Network Analysis of Traditional Word of Mouth

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Abstract: Network analysis of Word of Mouth (WOM) examines how customers exchange opinions within their social networks. Compared to standard survey questions, which typically measure the likelihood to recommend, the network approach provides more metrics (e.g., average path length, clustering coefficient, density, average degree) that can be used to diagnose customer chatter. Unfortunately, traditional WOM has not benefitted from network analysis, which usually is applied to online WOM due to the availability of stored data. Despite the pervasiveness of online WOM, recent commercial reports reveal that traditional WOM still surpasses online WOM by a large margin. Traditional WOM is also perceived as more trustworthy and persuasive than online WOM. Thus, given the heavy reliance on traditional WOM and the advances made in network analysis that deal with online WOM, the main purpose of this study is to demonstrate that network analysis is a viable option for gaining insights in traditional WOM. This is the first study to utilize a survey method for collecting WOM network data for a wide range of products, which allows a direct comparison of their network structures. While network analysis may be more demanding on the researcher and the respondents, as the study illustrates, it also is more diagnostic than a standard survey. The main study utilized network analysis by using an alter-alter method, which was used to map the WOM networks structures for multiple products. Specifically, we examined the WOM networks structure as a function of product type (search, experience, and credence products) and opinion valence (positive vs. negative). The results reveal that WOM networks are affected primarily by product type. People are most likely to share opinions about experience products, followed by opinions about search products, and least likely to talk about credence products. The effect of opinion valence is limited. These findings are of practical relevance because they show that WOM can be managed by including search, experience, or credence qualities in promotional messages. This study also is the first to compare WOM networks to the existing social network, which can serve as a benchmark for evaluating WOM campaigns. The results reveal that for most products, people do not utilize all of their social connections for WOM, but there are exceptions, such as sharing a positive opinion about a movie, where WOM chatter can exceed the social network. Introducing a new method for studying traditional WOM also brings new research questions, and the study concludes with limitations and future research directions. Overall, the conclusion is that network analysis is a viable technique for studying traditional WOM.

Keywords Word of Mouth; WOM Valence, Network Analysis; Social Networks; Search, Experience, Credence

1. Introduction

Network analysis of Word of Mouth (WOM) examines how customers exchange opinions within their social networks. Compared to standard survey questions, which typically measure the likelihood to recommend, the network approach goes one step further and examines to who else in the network a person talks to. This allows capturing the paths of WOM within society, thus forming a network of opinions. The network approach provides multiple metrics of practical relevance; for example, how quickly WOM disseminates through society; to how many people, on average, a person shares WOM; what proportion of the population shares WOM; or whether people tend to share WOM within their social group, or randomly to everyone else.

Network analysis is applied mainly to online WOM. One reason for this is the availability of stored data from social media websites and emails, where the interconnectedness of people can be extracted. Traditional WOM, on the other hand, almost never benefited from network analysis. The main reason for this is that collecting personal

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network data in an offline context is challenging and the methodology remains unfamiliar (McCarty, Killworth, and Rennell, 2007). This asymmetry leaves the social network aspects behind traditional WOM largely unexplored.

An indirect reason for the lack of network analyses in traditional WOM is the increased interest in online WOM. Currently, the ratio of published research on online/electronic WOM vs. offline/traditional WOM for the period 2015-2020 is: 2:1 at ABI/Inform; 1.5:1 at Google Scholar; and 7:1 at Business Source Premier. However, the increased research interest in online WOM should not negate the importance of traditional WOM. Traditional WOM surpasses online WOM and even during the COVID-19 pandemic, 83% of WOM was traditional (66% face-to-face and 17% on the phone), (Engagement Labs, 2021). Overall, practitioners advise that failing to pay attention to natural conversations is a mistake because online and offline WOM are different, but work seamlessly together (Fulgoni and Lipsman, 2015).

Considering the strong standing of traditional WOM and the advances in network analysis due to online WOM, this study fills a gap by demonstrating how a network analysis can be applied to traditional WOM to answer questions of practical relevance. The survey methodology we suggest is applicable for academic or applied research.

