Decision Support Systems 67 (2014) 21–29

Contents lists available at ScienceDirect

Decision Support Systems

journal homepage: www.elsevier.com/locate/dss

Finding disseminators via electronic word of mouth message for effective marketing communications

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ARTICLE INFO

Article history:
Received 1 October 2013
Received in revised form 18 June 2014
Accepted 22 July 2014
Available online 7 August 2014

Keywords:
Opinion leader
Electronic word-of-mouth
Online user reviews
Marketing communication

ABSTRACT

It has become increasingly important for companies to utilize electronic word of mouth (eWOM) in their marketing campaigns for desired product sales. Identifying key eWOM disseminators among consumers is a challenge for companies. WOM is an interpersonal communication in which a sender spreads a message to receivers. Previously, researchers and practitioners have searched for opinion leaders by examining senders and receivers due to limited records on WOM message. Our study identifies three types of opinion leaders through eWOM using a message-based approach that elicits more accurate and comprehensive information on opinion leadership than sender-based and receiver-based approaches. We demonstrate that eWOM of opinion leaders drives product sales due to their product experience and knowledge background. Our findings suggest that companies can increase product sales via effective use of eWOM of such opinion leaders. Managerial and marketing implications are addressed.

1. Introduction

When HTC introduced the Windows-based smartphone, it recruited 1000 T-Mobile or AT&T customers to write product reviews and Facebook and Twitter posts, reaching more than 234,000 consumers and significantly increasing the brand awareness [12]. When Dunkin' Donuts launched Latte Lite, it used 3000 consumers to spread the word about the new beverage, reaching 111,272 consumers over twelve weeks and increasing sales by 26% in test markets [13]. Both examples illustrate that electronic or online word of mouth (eWOM) has become an important factor in consumer buying decisions [37]. Consumers trust eWOM more than advertisements, as they regard their peers as more reliable than companies [65]. As such, companies receiving favorable eWOM have a better chance to increase sales [21]. Although eWOM is implemented by consumers, companies can initiate eWOM campaigns for marketing communications [35]. To launch an effective eWOM campaign, companies need to identify a small number of disseminators known as opinion leaders who exert personal influence upon other people [68]. The challenge is: How can companies choose eWOM opinion leaders from ecommerce sites?

Identification of opinion leaders relies on the "two-step flow of communications" theory: as senders, opinion leaders cultivate their knowledge from a variety of sources including mass media in the first step, and then spread their opinions (messages) to the general public (receivers) via WOM in the second step [47]. Thus, sender, message, and receiver are key components in the WOM process [6,20], and provide three important bases for searching for opinion leaders. Information on WOM content (i.e., message) has generally been unavailable to companies in the past because interpersonal communication such as a chat between friends leaves no record for analysis [20]. As a result, researchers turn to senders and ask whether they really are opinion leaders by a questionnaire survey [50]. However, a survey may capture self-confidence rather than opinion leadership for two reasons [61,68]. Firstly, consumers often have no clear sense of the possible influence of their opinions. Secondly, they tend to overstate influence due to strong confidence in their own opinions.

An alternative identification approach, the network structure approach, examines how many receivers a sender can reach. The network structure approach can identify senders who are highly connected with receivers in a social network [41]. While the network structure approach avoids overestimation issues by using objective measures, it may underestimate opinion leadership. The network structure approach also requires knowledge on consumers' social networks that are often private information [5,43]. Moreover, even when companies acquire information about consumers' social networks, consumers' influence over strangers outside their social networks in an online setting is difficult to determine. Therefore, the network structure approach is not suitable for identifying eWOM opinion leadership. Unlike traditional WOM, eWOM leaves digital records on the Internet, and therefore provides companies with accessible information [20].

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http://dx.doi.org/10.1016/j.dss.2014.07.006

Since message is a key component in the original theory by Katz and Lazarsfeld [47], we wonder: Can companies explore the rich information contained in eWOM message to identify opinion leaders? If so, can companies use such opinion leaders as disseminators to launch effective marketing campaigns via their eWOM?

In this paper, we introduce a new message-based method to measure opinion leadership from eWOM. By using objective measures available from online user reviews, we identify three influential disseminators for products with qualities difficult to access before consumption (experience products). The first type is communicative opinion leaders who write a large number of reviews. The second type is buzz-generating opinion leaders whose online reviews generate contagious talk about a brand, service, product, or idea [11]. The third type is trustworthy opinion leaders whose online reviews are useful to fellow consumers. Practitioners are using eWOM to identify opinion leaders: for example, Amazon publishes the top 10,000 reviewers on its website. Although the exact ranking method is a secret, communicativeness and trustworthiness are reported to be important factors [66]. However, empirical evidence that such opinion leaders have effects on product sales is absent in the literature.

To understand if opinion leaders identified by the message-based approach can be used as disseminators to launch effective marketing campaigns, we examine the effects of opinion leaders' eWOM on product sales. Building upon the literature on eWOM created by the general public, we suggest that companies focus on two aspects of opinion leaders when developing eWOM marketing communication campaigns: product experience and knowledge background. For product experience effects, we study opinion leader eWOM's impact on sales in terms of product popularity/awareness, customer satisfaction (for quality assurance), and horizontal product differentiation. For knowledge effects, we examine whether sales can be affected by the breadth and focus of opinion leaders' product knowledge. Our findings reveal that opinion leaders' eWOM drives product sales due to their product experience and product knowledge, which suggests that companies can increase product sales via effective use of eWOM of opinion leaders.

This paper is organized as follows. In Section 2 we present our literature review and hypothesis. We then discuss data and modeling in Section 3 and present the empirical results and managerial implications in Section 4. Section 5 concludes and addresses the limitations of this study and future research directions.

