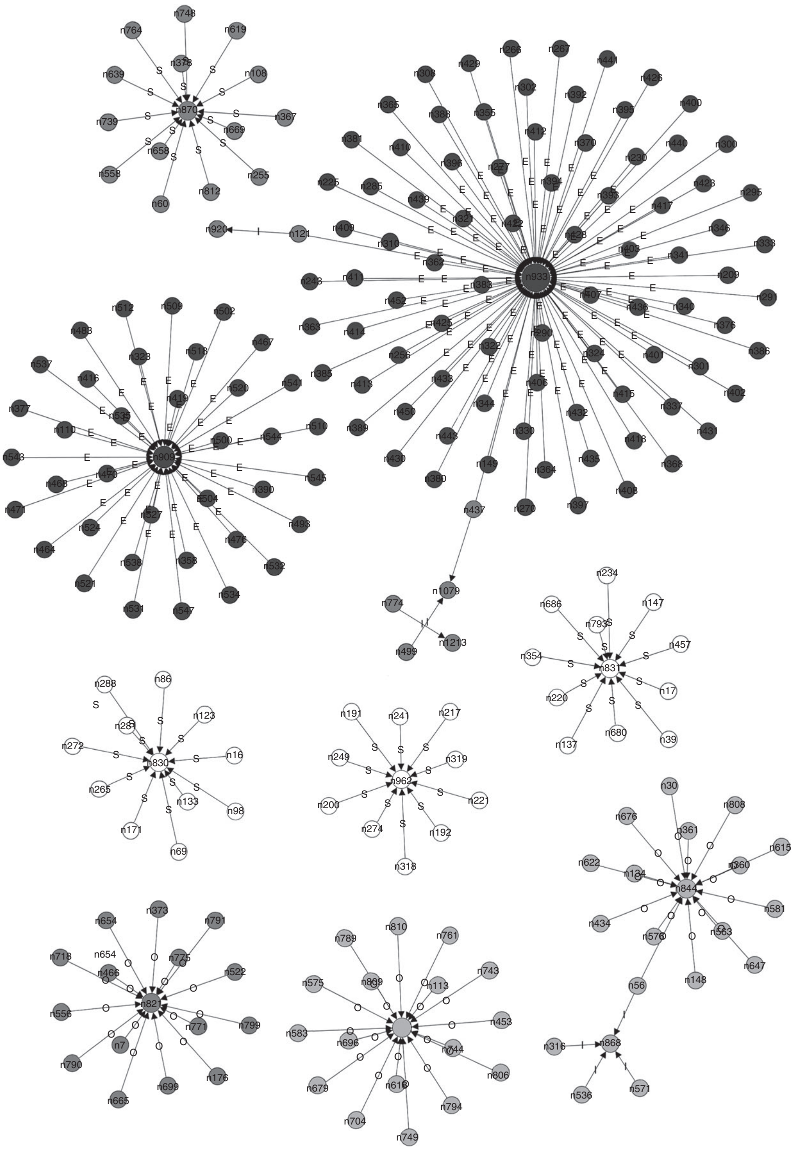
In response to our *RQ1* that addresses the types of social networks created in IKEA-related tweets or retweets, Figure 3 shows part of the social networks based on the 4,000 tweets and retweets data set. The arrows represent those users who retweeted or mentioned other tweets.

These social networks indicate the users' eWOM patterns. The most prominent category was Exclude. However, this category usually contained pointless tweets, jokes, or publicity from a third party (e.g. promotions, PR, event news). Sharing usually originated from satisfied customers, while Opinions resulted from dissatisfied customers. Neutral tweets accounted for the highest percentage in the networks, as well as those engaged in Information, Sharing, and Opinion, in that order. In contrast, neither Question nor Reply was identified after the model application.

Our *RQ2* explores what types of eWOM behavior can be observed in IKEA-related tweets or retweets when customers are engaged with the brand on SNS. According to PageRank, there were two users (in our original data set, #933 and #909) who most actively participated in the information transmission. However, these users belonged to Exclude, thus were not the prosumers we defined. Among others, three users were actively engaged in Sharing (#962, #830, and #831), all of whom were considered satisfied customers. With regard to Sharing, these users experienced something positive or favorable about IKEA and were willing to share their feelings or thoughts with the other users. In light of our theoretical framework, this category corresponds to knowledge sharing, which could potentially lead to prosumption behavior. In contrast, Opinion represents subjective statements that could be positive or negative. In fact, we also found three users (#821, #844, and #912) who were dissatisfied and tried to disseminate an unfavorable Opinion. Finally, there was only one important Neutral user (#870) who actively engaged in Sharing.