2. Literature Review

2.1 Traditional WOM

Research on traditional WOM is substantive and here are some selected highlights. The value of WOM is in its persuasive power. It was found fairly early that WOM is more influential than advertising (Katz and Lazarsfeld, 1955) and it has remained in the focus of marketers ever since (Berger, 2016). Customers acquired through WOM referrals have higher customer equity and generate more profit (Villanueva et al., 2008; Trusov et al., 2009; Schmitt, Skiera, and Van den Bulte, 2011). WOM plays a key role for service organizations, especially those offering complex services that are difficult to evaluate as it is perceived to be highly credible information (Silverman, 2001). From the perspective of a company, De Matos and Rossi (2008) summarize that WOM is driven by satisfaction, loyalty, quality, commitment, trust, and perceived value. From the perspective of customers, however, WOM is driven by self- and social-motives like the desire to achieve self-enhancement, self-affirmation, bond with others, altruism, helping behavior, etc. (Alexandrov et al., 2013, Berger, 2014). Customers with extreme levels of satisfaction or dissatisfaction are more likely to share experiences than customers with neutral opinions (Anderson, 1998). Communication channels (i.e., oral vs. written) affect the content of the message (Berger and Iyengar 2013), which suggests that online and traditional WOM elicit different responses.

2.2 Why Traditional WOM Matters

Compared to online WOM, there are several reasons to continue researching traditional WOM. First, there have been concerns about the trustworthiness of online WOM and the ease of its manipulation (Anderson and Simester, 2014; Aral, 2014; Luca and Zervas, 2016; Mayzlin, Dover, and Chevalier, 2014). Even B2B buyers trust referrals from friends and colleagues more than online reviews or information provided by vendors (Neumann, 2017). Amazon has a problem with fake reviews (Nguyen, 2021). In 2020, Amazon stopped more than 200 million fake reviews (Coldewey, 2021), and is seeking help from social media companies to curtail the problem (Musil, 2021). Most of the reviews on Amazon are authentic, but for some categories, the proportion of fake reviews can be as high as 61% (Sterling, 2018), which often are generated by “fake review factories” that run on Facebook (Collinson, 2018; Dwoskin and Timberg, 2018). Another practice that may affect the trust in online WOM is the growing influencer industry, which is becoming a profitable business model. The goal of influencers is to acquire paid promotions, and to achieve higher visibility, some of them purchase fake followers (Confessore et al., 2018).

Offline WOM has a stronger effect on purchase intentions than online WOM (Baker, Donthu, and Kumar, 2016). In a meta-analysis, Rosario et al. (2016) found that WOM has a stronger effect for tangible goods than for services, which suggests that not all products benefit equally from WOM. The evidence presented in traditional WOM has a stronger effect on its perceived usefulness than the evidence presented in online WOM (Martin and Lueg, 2013). Meuter, McCabe, and Curran (2013) compared traditional WOM with different forms of online WOM and concluded that traditional WOM referrals had more influence on respondents' trust perceptions and behavioral intentions about a choice of a service provider compared all other forms of online WOM. Online WOM does not predict offline behavior well (Fay and Larkin, 2017). Finally, people are more likely to share WOM traditionally face-to-face than online (Eisingerich et al., 2015).

2.3 WOM as a Network

In general, network analysis examines the structure and behavior of complex networks. For example, the structure of the power grid (Pagani and Aiello, 2013) or the resilience of the Internet against breakdowns (Cohen et al., 2011) are topics based on network analysis. In social sciences, network analysis has been advanced mainly through sociology (e.g., Carrington, Scott, and Wasserman, 2005; Wasserman and Faust, 1994) as it examines the interconnectedness of people in the society. Social networks have a specific structure: people are densely interconnected in social cliques, and the cliques are loosely connected to each other. Network analysis has become particularly popular in social sciences after the seminal work of Watts and Strogatz, (1998), who formulated the mathematical mechanics of clustered networks, where clusters are similar to social cliques. The authors called clustered networks “small-worlds”, and it was quickly noted that social networks can be described by the mechanics of small-worlds (Watts, 1999, 2003; Newman and Park, 2003). One advantage of small-world networks is that they are more efficient in disseminating information when compared to random networks, which have no clustering but random connections (Watts, 2003). That is, for the same number of connections, it is faster to reach on average any other connection in a small-world network than in a random network.

Network structures can be represented by multiple parameters, but network analysis of online WOM has focused on a few useful parameters (Libai et al., 2013). Table 1 lists the definition of four network parameters and their interpretation in a WOM context. This study demonstrates how the network parameters in Table 1 can be estimated for different products.