2. Literature review and hypothesis development

Opinion leader WOM has long been used to promote products or to criticize competitors' offerings [44,47]; its positive impact on new product introduction was first reported by Arndt [3]. In recent years, online social networks and social media platforms have further helped the spread of eWOM. What sets eWOM apart from traditional WOM is the combination of (1) unprecedented scale, (2) the possibilities for eWOM designers to control and monitor eWOM operation, and (3) unique properties of online interaction [26]. One of the most important capabilities of the Internet is interactive communication at a larger scale: "for the first time in human history, individuals can make their personal thoughts, reactions, and opinions easily accessible to the global community of Internet users", and the interactive communication provides an online feedback mechanism to serve multiple functions, including brand building and customer acquisition, product development and quality control, and supply chain quality assurance [26].

Electronic commerce performs better than the traditional market in acquiring customers [77]. One advantage of electronic commerce is the availability of eWOM. Consumers read eWOM for several reasons: (1) to obtain buying-related information, (2) to achieve social orientation through information, (3) to have a sense of belonging to a community, (4) to gain financial reward, and (5) to learn to consume products. However, their main purpose is to save decision time and to make better decisions [40]. For such reasons, companies are interested in providing eWOM as "free sales assistance" [18]. In order to identify key eWOM disseminators, companies need to understand why review writers post their opinions, and prior research suggests the following reasons: (1) to add value to community by helping others (focus-related utility), (2) to seek advice from other community members after purchasing (consumption utility), (3) to gain approval from other community members (approval utility), (4) to moderate consumer interaction with other consumer and companies (moderator utility), and (5) to balance their emotions through expressing their opinions (homeostase utility) [39].

2.1. Identifying opinion leaders using eWOM message

To be effective in viral marketing campaigns, companies must identify opinion leaders properly and then let them communicate information to their followers [43]. Opinion leaders are consumers who provide information to others that influences their consumption decisions [22] by obtaining key information through research and shaping their own opinions earlier than the general public. Opinion leaders in women's fashion, for example, acquire fashion knowledge from fashion magazines first and then spread it to followers via WOM [70].

Rogers and Cartano [68] summarize three methods of identifying opinion leaders: (1) the self-report method, i.e. using surveys to ask consumers to identify whether and to what extent they are opinion leaders; (2) the key informant method, i.e. using surveys to ask consumers whom they listen to; and (3) the network structure method, i.e. using social networks to compute network centrality and other network structure-related measures. The first two methods are sender-based and the third is receiver-based. The self-report method seems to be most popular due to existing scales such as King and Summers' [50], although the key informant method has also been used in a recent study [59]. In addition, consumer demographics [1] and loyalty [35] are considered in conjunction with surveys to identify opinion leaders. The main findings of the extant literature are that self-reported and peer-nominated opinion leaders influence the choices of their followers. However, self-reported surveys may capture self-confidence rather than opinion leadership [2,42]. Rogers and Cartano [68] noted that sender-based surveys are "dependent upon the accuracy with which respondents [senders] can assess and report their self-images on opinion leadership". Both self-report and peer-nominated methods share survey biases such as inconsistent interpretation of survey questions and recall inaccuracy, which can lead to overestimation or underestimation of the degree of opinion leadership [24]. Recall inaccuracy bias is a particular issue because consumers receive eWOM from a large number of strangers on the Internet.

The network structure method has been widely used by marketers and network analysis researchers [41,43]. Network analysis determines opinion leaders by identifying those who connect with many people (i.e., hubs) and those who connect two clusters of densely connected people (i.e., bridges) in a social network [41]. However, other researchers suggest that impact of WOM is driven by a large number of easily influenced people rather than by opinion leaders [74]. The receiver-based approach is built upon the argument that opinion leaders spread word of mouth via their personal influence networks [67]. Since the advent of the Internet in the 1990s, WOM is no longer restricted to personal influence networks because the Internet allows one to reach strangers at a larger scale [26]. While individuals can arguably expand their social network to include the strangers, Dunbar's number (150) suggests a cognitive limitation in the number of social relationships that people can maintain [30]. Existing evidence suggests that the Internet does not remove the cognitive/biological constraints on human communication [36]. As noted by Weimann and colleagues, the network structure method "works best in a closed, self-contained social setting, such as hospitals, prisons, or army bases" [75]. However, a defining feature of eWOM is its potential to reach large numbers of strangers outside a sender's own social network [26]. Our method is therefore not restricted to a sender's social network, and can capture the influence of opinion leadership outside a given social network.

In this paper, we identify opinion leaders through eWOM by using a dataset of Amazon user reviews and product sales rank. The dataset is described in the following section. In order to determine key eWOM opinion leaders, we consider three attributes of Amazon online user reviews: the number of reviews a reviewer has written, the amount of buzz a reviewer has generated, and the trustworthiness of a reviewer.[2]

In the original voting study that introduced the concept of "opinion leader", Lazarsfeld and colleagues wrote that opinion leaders "were the interested, highly articulate voters who gave political advice or even tried to convert other citizens" [52]. Thus, a key behavior of eWOM opinion leaders is their ability to communicate with other consumers about their product experience [28]. The reasons for communication can be either altruistic or self-serving: to help consumers and companies sell products [72] or to reduce opinion leaders' emotional tension when they feel strongly about a product [28]. In their survey which became the basis for sender-based methods, King and Summers [50] ask consumers whether they like to talk to their friends (Item 1 in their scale) and similar questions (Items 3, 5, and 6). In this paper, we measure opinion leaders' communicativeness by observing their reviews on multiple products over time. By counting the number of reviews a consumer posts, we can identify the most communicative opinion leaders.