Limitations

To make our findings more objective, we should recognize a few limitations. First, the study examined only one brand, IKEA. Future research should examine a wider range of brands to increase the generalizability of the findings. Second, the study proposed three forms of eWOM. Yet, we may need to refine this classification to capture more detailed communication patterns in tweets. Third, this research chose to ignore pointless jokes or comments that were irrelevant to our study purpose. However, it



Notes: The color of the node represents a cutomer's emotional state. The color of the edge represents the form of eWOM. The size of the node represents its improtance, according to the PageRank algorithm.
Edge: E, Exclude; I, Information: S, Sharing; O, Opinion; Q, Question; R, Reply.
Nodes: ▭ = Satisfaction; ▭ = Dissatisfaction; ▭ = Neutral; ▭ = Exclude

Figure 3.
Social networks based on the 4,000 tweets and retweets data set

might be interesting to explore what motivates these types of tweets or retweets (e.g. culture, demographics, and product). There may be hidden reasons behind these comments, as the amount of Exclude was so overwhelming.

Implications

This study intended to capture evidence of customer engagement in social networks. Data mining was applied to tweets about IKEA. Based on the findings, we offer several important theoretical and managerial implications.

Theoretical implications

First and foremost, this study is a pioneering attempt to explicitly relate Web 2.0 to S-D logic. Although value co-creation in the context of SNS has attracted considerable interest from both scholars and practitioners, the number of empirical explorations has been somewhat limited. Theoretical juxtapositioning of marketing concepts and Web evolution (Table I) pinpoints important overlaps between the two disciplines, justifying our rationale for the present research. Our study strengthens a commonly stated social belief that social media indeed serves as an interactive and participative environment where customers actively engage in value co-creation.

Next, this study envisages customer engagement as a catalyst of S-D logic and proposes three forms of eWOM as a reflection of non-transactional customer engagement. Our findings indicate that the social networks created by IKEA's followers seem balanced in terms of Opinion and Sharing. As for Opinion, dissatisfied customers deposit their negative experiences but without any explicit intention to disseminate or circulate. On the other hand, satisfied customers are willing to share their positive experiences with others. From our view, not only positive but also negative experiences provide credibility to the "dialogues" in the social networks.

This observation may hold a key to understanding why customer engagement is important in terms of social capital. As we reviewed in the conceptual framework, social capital is created though eWOM. Popular SNS, such as Twitter, may offer relational and cognitive dimensions of social capital where customers develop their willingness as well as their capability to act together, build personal relationships, and share meaning. It makes more sense to think that satisfied customers may be able to leverage what they share through eWOM in a more effective way. The main contribution of this sharing is the value co-creation. However, in order to take advantage of the value they offer, firms also need to participate in the dialogue taking place in social networks.

Despite the danger of oversimplification, we argue that our study hints at the possible existence of prosumers. According to the definition, prosumers are proactive and informed consumers who act as leading influencers and market drivers. Our findings suggest that there are IKEA customers who act as "nodes" and actively share their own consumption experiences through eWOM. This seems to be a prosumption-like behavior. Although the terms may inherently sound synonymous to opinion leaders, prosumers are the buyers who create products for their own consumption (Xie *et al.*, 2008). Our interpretation is that in such spontaneous SNS as Twitter, customers may retweet comments associated with the brand to obtain quicker feedback so that they can improve their future consumption experience.

Managerial implications

Our results indicate that in IKEA's social networks, there are two types of customer engagement. The first type relates to the transmission of value co-creating statements where customers provide others with their positive experiences as users (Sharing) or their objective information of the brand (Information). This type of customer engagement enhances pro-firm attitudes in the social network, which could eventually develop customer loyalty. In contrast, the second type of customer engagement relates to the transmission of ill-natured statements where customers provide others with negative opinions about the brand (Opinion).