Table 1: Summary of Network Properties

Network parameter	**Description**	**WOM interpretation**
Average path length (*L*)	The average number of hops a person needs to make to reach any other person in a network. The famous “six degrees of separation” is *L=6* (Travers and Milgram, 1967).	On average, how many times WOM should be shared to reach any other person in a network.
Clustering coefficient (*C*)	The average interconnectedness of a person’s friends. If *none* of the friends of a person know one another, then *C=0*; and if *all* friends of a person know one another, then *C=1*. It is the average probability that any two friends of a person know each other (Watts, 2003; Newman, 2003a).	The average WOM chatter among the friends of a person. If *none* of the friends shares WOM among themselves, then *C=0*; and if *all* friends of a person share WOM to everyone else, then *C=1*.
Network Density	The ratio of the existing connections to all possible theoretical connections in a network.	The ratio of the actual WOM to the maximum WOM (i.e., all people talking to one another).
Average degree	The average number of social connections a person has.	The average number of people to which a person shares WOM.

Network analysis allowed for new insights in WOM, some of which are described next. Seeding a WOM campaign using the network of the well- connected people can increase the effectiveness of the campaign by eight times compared to a random seeding strategy (Hinz et al., 2011). WOM campaigns generate value in two ways: by acquiring customers who would not otherwise purchase; and by accelerating a purchase (Libai et al., 2013). Network structure affects customer defection (i.e., brand switching), and the exposure to a defecting friend increases the defecting hazard by 80% (Nitzan and Libai, 2011). In the initial phase of product adoption, the WOM networks are small, and friends have a stronger and more consistent effect than strangers, but as the network grows, the effect of strangers increases (Zhang, Liu, and Chen, 2015). Overall, social network structure is essential for achieving social contagion, even when controlled for marketing efforts (Iyengar, Van den Bulte, and Valente, 2011, Watts 2007). A simulation study by Li and Du (2017) showed that online WOM is better suited for customers with diverse opinions, but offline WOM is better suited for higher margin products.

All of the aforementioned insights, however, are based exclusively on online WOM or simulations. There only are a handful of studies examining traditional WOM as a network. Brown and Reingen (1997) examined the effect of social ties in a WOM network. Frenzen and Nakamoto (1993) were one of the first to discuss the effect of WOM structure on retransmission of opinion. More recent studies examine WOM networks but only in a healthcare context (Idonthyengar, Van den Bulte, and Valente, 2011). Even large scale studies comparing offline WOM and offline WOM examine it only on individual level without estimating macro network properties (Baker, Donthu, and Kumar, 2016). To the authors' knowledge, currently there are no studies examining the network structure of traditional WOM in a broader context or providing guidelines how it can be done or used in practice. This study fills the gap and helps keep research on traditional WOM on par with online WOM.

3. Theoretical Development

3.1 Factors Affecting WOM

People do not share WOM with everyone, but approach it selectively. For example, they may share opinions about health services with some people, and opinions about cars with others. Therefore, WOM can spread in different ways through a social network. This study explores two factors that can affect the structure of traditional WOM networks: *valence of opinions* and *product type*. WOM valence (i.e., positive vs. negative) is studied well (de Matos and Rossi, 2008; Berger, 2014; Liu et al., 2021) and is of key importance because naturally marketers want to maximize positive WOM and minimize negative WOM.

Network research for product type is limited for several reasons. Previous studies often use simulation to support their findings (Watts and Dodds, 2007; Libai et al., 2013). The analyzed data often is secondary (e.g., emails, YouTube, etc.) (De Bruyn and Lilien, 2008; Liu-Thompkins, 2012) and limited to popular online products like electronics (Smith et al., 2007; Hinz, Schulze, and Takac, 2014). Even in the large scale study of Baker, Donthu, and Kumar 2016, who utilized customer social ties in their analysis to compare online WOM and offline WOM, the impact of product-type was not considered while examining purchase and retransmission intentions. From a networking perspective, knowing how WOM for different product types is likely to spread within a social network is of high practical importance because it can help understand what type of products are fit for WOM.

At a general level, product type can be classified on the search-experience-credence continuum (Ford, Smith, and Swasy 1988; Zeithaml, 1981). In brief, products high on search qualities can be evaluated before they are purchased (e.g., laptop, jacket, etc.), products high on experience qualities can be evaluated only after they are consumed (e.g., movie, restaurant, vacation, etc.), and products high on credence qualities are difficult or impossible to evaluate even after they are consumed (e.g., healthcare, legal services, car repairs, etc.). It has been suggested that most goods are high on search and experience qualities, and most services are high on experience and credence qualities (Zeithaml, 1981).

3.2 Research Questions

The study answers three research questions regarding the effect of product type and opinion valance on the network structure of traditional WOM.