A second characteristic of eWOM opinion leaders is that their eWOM reaches a large number of consumers and thus creates buzz. Godes & Mayzlin [35] adopted the King and Summers scale to measure how many followers an opinion leader reaches. Item 4 in the Godes & Mayzlin scale asks: "During the past six months, I have told ____ about [product] category (7—no one to 1—a lot of people)". Buzz is generated around a product when a large number of followers receive eWOM [11, 31]. Previous studies suggest that opinion leaders are progressive attention-seekers [70] and fulfill their self-enhancement motivation via buzz creation [33]. The reviews written by buzz-generating opinion leaders can increase product/brand awareness among followers, which benefits sales whether the buzz is positive or negative [7]. We thus identify buzz-generating opinion leaders as consumers whose reviews spark the most interactions among other consumers.

A third characteristic of eWOM opinion leaders is that their eWOM is a trusted source that provides helpful information. Trust is an important issue in electronic commerce and eWOM studies (e.g., [26,80]), as it is one of the main reasons for followers to seek advice from opinion leaders. Although an expert in a broadcast knows more about voting than the average citizen, followers "can trust the judgment and evaluation of the respected people among their associates" [52]. For example, the dual-process theory suggests that consumers find information from trustworthy sources more persuasive [15,64]. King and Summers [50] measure this characteristic by asking (Item 7): "Do you have the feeling that you are generally regarded by your friends and neighbors as a good source of advice about [products]?" In the offline world, WOM is spread through consumers who know each other, such as friends and neighbors; in an online setting, eWOM is disseminated freely among strangers. Manipulating online user reviews is a known phenomenon [62], which makes it important for consumers to receive eWOM from trustworthy opinion leaders. An indirect approach to measure trustworthiness is analyzing the structural, lexical, and semantic aspects of eWOM, which are found to be associated with trustworthiness [10]. Amazon and other companies have implemented a more direct approach whereby consumers provide feedback as to whether eWOM is helpful. In our study, we identify the most trustworthy opinion leaders as the consumers who receive the most helpful votes on their user reviews.

[2] A firm can generate the same information by developing their own online user review database similar to Amazon's.

In summary, our approach measures the behaviors central to opinion leadership determined by the self-report approach. However, instead of the subjective measures collected in a survey, our approach uses objective measures like the ones used in a network structure approach. Our approach also addresses four challenges endemic to the self-report and network structure methods. Consumers do not know all opinion leaders, as consumers only know a limited number of peers [30], and companies cannot directly compare different opinion leaders reported in either the self-report or key informant approaches. However, our approach allows us to identify all opinion leaders among a large number of consumers and compare their relative strengths in opinion leadership. While a network structure approach may miss opinion leadership expressed in eWOM, our approach does not need information about consumers' private social networks that are not observable to companies, and eWOM of the opinion leaders we identified can reach strangers outside of their social networks.

2.2. Product experience effects of opinion leaders' eWOM on sales

Opinion leaders' eWOM affects three aspects of product experience: product awareness/popularity, customer satisfaction, and horizontal product differentiation. We first examine the relationship between sales and product awareness/popularity of eWOM. Product awareness is the first phase in a consumer's buying decision – without product awareness, consumers will not have the interest or desire to consider a particular product that leads to a buying decision. The amount of eWOM influences consumers in two ways: eWOM increases exposure to a product and therefore increases consumer awareness of its existence [54]; and a large amount of eWOM suggests a product's popularity [17,79]. Previous studies reveal that the amount of eWOM created by the general public drives sales [21,27,29,54]. To examine whether the same relationship exists between product sales and eWOM created by opinion leaders, we propose the following hypothesis:

H1a. *Product awareness/popularity* expressed in eWOM of opinion leaders is positively associated with product sales.

Consumers communicate their satisfaction using online user ratings [18,71]. Positive ratings created by the general public can improve consumer attitude, while negative ratings created by the general public can worsen consumer attitude [54]. Customer satisfaction among the general public has been found to have a positive impact on future sales [4,78]. We examine this relationship in the following hypothesis:

H1b. *Customer satisfaction* expressed in eWOM created by opinion leaders is positively associated with product sales.

Companies can use vertical or horizontal differentiation strategies to attract consumers. Vertical differentiation refers to unique product features on which all consumers have consistent assessments. For example, when considering two car brands with otherwise comparable characteristics, consumers will prefer to buy brand A over brand B if A has better fuel economy. Thus, brand A can obtain a competitive advantage by strengthening its vertical differentiation in fuel economy. Horizontal differentiation refers to unique product features on which consumers have different assessments. Comfort and sportiness are examples of horizontal product differentiation in car design; unlike fuel economy, consumers rank such product features differently due to personal preference and lifestyle. Comfort and sportiness are often incompatible features and preferred by different segments of consumers, e.g., retirees and young men. The same product can satisfy some consumers and thereby receive high ratings while simultaneously disappointing and receiving low ratings from a different consumer segment; consequently, variance of user ratings is high. Companies use horizontal differentiation to attract a specific consumer segment. Cars with sporty features are more likely to attract young men while cars with comfort features are more likely to attract retirees. Cars with neither sporty nor comfortable features will lose consumers in both market segments to horizontally differentiated cars. Horizontally differentiated products are preferred by consumers who are well matched to the products, and have higher sales than non-horizontally differentiated products [23,71]. We examine this relationship in the following hypothesis:

H1c. *Horizontal product differentiation* shown in eWOM of opinion leaders is positively associated with product sales.