Prior research finds that the "self-proclaimed" friends and followers in Twitter do not show actual interactions among people. Huberman *et al.* (2008) identify two different types of networks: (a) a very dense network consisting of followers and followees; and (b) a sparser and simpler network of actual friends. They claim that type (b) is a more influential network in Twitter, because "users with many actual friends tend to post more updates than users with few actual friends." Accepting the danger of overinterpretation, we argue that what we found in our study might correspond to this type of network. Those consumers involved in these networks are truly engaged customers who trigger co-creation, but are hidden and need to be discovered beyond "hashtag" and "followers."

For this reason, firms are strongly encouraged to use data mining techniques and identify prosumers in their online environment. Since prosumers are proactively engaged in collaboration and participation in the product development, firms could take great advantage of the process in that customer needs could be directly reflected on the product design, features, and presentations. In addition, prosumers are also energetic endorsers of positive feedback, thus firms could leverage the power of eWOM. This would provide firms with an enormous advantage in market competitiveness and brand loyalty.

It is important to note that prosumers significantly differ from opinion leaders. Opinion leaders are willing opinion givers with profound knowledge and interests in particular products (Chan and Misra, 1990), while prosumers are willing collaborators in product development. In other words, opinion leaders are not necessarily a part of the product development process, but prosumers are. However, while the role of opinion leaders in SNS has frequently been examined (e.g. Kaiser and Bodendorf, 2012; Ko *et al.*, 2008), the portrayal of prosumers on the internet has been only anecdotic or sketchy.

In this light, one of the realistic strategies for firms to increase prosumers may be the use of celebrities. Celebrities are often used for an endorsement purpose, but firms should pay closer attention not only to their testimonial or decorative role, but also to their followers. Firms should find ways to convert these followers into prosumers and provide opinions and advice or encourage them to be involved in the product development process. Probably, firms could offer attractive giveaways or incentives to participate in customer feedback that would be directly connected to the product development process. In this way, firms could use celebrities as endorsers in a double sense – for the product and for the prosumers.

With regard to the second type of customer engagement or ill-natured statements, dissatisfied customers who post opinions tend to be emotional and upset about their experience. In a sense, they are judgmental and critical, even though their complaints may be based on an exceptional case or a merely anecdotal incident. These types of opinions may seriously harm a firm's value co-creation and thus need to be taken care of as soon as possible. In other words, firms should not only carefully monitor, but also examine and analyze what is being said about their brands in social networks so that satisfied customers' ability to produce goodwill are not be interrupted, muddled, or damaged by dissatisfied customers. Perhaps a firm could occasionally intervene in retweets to diffuse the situation and propose actionable solutions for those customers who claim to have had unfavorable experiences.

In this regard, firms could use Twitter to make public (or even blogcast) how they resolve complaints or problems for unsatisfied customers. Such a process of problem solution could serve as an opportunity to demonstrate their commitment to improving service quality and customer satisfaction. In doing so, firms may want to ask those unsatisfied customers to participate in and collaborate with the problem solution process. This may lead to a service recovery paradox – a good recovery solution would produce a situation in which a customer's post-failure satisfaction exceeds pre-failure satisfaction (De Matos *et al.*, 2007). Showing how angry and frustrated customers could turn into loyal customers is an excellent example of negative Opinion handling, which could ultimately lead to post-failure customer engagement.

This turns our attention to the issue of customer loyalty. The fact that satisfied customers are willing to share their positive experiences means that their loyalty to the brand will be greater after they share. This might imply that IKEA's Twitter networks could serve as a platform to enhance customer loyalty, and thus the firm should integrate Twitter into their loyalty program. However, this question as to whether Twitter could enhance customer loyalty goes far beyond the scope of the current study, and requires further investigation in the future.

Conclusion

This study seeks to create more synergy between marketing and internet research by making a case for Twitter use by IKEA's customers. Applying data mining techniques, we classified customers' emotional state and dialogue acts. Based on these classifications, we performed social network analysis. Our intent to seek prosumers in terms of active customer engagement via eWOM was successful: we learned that satisfied customers tend to share their favorable experiences with others, and we discovered distinct nodes with active eWOM activities. Our interpretation is that these nodes – identified by social network analysis via PageRank – can be prosumers who actively participate in value co-creation with IKEA. While our study examined only one firm with a limited number of tweets, our findings may serve as an interesting stepping-stone for future research on customer engagement in Twitter.

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