It is expected that product type, as represented by the search-experience-credence framework affects WOM. The reason for it is that the perceived risk increases moving from search and experience to credence qualities (Mitra, Reiss, and Capella, 1999). Sharing WOM may pose a risk to the sender, which Frenzen and Nakamoto (1993) call moral hazard. For example, the difficulty of evaluating credence qualities leaves a person with incomplete information and decreases their ability to help others. Also, some customer experiences may be too subjective, and thus not transferable to others. In such scenarios, customers may feel hesitant to share their opinions. According to Frenzen and Nakamoto (1993), the higher the moral hazard, the lower their willingness to share WOM. Therefore, it is important to understand the effect of product type on WOM.

RQ1: What is the effect of product type on WOM?
It has been suggested that people are more likely to share negative WOM than positive WOM (Hanna et al., 2013). The empirical evidence, however, does not confirm this. Some studies find a small, but not substantial, difference

(Anderson, 1998; East et al., 2007), and others find no statistical difference between positive and negative WOM (Jansen et al., 2009). Examining the total WOM from a large database, Baker, Donthu, and Kumar (2016) found that people share up to seven times more positive WOM than negative WOM, which was similar to the findings of Carl (2006). There is also the argument that people share negative WOM because of its diagnostic nature while spreading of positive WOM arises due to its assisting role in a decision-making process (Bi, Zhang, and Ha, 2019). None of the cited research, however, has compared positive and negative WOM using a network approach.

RQ2: What is the effect of opinion valence on WOM?

People are connected through their social networks, but they may not indulge in WOM behavior with all social ties. From a managerial point of view, it is useful to know the extent to which WOM would spread through a social network. If WOM cannot reach the capacity of the existing social network, then it may not be a useful promotional tool. Therefore, comparing WOM networks for different products types and opinions to the entire social network is essential. The social network can serve as a benchmark for evaluating the effectiveness of WOM campaigns. Understanding when WOM will spread to a large rather than a smaller fraction of the social network is critical for allocating promotional spending. To the best of the authors' knowledge, no studies have compared WOM network to a social network.

RQ3: How do WOM networks (i.e., for different products types and valence) compare to a social network?

4. Research Method

4.1 Product Selection

An initial selection including 15 products was created based on established prior research (Murray, 1991; Ford, Smith, and Swasy, 1988), and an informal focus group with the intended respondents confirmed the relevance to their lifestyle. The guiding principle for the product selection was the search-experience-credence definition by Ford, Smith, and Swasy (1988). The initial products were: for search products - *windbreaker jacket, laptop, barbeque grill, running shoes, digital camera*; for experience products - *restaurant meal, haircut, furniture rental, vacation, movi*e; and for credence products - *teeth cleaning, tax advice, home maintenance, eye examination, auto repair*.

Table 2: Pretest Results for Product Type Classification

Product Type	Search-Experience-Credence Agreement	Goods vs. Services
Search		
Windbreaker Jacket	80%	1.08
Laptop Computer	76%	1.71
Digital Camera	78%	1.57
Experience		
Restaurant Meal	96%	4.37
Vacation	94%	5.63
Movie	94%	4.70
Credence		
Tax advice/preparation	59%	6.65
Home Maintenance	60%	6.41
Auto Repair	61%	6.39

A pretest study checked which products correctly represented the search-experience-credence classification. Forty-nine students from a Midwestern university in the United States of America were provided with the definitions of each product category, and then asked to classify the 15 products as either search, experience, or credence dimensions. Following Girard and Dion (2010), we retained products with at least 50% agreement among respondents. In addition to the product classification question, respondents were asked to evaluate on a 7-point scale the degree to which each product was a typical goods or service (1-Goods to 7-Service). The results in Table 2 are consistent with Zeithaml (1981), indicating that most search products are goods, most credence products are services, and experience products share goods and service qualities, which confirms that the final products selection is appropriate.

4.2 Supplementary Study: Online WOM vs. Offline WOM Sharing Intentions

In a supplementary study, we tested the preferred type of WOM (i.e., online vs. traditional) for the selected products. Eisingerich et al. (2015) suggested a preference for traditional WOM over online WOM, but we wanted to verify it in the context of this study. A short survey asked how likely a person would be to share their opinion (valence was not specified) about each of the 9 products on an online platform or in a traditional conversational. Each response was measured on a *1-Not at all* to *5-Definitely will* scale. The survey was sent to random respondents on Amazon Turk, from where we obtained 89 usable responses. Each respondent answered multiple WOM questions, and to remove any interpersonal variation, we used a general linear mixed model, where respondents were coded as random variables and the averaged product types (i.e., search, experience, credence) and WOM type (i.e., online vs. traditional) were fixed factors. Based on the effect size represented by the Partial Eta Squared, η^2, all effect were large with $\eta^2 > .14$. The highest variation in WOM was due to interpersonal variation (η^2=.36), followed by WOM type (η^2=.28) and product type (η^2=.27). All effects were significant at p<.00. The results confirm that, on average, people are more likely to share traditional WOM by 1.12 points on the 5-point scale when compared to online WOM. This finding confirm the preference for traditional WOM for the products in the study.