2.3. Individual and collective knowledge effects of opinion leaders' eWOM on sales

To understand whether opinion leaders can be used as disseminators to launch effective marketing campaigns via eWOM, it is important to consider who they are [46]. Opinion leaders have strong personal interest in products and are enthusiastic about product ownership and use [72]. They are also motivated to contribute their knowledge to other consumers [19,39]. Merton [56] discussed two types of opinion leaders: *monomorphic* opinion leaders are experts in a limited number of product categories, while *polymorphic* opinion leaders have knowledge in a variety of product categories. The opinion leadership literature suggests that both types have advantages. According to Childers [22], opinion leadership is product category specific. The more a consumer purchases and consumes within the same product category, the more likely the consumer is to acquire complex category knowledge. Consumers with such consumption-based expertise need less cognitive effort to comprehend and evaluate new products in the same category. However, the specificity of their expertise suggests that monomorphic opinion leaders are likely to lack knowledge about other product categories. In contrast, Feick and Price [34] found influential consumers, or market mavens, who have broad product category knowledge. Market mavens tend to have earlier awareness of new products across product categories, and to use multiple information sources to acquire general marketplace information. However, polymorphic consumers lack the focus and depth of product category knowledge compared to monomorphic consumers. Therefore, companies will find it difficult to recruit opinion leaders with both monomorphic and polymorphic characteristics. To address this conflict, we propose that companies recruit individual opinion leaders with broad product category knowledge (polymorphic characteristics of individual opinion leaders). At the same time, their collective product category knowledge should overlap and therefore be focused (collective monomorphic characteristics of opinion leaders). We thus propose the following hypotheses:

H2a. Polymorphic characteristics of individual opinion leaders are positively associated with sales.

H2b. Collective monomorphic characteristics of opinion leaders are positively associated with sales.

3. Data and model

3.1. Data

Identifying opinion leaders from observed behaviors such as WOM is the most expensive method, although highly accurate [75]. Fortunately, online user reviews are now available to companies and can serve as a proxy for overall WOM [79]. This approach is consistent with recent research findings that link online consumer behavior with product sales [51]. We use an Amazon user review dataset from a study by Leskovec and colleagues to identify opinion leaders and examine their eWOM effects on product sales [53].

Our dataset contains a sample of 350,122 book, music, video and DVD titles, which, as experience goods, have qualities difficult to ascertain before consumption, making user reviews helpful for consumers [60,63]. A user review on Amazon contains both a star rating and a text review. For each title, three statistics of star ratings created by the general public are available: average rating, number of reviews, and variance. On average, a title receives 13.98 reviews from the general public with an average rating of 4.33 and variance of 0.68 (Table 1). Amazon organizes titles into relevant product categories under four broad product lines: books, music, videos, and DVDs. Each product category has a tree structure. The four product lines sit at the top level of the tree. The deeper the level is, the finer the category is. For example, Jane Austen's *Sense and Sensibility* belongs to the category:/Books/Literature & Fiction/World Literature/British/19th Century. The number of categories (category count) for a title ranges from 1 to 116 with an average of 4.88.

Table 1
Descriptive statistics on all books.

Variable	Mean	Std. Dev.	Median	Min	Max
Sales rank	345,400	390,841.8	213,100	1.00	3,766,000
Volume of all consumer ratings	13.98	57.51	4.00	1.00	5,545.00
Average of all consumer ratings	4.33	0.75	4.50	1.00	5.00
Variance of all consumer ratings	0.68	0.91	0.22	0.00	4.00
Std. dev. of all consumer ratings	0.58	0.58	0.47	0.00	2.00
Category	4.88	4.39	4.00	1.00	116.00

Note: total number of books is 350,122.

A key Amazon feature that enables us to identify opinion leaders is reviewer identity, as Amazon displays reviewer names. We find 2,145,885 unique consumers from 1995 to 2005 in the dataset. On average, each consumer writes 4.37 reviews, and the most prolific one has 8659 reviews. The number of reviews a consumer has written is a proxy for communicativeness. The number of votes (either helpful or not) is a proxy for buzz generated by a consumer's reviews, while the number of helpful votes is a proxy for how trustworthy the consumer is. On average, each consumer receives 26.43 votes and 12.83 helpful votes (Table 2).

3.2. Identifying opinion leaders from online user reviews

We choose to identify opinion leaders using *individual consumers* as our unit of analysis. Although some researchers treat all reviewers as opinion leaders [25], we are interested in examining a much smaller set of reviewers because it is costly for a company to recruit all available reviewers [75]. The theoretical basis for considering a subset of reviewers is that opinion leadership is not a dichotomy; rather, it varies in a continuous fashion [22,67]. Since opinion leadership is a continuous variable, we choose the top 1% (21,458) of reviewers in the dataset in each of the three opinion leadership characteristics discussed in Section 2.[3] Specifically, we identify the top 1% of communicative, buzz-generating, and trustworthy opinion leaders according to the number of reviews written, the number of votes received, and the number of helpful votes received. It is worth noting that these three types of opinion leaders are not mutually exclusive. The total size of the three sets is $21{,}458 \times 3 = 64{,}371$, but the number of distinct opinion leaders in the three sets is 34,340 (Table 3). 12,109 consumers are both communicative and buzz-generating opinion leaders; 11,819 consumers are both communicative and trustworthy opinion leaders; and 16,989 consumers are both buzz-generating and trustworthy opinion leaders. Only 10,886 consumers belong to all three sets. The

[3] Our empirical results are robust for different percentages of opinion leaders, for example, top 0.5%, 1%, 2%, 4%, 8%, and 10% of reviewers in the dataset. Word of Mouth marketing practitioners Ed Keller and Jonathan Berry estimate opinion leaders at 10% of the population. The opinion leaders in our analysis are 1% of the consumers who write reviews. Since the set of consumers who write reviews is not larger than the entire consumer population, the opinion leaders in our analysis are no more than 1% of the consumer population. Thus, we provide empirical evidence that the set of opinion leaders can be smaller than suggested in Keller & Berry [48].

Table 2
Descriptive statistics on reviewers with unique identities.