An interesting result emerged about product type, where WOM for experience products was the most likely to be shared (b=1.33), followed by WOM for search products (b=.56), and WOM for credence products (b=.00), which served as a benchmark in the model. Although not discussed here, the network analysis approach in the main study confirms this pattern.

4.3 Main Study Data Collection

The goal of network analysis is to map how WOM flows through society, but the data collection for networks comes with two caveats. First, traditional WOM requires sampling from a network, because unlike online WOM, face-to-face conversations are not stored in databases. In contrast to traditional statistics, however, for most network parameters, there is no inferential mechanism to generalize from a sample to the population. The estimation of a network parameter can be affected by a variety of factors including: missing data (Kossinets, 2006), the size of the sample (Anderson, Butts, and Carley, 1999), or the sampling method (Frank, 2002). Second, network analysis produces large datasets organized in matrixes. Usually, a question on a survey results in a single data column. In network analysis, each respondent answers a single question in reference to multiple other respondents in the social network, which results in a matrix (a.k.a. adjacent matrix). This data collection method is called alter-alter, where alters are the connections in a person's network. Thus, each question results in an adjacent matrix representing the network of relationships for the particular question. Therefore, one question asked to *n* respondents can generate up to *n(n-1)* data points. Because the alter-alter method is demanding on respondents, the samples usually are small (McCarty, Killworth, and Rennell, 2007).

Despite the aforementioned shortcomings, previous research has established practical guidelines for studying social networks. Studies based on simulations have demonstrated that sampling still provides good parameter estimates (Galaskiewicz, 1991). Sampling about 10% of a medium size population (e.g., N<500) has shown to capture representative information about the social network (McCarty, Killworth, and Rennell, 2007). For large populations, Leskovec and Faloutsos (2006) recommend sampling a minimum 15% of the population. Ideally, it is recommended to sample 20%-40% of the network to guarantee accurate estimates of all network parameters. According to Iyengar, Van den Bulte, and Valente (2011), however, if the goal of the research is not to estimate the parameters of an entire network (e.g., for epidemiological research), but is focused on differences between network parameters, then using a sample is appropriate. In other words, sampling can be used for relative comparisons. Finally, one widely applied practice is to validate network estimates externally by comparing them to the properties of previously estimated networks to make sure they are in line with expectations (Libai et al., 2013).
There are probabilistic and non-probabilistic sampling techniques for networks (Leskovec and Faloutsos, 2006), two of which should be noted. One approach is to sample nodes randomly, which provides fairly good estimates. However, random sampling is not the best sampling technique. A second approach is the "forest fire" sampling

method, where the sample is a patch of the network similar to burnt forest and provides better overall estimates. Importantly, "forest fire" is *not* a form of random sampling, and captures a complete network segment without randomization. This may be counterintuitive to traditional statistical reasoning, where randomization is preferred, but in network analysis, it is more important to not lose connections. Both sampling techniques provide good estimates of average path length, clustering coefficient and other network parameters, which are of interest to this study.

Based on the guidelines above and the intention of the study, we randomly recruited 67 students, which represents 12% of all students in a college at a Midwestern university. The college, according to the participants, was their natural environment and defined their typical social network. Because we intended to collect information about multiple products, and because the alter-alter method is demanding on respondents, the data collection consisted of three rounds over a two-week period. The need for prior commitment of the respondents was necessary in order to avoid comparing WOM networks based on different people. It also allowed listing all names on the surveys prior to the data collection. Essentially, our approach amounted to a random sample, which was held constant. The reason was that it was impossible to "start a fire" for every product and keep the respondents the same for all products. In addition, it allowed comparing the WOM network for all products to a single social network serving as a benchmark. Had we focused on WOM for a single product, then we could have applied the forest fire technique, which is discussed in the implications section.

The intention to share positive and negative WOM was measured for each of the nine products, and two questions measured the strength of social ties to every person in the network. The WOM questions were dichotomous, using a "Yes/No" check format. For example: "Imagine that you had a [positive/negative] experience for a particular [product]. Would you share your experience with [student name] (spontaneously or if asked)?" The products and valence were randomized. The underlying social network was measured with the following questions: "How close is your relationship with [student name]?" ranging from *1-Not at All* Close to *7-Very Close*, and "How often do you interact with [student name]?" ranging from *1-Never* to *7-Very Often*. An example of the survey is included in Figure 1. Although providing only checkmarks, answering the 20 questions for *each* of the 67 members in the segment was daunting, and the three data collection rounds eased the burden. Six respondents did not participate in all rounds, and their responses were removed, which resulted in 20 (61 x 61) adjacent matrixes.