Variable	Mean	Std. Dev.	Median	Min	Max
Number of user reviews written	4.37	14.62	1	1	8,659
Number of votes received	26.43	218.03	6	0	66,540
Number of helpful votes received	12.83	118.27	3	0	55,800
Product category knowledge	392.80	1561.29	31	1	35,640

Note: total number of reviewers is 2,145,885.

overlap between different types of opinion leaders is consistent with extant literature [43].

3.3. Opinion leaders' eWOM

Since we are interested in the impact of opinion leaders' eWOM on the sales of a title, our unit of analysis is an individual product. We find 199,253 titles in the dataset that have at least one review from a communicative opinion leader (Table 4). Following the literature, we use a log transformation of sales rank as a proxy for sales [21]. To test product experience effects of eWOM (H1a-c), we collect star ratings from communicative opinion leaders for each title. Based on these ratings, we compute three statistics for each title: number of ratings (volume), average rating (valence), and standard deviation (SD). We operationalize product popularity/awareness in H1a as the number of ratings (volume). Average rating (valence) is a proxy for customer satisfaction in H1b. Standard deviation (SD) measures the variation among user ratings for a title. The higher the standard deviation is, the greater the variation in consumer satisfaction with a title is. Thus, standard deviation is a measure of horizontal product differentiation in H1c. On average, a title receives 6.02 reviews from communicative opinion leaders. The average rating is 4.24, and the standard deviation is 0.40 (Table 5).

To measure product category knowledge, we collect all titles in the dataset that a unique consumer has written reviews for, and identify the product category for each title. Let A_i denote the set of product categories reviewed by i^{th} opinion leader. For example, an opinion leader i has reviewed the set $A_i = \{\text{cooking, cooking, romance}\}$. We then count the total number of *distinct* product categories of the titles and use the number as a proxy for product category knowledge. Let $|A|$ denote the number of distinct elements in the set A. In the previous example, $|A_i| = 2$ because there are two distinct categories, i.e., cooking and romance in the set. The median product category knowledge for a unique consumer is 31 (Table 2). Suppose that I communicative opinion leaders write user reviews for a title. Then *average knowledge* of communicative opinion leaders for the title, denoted by *know*, is defined as:

$$Know = \sum_{i=1}^{I} |A_i|/I.$$

The I opinion leaders can have overlapping knowledge. For example, a book has two communicative opinion leaders writing reviews. Consider two cases. In the first case, one communicative opinion leader has knowledge in the categories of children's books and science fiction, and the other leader has knowledge in the categories of cooking and romance. In the second case, both opinion leaders have knowledge in two categories: children's books and science. The average knowledge is the same (2 categories) for both cases. However, the combined knowledge is more focused in the second case than in the first case. To capture such focus, we define *average distinct knowledge* of communicative opinion leaders, denoted by $know_d$ as:

$$Know_d = \left|\cup_{i=1}^{I} A_i\right|/I.$$

where $\cup_{i=1}^{I} A_i$ is the union of product category knowledge of I opinion leaders who write reviews for a title. In the previous example, the average distinct knowledge is 2 for the first case and 1 for the second case. Average knowledge captures the knowledge breadth of *individual* opinion leaders; the *larger* the average knowledge is, the broader (i.e., more polymorphic) the individual knowledge is. Average distinct knowledge measures the collective knowledge focus of opinion leaders as a group; the *smaller* the average distinct knowledge is, the more focused (i.e., monomorphic) the collective knowledge is. On average, each title has been reviewed by communicative opinion leaders with an average knowledge of 3710 product categories and an average distinct knowledge of 2874 product categories (Table 5).

We add two control variables for each title. The first is category count, or the number of categories a title belongs to. As shown in Table 5, on average a title belongs to 5.34 categories. As described in the Data and Model section, Amazon's categories have a tree structure. We use the top level of categories as a control variable and refer to it as *group*. Book is the group with the largest number of titles, Music the second largest, Video the third, and DVD the smallest (Table 4).

We specify the following model to empirically test our hypotheses.

$$sales = \alpha_0 + \alpha_1 group + \alpha_2 count_{cat} + \alpha_3 volume^j + \alpha_4 valence^j + \alpha_5 SD^j + \alpha_6 know^j + \alpha_7 know_d^j + \epsilon$$

Sales	logarithm of sales rank of a title
J	type of opinion leader (i.e., communicative, buzz-generating, trustworthy)
Group	top level category (i.e., book, music, DVD, video) to which a title belongs
$Count_{cat}$	number of categories to which a title belongs
$Valence^j$	average review by type j opinion leaders
$Volume^j$	number of reviews by type j opinion leaders
SD^j	standard deviation of reviews by type j opinion leaders
$Know^j$	average product category knowledge by type j opinion leaders
$Know_d^j$	average distinct product category knowledge by type j opinion leaders

Table 3
Overlapping opinion leaderships.

Type of Opinion Leader (OL)	Number
Total size of three sets of OL's	64,371
Distinct OL's in the three sets	34,340
Both communicative and buzz-generating OL's	12,109
Both communicative and trustworthy OL's	11,819
Both buzz-generating and trustworthy OL's	16,989
Communicative and buzz-generating and trustworthy OL's	10,886

Table 4
Summary statistics of group for three types of opinion leaders.

	Communicative	Buzz-generating	Trustworthy
Total number of titles	199,253	200,618	196,423
Number of books	129,615	134,189	131,739
Number of music CDS	46,913	44,257	42,970
Number of videos	10,725	10,554	10,330
Number of DVDs	12,000	11,618	11,384

4. Results and discussion

We test our model (Table 6, model 3) against two alternative models: model 1 includes only product effects, and model 2 includes product effects and individual knowledge effects. We conduct regression analysis on 90% of the total sample and then use the estimated parameters to conduct a prediction exercise on the remaining 10%

Table 5
Summary statistics of variables for three types of opinion leaders (OL's).