	Product 1	Product 2	Product 3
Name 1	**x**	**x**	**x**
Name 2		**x**	
Name 3	**x**		**x**
…			
Name 67	**x**	**x**	

Figure 1: Survey Format Example

5. Results

Examining the research questions proceeded with combining the nine products into search, experience, and credence categories for both positive and negative WOM. For example, the three experience products (restaurant meal, vacation, and movie) for positive WOM were combined into a single network. This was done by retaining only the common ties used to share information for all products within a category. For example, if a person shared their opinion about digital camera to 5 people, and their opinion about a laptop to 7 people, and 4 people were common for both products, then only the 4 people were retained in the combined network. As products are combined, the non-common ties are lost, and to ensure equivalence in the process, the number of products per category were kept the same. This resulted in six aggregated data matrices, one for each product type and valence.

Table 3 contains the summary of the estimated network parameters. The data is in line with previously studied social networks, which provides an external validation of the results. The clustering coefficients of all WOM networks are similar to those of other popular social networks like Facebook, Orkut, and Flickr, typically ranging between .200 and .500 (Hardiman and Katzir, 2013; Ugander et al., 2011). The WOM densities are similar to the densities of the IMDB social network (18%), and peer-to-peer file sharing (25%) (Melancon, 2006). The average degrees of the WOM networks are similar to the degrees of YouTube (8.5), email network (9.6), and services network (13.5) (Libai et. al, 2013). Finally, the small-world test ratio, *S*, if greater than one, indicates that a network is a small-world (Humphries and Gurney, 2008). The *S* ratio for the social network is 1.49, which is similar to the ratio of 1.34 of student social networks from previous studies (Humphries and Gurney, 2008). Regarding the social network, averaging the two ties strength questions revealed that 82% of the ties had strength of less than two, indicating no relationship; 1.3% of the ties were larger than 6. indicating the strongest relationship; and the reaming 17% of the ties had moderate values.

Table 3: WOM Networks Estimates

	Positive WOM					Negative WOM				
	L	*C*	Deg.	Dens. (%)	S[a]	*L*	*C*	Deg.	Dens. (%)	S[a]
Search Products										
Windbreaker Jacket	2.30	0.35	8.34	13.90	2.08	2.43	0.29	7.42	12.40	1.96
Laptop Computer	2.13	0.36	11.18	18.60	1.55	1.98	0.45	13.38	22.30	1.61
Digital Camera	2.46	0.24	7.36	12.30	1.63	2.04	0.45	12.62	21.00	1.70
Combined Search Products	*3.22*	*0.22*	*4.32*	*7.20*	*2.68*	*2.79*	*0.24*	*5.15*	*8.60*	*2.45*
Experience Products										
Restaurant Meal	2.03	0.48	13.49	22.50	1.65	2.15	0.37	11.15	18.60	1.55
Vacation	2.14	0.41	11.07	18.40	1.75	2.22	0.26	8.72	14.50	1.49
Movie	1.94	0.49	14.74	25.60	1.47	2.16	0.34	10.74	17.90	1.53
Combined Experience Products	*2.18*	*0.43*	*8.74*	*17.90*	*1.88*	*2.78*	*0.26*	*6.23*	*10.40*	*2.03*
Credence Products										
Tax Advice/Preparation	2.87	0.29	5.44	9.10	2.63	2.98	0.27	4.95	8.30	2.76
Home Maintenance	2.59	0.30	6.41	10.70	2.36	2.75	0.25	6.16	10.30	1.97
Auto Repair	2.65	0.19	6.51	10.80	1.44	2.74	0.17	5.71	9.50	1.54
Combined Credence Products	*3.56*	*0.16*	*2.84*	*5.20*	*3.14*	*4.24*	*0.13*	*2.62*	*5.40*	*2.00*

Social Network Parameters	*L*	*C*	Deg.	Dens. (%)	S[a]
Social Network (All Ties)[b]	1.90	0.41	13.48	22.50	1.49

NOTES: L – Average path length; C – Clustering Coefficient; Deg. – Degree; Dens. – Density; S – Small-World Test Ratio. The estimates were done through the software Gephi.