Variable	Communicative OL		Buzz-generating OL		Trustworthy OL	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Log sales rank (*Sales*)	11.57	1.60	11.60	1.61	11.59	1.61
Category count ($count_{cat}$)	5.34	4.95	5.32	4.92	5.33	4.93
Number of reviews (*Volume*)	6.02	17.57	5.48	16.08	5.07	13.70
Average rating (*Valence*)	4.24	0.86	4.23	0.88	4.26	0.87
Std. dev. of rating (*SD*)	0.40	0.50	0.40	0.52	0.37	0.50
Average knowledge of opinion leader (*Know*)	3,710.00	4,793.44	3,615.00	4,734.73	3,752.00	4,841.30
Average distinct knowledge of opinion leader ($Know_d$)	2,874.00	4,453.40	2,850.00	4,386.47	2,955.00	4,479.02

holdout sample. Comparison of in-sample fit and prediction error on hold-out sample suggests that our model (model 3) fits the sample the best (Table 6), indicating the importance of individual and collective knowledge effects in predicting sales. The rest of the discussion is related to Model 3.

4.1. Control variables

Table 7 shows our estimation results for communicative, buzz-generating, and trustworthy opinion leaders. All estimates are significant, with p-values less than 0.001. The intercept estimates in Table 7 are interpreted as the intercept for the book group, since group is a factor variable. The music group estimate for communicative opinion leaders is −1.289 (Table 7, column 3), where the minus sign implies that, as a group, music titles have higher sales than book titles since a lower sales rank means higher sales. Comparing music, video, and DVD estimates, we find that video has the highest sales, DVD the second highest, music the third highest, and book the lowest.

The category count estimate is −0.015 for communicative opinion leaders (Table 7, column 3), which implies that sales increase with category count. An explanation for this is that category count is a proxy for content diversity of a title — a title with more diversified content appeals to a wider consumer demographic. We find similar results for the intercept and control variables for buzz-generating and trustworthy opinion leaders (Table 7, columns 4 and 5).

Table 6
Model validation for three types of opinion leaders.

Communicative opinion leader	In sample (AIC[a])	Holdout sample (RMSE[b])
Model 1: product effects	580,949.7	3.08243
Model 2: product effects and individual knowledge effect	580,926.2	3.085003
Model 3: product effects, individual, and collective knowledge effects	578,814.3	3.069971
Buzz-generating opinion leader	In sample (AIC)	Hold-out sample (RMSE)
Model 1: product effects	585,062.6	2.996442
Model 2: product effects and individual knowledge effect	585,064.1	2.996828
Model 3: product effects, individual, and collective knowledge effects	582,926.5	2.98545
Trustworthy opinion leader	In sample (AIC)	Hold-out sample (RMSE)
Model 1: product effects	574,885.2	2.997787
Model 2: product effects and individual knowledge effect	574,887	2.998035
Model 3: product effects, individual, and collective knowledge effects	573,064.2	2.987717

[a] Akaike's Information Criterion (AIC) is defined as $AIC = -2 \times \log l + 2 \times p$ where l is likelihood and p is number of parameters. A smaller AIC indicates a better model fit.
[b] RMSE = Root Mean Square Error. A smaller RMSE indicates a better model fit.

4.2. Product experience effects of opinion leaders

The volume estimate for communicative opinion leaders is −0.013 (Table 7, column 3), which implies that high product popularity/awareness increases sales (H1a). The average rating estimate for communicative opinion leaders is −0.205 (Table 7, column 3), which implies that high customer satisfaction increases sales (H1b). The standard deviation estimate for communicative opinion leaders is −0.414 (Table 7, column 3), which implies that high horizontal product differentiation also increases sales (H1c).

While the literature shows that all three product effects are empirically supported by eWOM among the general population,[4] researchers have not found evidence that all three product effects are significant in one empirical setting. Customer satisfaction, consumer awareness/popularity, and horizontal product differentiation are all costly to accomplish. The extant literature seems to imply that marketers only need to focus on two product effects [21,23]. However, our results, based on eWOM from opinion leaders, suggest the importance of improving all three product effects at the same time. We find that H1a, b, and c hold for buzz-generating and trustworthy opinion leaders (Table 7, columns 4 and 5).

Our results also show that different types of opinion leaders may have different impacts on product effects. We find that communicative opinion leaders' eWOM has the strongest influence on customer satisfaction (−0.205 compared to −0.185 and −0.187; Table 7, row 8). In contrast, buzz-generating opinion leaders' eWOM has the strongest influence on horizontal product differentiation (−0.432 compared to −0.414 and −0.424; Table 7, row 9), and trustworthy opinion leaders have the strongest influence on product awareness/popularity (−0.017 compared to −0.013 and −0.014; Table 7, row 7).

4.3. Knowledge effects of opinion leaders

The estimated average knowledge for communicative opinion leaders is −9.607e-05 (Table 7, column 3), which implies that high average knowledge of communicative opinion leaders increases sales (H2a). Interestingly, the estimated average distinct knowledge for communicative opinion leaders is 1.047e-04 (Table 7, column 3), which implies that low average distinct knowledge increases sales (H2b).

Previous research suggests that an opinion leader needs to have both knowledge and influence [47,57]. Since opinion leaders have different breadths of product category knowledge, it is important to examine which kinds of opinion leaders can be more effective in driving sales [34]. Knowledge and influence, the two components of opinion leadership, are not independent. General knowledge impacts not only the content of eWOM, but also determines who will be influenced. Katz and Lazarsfeld [47] argue that personal influence does not flow from highly interested individuals to less interested individuals, but rather between those with shared interests. Therefore, if general knowledge

[4] The valence effect is shown in Chevalier & Mayzlin [21], Dellarocas et al. [27]; the variance effect is shown in Clemons et al. [23]; and the volume effect is shown in Chevalier & Mayzlin [21], Liu [54], Dellarocas et al. [27], and Duan et al. [29].

Table 7
Estimates of eWOM by three types of opinion leaders.

Variables	Hypothesis tested	Communicative opinion leader	Buzz-generating opinion leader	Trustworthy opinion leader
Intercept		13.39*	13.331*	13.331*
		(0.017)	(0.016)	(0.017)
DVD (*Group*)[a]		−2.159*	−2.226*	−2.236*
		(0.014)	(0.014)	(0.015)
Music (*Group*)[a]		−1.289*	−1.369*	−1.382*
		(0.007)	(0.007)	(0.007)
Video (*Group*)[a]		−2.497*	−2.550*	−2.560*
		(0.014)	(0.014)	(0.014)
Category count[a] ($Count_{cat}$)		−0.015*	−0.013*	−0.013*
		(0.001)	(0.001)	(0.001)
Volume of reviews (*Volume*)	H1a	−0.013*	−0.014*	−0.017*
		(0.0002)	(0.0002)	(0.0002)
Average rating (*Valence*)	H1b	−0.205*	−0.185*	−0.187*
		(0.004)	(0.004)	(0.004)
Std. dev. of rating (*SD*)	H1c	−0.414*	−0.432*	−0.424*
		(0.007)	(0.007)	(0.007)
Average knowledge of opinion leader (*Know*)	H2a	−9.607e-05*	−9.474e-05*	−8.663e-05*
		(2.106e-06)	(2.124e-06)	(2.106e-06)
Average distinct knowledge of opinion leader ($Know_d$)	H2b	1.047e-04*	1.065e-04*	9.753e-05*
		(2.271e-06)	(2.296e-06)	(2.277e-06)
Model fit (R-sq)		0.4241	0.4239	0.4243

[a] Control variables. *Significant at P-value less than 0.001. Standard Deviation is in bracket.

implies general interest, an opinion leader with broad product category knowledge will attract more followers [58].

Our findings support the view that broad (polymorphic) product category knowledge at the individual level increases sales (H2a; Table 7, column 3), and imply that the collective knowledge of communicative opinion leaders needs to be focused (monomorphic) (H2b; Table 7, column 3). Companies may therefore find it useful to recruit generalists with knowledge in similar content areas. We find that H2a and H2b also hold for buzz-generating and trustworthy opinion leaders (Table 7, columns 4 and 5). When comparing the three types of opinion leaders, we find that communicative opinion leaders have the strongest effects in terms of breadth of knowledge (−9.607e-05 vs. -9.474e-05 and −8.663e-05; Table 7, row 10), and buzz-generating opinion leaders have the strongest effects in terms of focus of knowledge (1.065e-04 vs. 1.047e-04 and 9.753e-05; Table 7, row 11).

5. Concluding remarks

Many executives have little idea of how to orchestrate a marketing campaign that exploits the full power of opinion leader eWOM [31]. Part of the challenge is the lack of a proper approach to identify eWOM opinion leaders. Practitioners and researchers have identified opinion leaders by examining senders (e.g., the survey method) and receivers (e.g., network structure methods). However, extant research has made no attempt to analyze the message component due to limited records on WOM interactions. Our study fills this gap by identifying three types of opinion leaders using eWOM message and demonstrating that product experience and knowledge background of opinion leaders positively affect product sales. Our research has a material implication for companies: we prove that companies can properly identify a small number of opinion leaders from online commerce sites for seeding strategies in viral marketing campaigns. Examining more than 2.1 million Amazon consumers in our dataset, we show that companies only need 21 thousand opinion leaders as disseminators whose eWOM can affect product sales, which reduces the sample size by an order of 100.

In this study, we also contribute to two streams of literature on opinion leaders and eWOM. While there is increasing interest in studying eWOM, the extant literature has generally focused on eWOM created by the general public, i.e., user reviews written by all consumers. Therefore, there is a separation between opinion leader literature and eWOM literature. Our paper fills the gap by studying opinion leader and eWOM together as the original interpersonal communication theory intends [47].

Our research findings contribute to the study of opinion leadership and eWOM with four sets of results. First, our method of identifying opinion leaders complements both self-reporting and network structure methods. By using this new approach, we identify communicative, buzz-generating, and trustworthy opinion leaders and find their eWOM positively associated with product sales, contrary to a prior study that has raised doubts about the influence of opinion leaders [74]. Furthermore, we find that three product experience effects of opinion leaders' eWOM – product popularity/awareness, customer satisfaction, and horizontal product differentiation – increase sales. Finally, we study the knowledge background of opinion leaders. Most researchers characterize opinion leadership as a combination of knowledge and influence, but the breadth of product knowledge can vary from several to many product categories [34,50]. Our findings suggest that companies should recruit opinion leaders who have broad knowledge (polymorphic) at the individual level, but whose knowledge is focused (monomorphic) at the collective level.

Many companies selling their products directly through their websites have now implemented online user reviews. For those companies (e.g., Nike) with their own dataset of user reviews, our study suggests an alternative seeding strategy for effective marketing communications. Companies without their own databases may consider building one to collect user reviews from their existing customers. Since most large retailers (e.g., Walmart, Target, Macy's) have incorporated online user reviews in their databases, manufacturers can promote their products via the eWOM of opinion leaders identified from their retailer's database. By cooperating with larger retailers, companies without online user review databases can still apply our approach to launch an effective seeding strategy for viral marketing.