[a] $S = (C/C_{random})/(L/L_{random})$, (Humphries and Gurney, 2008), where $L_{random} \approx \log(n)/\log(np)$, $C_{random} \approx p$ - network density, n = network size (Newman, 2003b).

[b] Tie strength was measured by two scales coded 1 to 7. Any strength from 2 to 7 was coded as a tie, and 1 indicated a lack of connection.

Research questions 1 and 2 were examined together through the average degree (i.e., to how many people a person shares WOM). WOM was the dependent variable in a general linear mixed model, where product type and product valence were the fixed factors, and each respondent was entered as a random variable. The results are presented in Table 4. The effect sizes represented by η^2 are the highest for product type (η^2 =.43), followed by respondents (η^2 =.38) and valence (η^2 =.02). Compared to WOM about credence products, on average, people are more likely to share WOM about experience products to 4.75 more people, and WOM about search products to 2.01 more people. For WOM valence, on average, people are more likely to share positive WOM to 0.63 more people than negative WOM. The main conclusion is that, after the effect of respondents is removed, product type has a substantially stronger effect on WOM than the valence of the opinion. Note that the relative importance of product types is similar to the results obtained from the preliminary study, which is based on a different sample and methodology. This confirmation provides additional validity for the network analysis approach.

Table 4: General Linear Mixed Model for WOM

Independent Variables		WOM (R^2=.50)	Partial Eta Squared, η^2
Intercept		1.26	
Product type	Search	2.01 **	.43
	Experience	4.75 **	
	Credence	0.00 [a]	
Valence	Positive	0.63 *	.02
	Negative	0.00 [a]	
Respondents [b]		-	.38

Notes: [a] Parameter set to zero; [b] Respondents were entered as random variables and the table shows only their cumulative effect size

** Significant at $p < 0.0001$; * Significant at $p < 0.05$

The third research question asks how the WOM networks compare to the underlying social network. To answer that question, a series of paired samples t tests compared the average degree of the social network to the average degrees of all WOM networks, individual or combined. The results revealed that the majority of the products do not activate the entire social network (Table 3), meaning that people talk, on average, to less people than their average social connections. The only exception is sharing a positive opinion about a movie that statistically exceeds the social network, where people are willing to share their opinion, on average, to 14.74 people (i.e., degree), although being connected, on average, to 13.48 people. From the combined WOM networks for search experience and credence products, positive WOM for experience products is the closest to the social network, with people sharing, on average, an opinion to 8.74 other people, but still significantly lower.

The values of the network parameters not specifically included in the research questions also reveal interesting patterns. For example, for the combined networks, on average, people share WOM to 3.4 times more people for positive experience products than for positive credence products (17.90 degrees vs. 5.20 degrees, respectively). At the same time, the clustering coefficients of these two networks (0.43 vs. 0.16) show that people talk less about credence products, even within their social clusters. In a social cluster, on average, it is 2.7 times more likely to hear an opinion about a positive experience product than an opinion about a positive credence product. However, the increased *S* ratio from 1.88 for positive experience products to 3.14 for positive credence products indicates that talking to people outside their social cluster diminishes much faster than talking within the cluster, which confirms the sensitive nature of WOM for credence products.

Network parameters show a substantial variability, even within the same product type. For example, people share a negative opinion about a digital camera, on average, to 7.36 people, and a negative opinion about a laptop to about 13.38 people. Even for the same products, people can share opinions with different valence quite differently: e.g., positive opinion about a digital camera shared, on average, to 7.36 people, but a negative opinion about a digital camera shared to 12.62 people; and for a windbreaker jacket, the direction is reversed. Overall, Table 3 demonstrates the richness of results when WOM is measured as a network. Although the goal of this study is not to make all possible comparisons, it is evident that a network analysis of WOM can be more informative, which opens the door for new enquiries and research questions.

6. Discussion & Managerial Implications

The network analysis of traditional WOM revealed several results that are useful to practitioners. WOM depends primarily on product type. People are most likely to share opinions about experience products, followed by search products, and credence products. For WOM valence, people are marginally more likely to share positive WOM than negative WOM. Generally, people do not utilize their entire social network for WOM, with the notable exception about positive movie experiences, where WOM can surpass even the social network.