This study also has several key managerial and marketing implications. Marketing practitioners claim that 10% of the population tells the rest how to make purchase decision [48]. We provide evidence that marketers can focus on opinion leaders, a much smaller percentage of consumers, to develop a seeding strategy. Our findings suggest that compared to regular consumers, opinion leaders have a much larger customer lifetime value (CLV) because of their ability to increase sales by means of eWOM. We also offer a novel approach to identify opinion leaders, which has been a major challenge in launching effective eWOM campaigns. Our method is both more accurate than traditional survey methods [35,59] in measuring opinion leadership, and more comprehensive than network structure methods [41,43]. We use objective measures of consumer behaviors that avoid the potential biases of inaccurate estimation of opinion leadership and measurement errors in surveys. Since it is difficult to entirely capture consumers' social networks (e.g. family, friends, colleagues, and other acquaintances) as the network structure method requires, our message-based method of opinion leader identification is much easier for companies to implement. While empirical evidence based on eWOM from the general population suggests that companies only need to focus on two of the three aspects of product experiences (customer satisfaction, popularity/awareness, and horizontal differentiation), our findings imply that companies should improve all three product experiences simultaneously to increase sales to a higher level. Finally, it is important to consider the knowledge background of opinion leaders. Companies need to strike a balance between knowledge breadth and depth/focus by recruiting individual opinion leaders with broad market knowledge and ensuring that their collective topic areas overlap as much as possible.

Recently, companies have noted that recruiting opinion leaders increases company sales through viral marketing campaigns. For example, Hasbro demonstrated how an effective viral WOM campaign could be in 2001 [69]. After hiring a marketing company to identify a number of popular children in Chicago, Hasbro gave them free samples of a new game P-O-X. As a result of the children's WOM, Hasbro sold one million units within weeks. Philips worked with BzzAgent to create a WOM campaign for its SONICCARE electric toothbrush in 2006 [14]. BzzAgent contacted 30,000 consumers as the initial set of WOM disseminators, and the campaign eventually reached 1.2 million consumers.

Opinion leader WOM has become so important to the pharmaceutical industry that the top 15 drug companies spent a third of their marketing expenditures on opinion leaders in 2004 [32], though industry practitioners observe that the practice of identifying opinion leaders is ad hoc [49]. Fashion industry companies use celebrities such as Madonna as opinion leaders [76], while the pharmaceutical industry uses physicians on editorial boards/scientific committees and with prestigious academic appointments [32,38,49]. When consumers are not celebrities or experts, practitioners use sender-based and receiver-based methods. For example, marketers used surveys to find the popular children selected as disseminators in Hasbro's P-O-X campaign [55], and pharmaceutical marketers are increasingly using network analysis methods to find opinion leaders [45,73].

Message-based approaches similar to the proposed in this paper are emerging in various industries. For example, the eWOM company BzzAgent measures engagement as the number of likes, comments, and retweets a consumer's post receives [9]. The opinion leaders identified through this process are similar to the buzz-generating opinion leaders in our paper. BzzAgent also considers the number of activities a consumer completes, and the opinion leaders identified by examining activities are essentially the communicative opinion leaders we proposed. While our study reflects the intense interest in message-based methods among practitioners, to the best of our knowledge, it is the first to build the approach from a historical and theoretical background and test it empirically.

How can companies implement the message-based method? We recommend that companies implement online user review systems using Amazon's patented design [8], and identify the top 1% of communicative, buzz-generating, and trustworthy eWOM opinion leaders among users by measuring eWOM volume, feedback received, and helpful votes received. Our findings show that all three types of opinion leaders are effective in increasing sales. In order to save cost, a company can focus on one type of eWOM opinion leader and offer them a new product for free or at a discount. We suggest that companies can increase sales by selecting a subset of the top 1% of opinion leaders that is polymorphic at the individual level and monomorphic at the collective level.[5] In order to induce positive eWOM from opinion leaders, companies should ensure that their products: 1) are horizontally-differentiated by including product features for different consumer demographics, 2) provide customer satisfaction through high quality products and services, and/or 3) contain features that are popularly discussed or described as desirable by opinion leaders.

Our study has a number of limitations that we hope may be addressed by future research. First, given the constraints of our dataset, we were unable to examine the impact of mediating or moderating factors, such as willingness to buy or online-store image/product image. The effects of factors such as consumers' willingness to purchase and company's marketing mix on the relationship between opinion leaders' eWOM and sales requires further information to study. Second, our dataset lacks information on communication mix in traditional media (e.g., the New York Times bestseller list). Future research should examine opinion leader's eWOM in both social and traditional media to characterize how they may interact with each other to influence product sales. Finally, although we have discussed the theoretical differences between message-based, sender-based, and receiver-based identification methods, we do not have the data necessary for an empirical comparison of all three methods. Researchers and practitioners may find it useful to conduct comparison studies if the data becomes available in the future.

This article presents a new opinion leader identification method rooted in the interpersonal communication theory that inspired sender- and receiver-based methods [47]. Katz and Lazarsfeld originated the idea to use key components of interpersonal communication to identify opinion leaders, and our research closes the loop by examining the message component using eWOM. It is not a coincidence that message-based methods are only emerging after eWOM. The sixty year delay reflects less on the importance of message to interpersonal communication than on the technology available to companies, consumers, and researchers to use and explore it. The message-based method proposed in this paper highlights two major changes that digital technology brings to interpersonal communication: eWOM overcomes both the lack of records on interpersonal communications and behaviors, and the limitations on the number of social connections that people can access or maintain. By demonstrating how to identify opinion leaders from a large number of consumers, this article shows that companies can collect useful business intelligence from increasingly large amounts of data available to them—a central theme emerging in big data analytics [16].

Acknowledgement

The authors thank Vithala Rao, Vrinda Kadiyali, Dan Huttenlocher, Jure Leskovec, Yvonne Chang, Robert Carling for their insightful comments, suggestions, and data support. The authors also thank the editor and two anonymous reviewers for their helpful comments.

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