From a practical point of view, the above suggests that WOM management should focus on product type. This does not imply ignoring negative WOM, because negative information weighs more than positive information in the mind of a person (Baumeister et al., 2001). However, managers could utilize product type in WOM by including search, experience, or credence qualities in the message they want people to talk about. As Levitt (1980) famously said, anything can be differentiated. Going one step further, one can argue that every product has search, experience, or credence qualities to some extent; to increase WOM, managers should focus on providing positive experiences, and to limit WOM, managers should focus on credence qualities. For example, motor oil is a typical credence product, which people naturally do not discuss much. To stimulate a discussion about it, WOM about motor oil should be bound to positive experiences like events, creative commercials, social events, rewards, etc. In this regard, one famous example was the partnership between DuPont and NASCAR, where Jeff Gordon promoted Tyvek on his car. Although for most people, house insulation has credence qualities, people talked about Tyvek due to the positive experience they had during the race. Similarly, if managers want to limit the effect of negative WOM, the failure of the product could be attributed to credence qualities that will be less likely to disseminate. This line of reasoning also can explain why some brands naturally relied on WOM to grow. In the past, brands like Avon and Oriflame, which sell cosmetic products in informal home settings, relied heavily on WOM within a personal network. After participating in home selling events, people could experience the benefits of the products and then follow the social vine to share their impressions. Customers are more prone to share positive WOM because of their other-orientation – concern for other customers and helping them to make an informed purchase decision (Bi, Zhang, and Ha, 2018)

Another practical application of WOM as networks is the rich information extracted from them, which can help companies understand and better manage the WOM traffic of their products. For example, clustered conversations with long path lengths may be an indication that customers are hesitant because there is something they do not understand. They may seem to talk to friends but would not share opinions with less known people. In such cases, the focus should be on clarifying the benefits of the product and motivating conversations with acquaintances and people from other social circles in order for the message to travel farther. One example is digital camera brands, where loyal customers can be designated as ambassadors for promoting the brand on social media or in their everyday lives. A monetary or symbolic compensation (e.g., early access to new products) is offered in return. A WOM with low clustering would indicate an absence of local chatter, which is not an optimal seeding campaign (Garber et al., 2004). Fixing such a problem would require targeting strong social connections, which, for example, could be achieved through referral incentives or group discounts.

The last managerial recommendation is related to data collection. Although we employed the random sampling technique due to the comparison of different products types, the “forest fire” sampling technique is more accurate and easier to implement in practice. Forest fire is similar to a snowball sampling, where a respondent passes surveys to the people they recommended the product to. The “fire” can be started in a social environment natural for the product of interest such as a neighborhood, organization, or a club. Because no connections should be lost, it is recommended to include incentives for taking the survey. Alternatively, random sampling could be applied to smaller networks such as people within organizations or professional groups (e.g., physicians, lawyers), where an approach similar to ours can be used.

7. Limitations and Future Research

Despite the insightful results, the study has limitations and leaves questions for future research. Combining different WOM networks into a single network leads to connections loss, because people naturally talk to different people about different products. We combined three products per category, which resulted in a loss of about 20% or more of the connections. All network parameters of combined products have lower WOM estimates than those of the individual products WOM networks. Although a combination allows generalizations, it still is not clear what the best practice is to deal with the loss of information. More research is needed in that direction to understand the reasonable limit of generalizations. It could be possible to represent a combined result with a corresponding level of uncertainty that reflects the combined deviation of the included networks.

The use of a small sample of university students is a limitation and future studies need to address this gap. It is important to replicate the results in non-student and student samples to see whether the results will change. It also is important to replicate the results in samples of different sized because in network analysis sample size can affect network parameters. For example, the *S* ratio, the average path length, and the clustering coefficient all increase as a function of network size. To mitigate these effects, the study kept the network segment and the products number constant. Therefore, the network results in Table 3, although very close to previously measured social networks, have value mainly as a comparative tool for finding differences and they answered the research questions. However, because this is a new approach for studying traditional WOM, replication in different settings are needed.

Several other research questions emerge from this study. First, although the provided managerial recommendations are consistent with the network theory, future research should test their causal validity in real life. For example, how exactly will the WOM network change if the efforts focus on increasing the clustering or on shortening the average path length? To what extent can negative WOM be suppressed if the company message focuses on credence vs. positive experience qualities? Second, product type is found to be the strongest predictor of WOM, but are there other characteristics that can be more predictive? For example, WOM networks might be affected more by industry, geographic region, or culture. Finally, it is worth exploring if positive and negative opinions tend to form positive and negative silos in the society. It is known that on social media, people self-separate in networks based on their political orientations. Do WOM networks exhibit such tendencies?

Overall, there are many questions the network approach can answer, and many more to be researched. We hope its introduction to tradition WOM will inspire more interest. Considering the strong standing of traditional WOM and the challenges in assessing the effectiveness of WOM campaigns in general (Libai et al., 2013), network analysis can be a new and helpful tool to improve the management of traditional WOM campaigns.

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