ELECTRONIC WORD-OF-MOUTH IN ONLINE ENVIRONMENTS: EXPLORING REFERRAL NETWORK STRUCTURE AND ADOPTION BEHAVIOR

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ABSTRACT: This article presents a network analysis of electronic word-of-mouth referral communication in a real life online environment. The goal of the paper was to clarify the existing terminology of electronic word-of-mouth behavior, to examine the kind of network structure that will emerge in the electronic environment, and finally to explore the impact of the network structure on the acceptance of an innovation in such a communication environment. Results indicated that the structure of an electronic communication network is different from the traditional interpersonal communication network structure. This study also showed that the network structure affects innovation adoption timing in the electronic communication environment, as a centralized network structure leads towards early adoption and as tie strength and adoption timing are related.

Word-of-mouth communication has received extensive attention from both academics and practitioners for decades (De Bruyn and Lilien 2004). In fact, one of the most widely accepted notions in consumer behavior is that word-of-mouth (WOM) communication plays an important role in shaping consumers' attitudes and behaviors (Brown and Reingen 1987), and that word-of-mouth has greater influence on consumer behavior than print ads, personal selling, and radio advertising in certain circumstances (e.g. Engel, Blackwell, and Kegerreis 1969; Katz and Lazarsfeld 1955). However, due to the development of information and communication technologies (like the Internet), consumers' communication environment has been changed and enriched. It has been said that the new communication structure is an amorphous web of connections (Ahuja and Carley 1999). Electronic peer-to-peer communication can take place in many alternative ways, like emails, discussion forums, and news groups. Dellarocas (2003) describes the phenomenon as follows: "word-of-mouth is being given new significance by the unique property of the Internet" (p. 1407).

One of the most important capabilities of the Internet related to previous mass communication technologies is its bi-directionality (Dellarocas 2003). With the growth of the Internet, electronic peer-to-peer communication has become an important phenomenon (De Bruyn and Lilien 2004); e-communication enables people to share information and opinions with other people (Hennig-Thurau et al. 2004) more easily than ever before. However, Internet-based peer-to-peer communication differs from the face-to-face interpersonal communication, common in traditional word-of-mouth, in several ways. First, the Internet allows people to reach many other people in a one-to-many process - similar to that of the mass media (Hennig-Thurau et al. 2004), while on the other hand email messages are like interpersonal communication in that they can be personalized to the individual (Phelps et al. 2004). Second, electronic referrals are usually unsolicited (i.e. they are sent to recipients who are not looking for information) (De Bruyn and Lilien 2004). However, as De Bruyn and Lilien (2004) have noted: "despite an abundant literature [on word-of-mouth], little attention has been given to unsolicited WOM communication of any sort, much less electronic ones" (p. 6).

As the communication environment has changed, the research on word-of-mouth has been updated. Previous studies have contributed to the understanding of electronic word-of-mouth behavior by examining online feedback mechanisms (Dellarocas 2003), consumers' motivation to articulate themselves on consumer opinion platforms (Hennig-Thurau et al. 2004), responses and motivation to pass along email (Phelps et al. 2004), and the effects of electronic referrals on different stages of the decision making processes (De Bruyn and Lilien 2004). However, it appears that a considerable potential exists for electronic word-of-mouth research, as there are several significant gaps in the understanding of electronic word-of-mouth behavior. First, at the macro level, there is a lack of understanding of several issues, such as how electronic word-of-mouth interaction in small groups (like virtual communities) or dyads aggregates to form large scale patterns in the diffusion of information. Second, at the micro level, very little is known about the structural context within which electronic word-of-mouth communication is embedded.

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The goal of the present study was threefold: (1) to define electronic word-of-mouth behavior, (2) to examine what kind of electronic referral network structure will emerge, and (3) to study the impact of the network structure on the acceptance of an innovation in the e-environment. Thus, the present study extends the work of Ahuja and Carley (1999), Abrahamson and Rosenkopf (1996), and Reingen and Kernan (1986) among others, by (a) applying formal quantitative network analysis methodology to analyzing electronic referral networks, (b) examining the effect of online network structure on adoption behavior, and (c) extending the research in word-of-mouth behavior by exploring electronic word-of-mouth in real life settings.

This paper consists of four sections. First, the conceptual foundations of electronic word-of-mouth behavior are studied. This is followed by the theoretical underpinnings and research questions regarding the electronic referral network structure and the effect of network structure on adoption behavior. Then the employed methodology, applied analysis methods, and achieved results are described. The findings and their implications, as well as the limitations of the study and further research issues are discussed in the final section of the paper.

Word-of-Mouth Communication in Online Environments

It is widely accepted that word-of-mouth communication plays an important role in shaping consumers' attitudes and behavior (Brown and Reingen 1987). Word-of-mouth has been shown to have a substantial impact on product choice (Kiel and Layton 1981), as well as in choosing services (Ennew, Banerjee, and Li 2000; Keaveney 1995). For example, Katz and Lazarsfeld (1955) found that word-of-mouth was the most important source of influence in the purchase of household goods and food products. Their research revealed that word-of-mouth was actually much more effective in influencing consumers' behavior than mass media (newspapers, magazines, and radio advertising) or personal selling. However, word-of-mouth is gaining new significance by the unique properties of information and communication technologies, like the Internet (Dellarocas 2003), and thus it is important to explore how the electronic environment may affect word-of-mouth behavior.

Electronic Peer-to-Peer Communication

The research tradition on electronic communication is relatively new and still developing, and thus competing and overlapping definitions have been presented to describe the phenomenon. Authors refer to interactive marketing (Blattberg and Deighton 1991), viral marketing (term coined in 1997 by Steve Jurvetson and Tim Draper, Hotmail's venture capitalists [see Montgomery 2001]), Internet communication (Bellman, Lohse, and Johnson 1999), Internet word-of-mouth and word-of-mouse (c.f. Goldenberg, Libai, and Muller 2001), online feedback mechanisms (Dellarocas 2003), stealth marketing (Kaikati and Kaikati 2004), buzz marketing (Thomas 2004), electronic word-of-mouth communication (Hennig-Thurau et al. 2004), interactive or electronic word-of-mouth advertising (Phelps et al. 2004), and electronic referral marketing (De Bruyn and Lilien 2004) when they describe the phenomenon. Thus, in order to explore electronic word-of-mouth, we first need to define the key concepts (viral marketing and word-of-mouth) and their relationships.

Several competing definitions have been proposed for viral marketing. Viral marketing has been seen as word-of-mouth advertising in which consumers tell other consumers about a product or service. However, Modzelewski (2000) argues that "true viral marketing differs from word-of-mouth in that the value of the virus to the original consumer is directly related to the number of other users it attracts" (p. 30). According to Montgomery (2001) viral marketing is "a type of marketing that infects its customers with an advertising message, which passes from one customer to the next like a rampant flu virus" (p. 93). However, he does not differentiate between viral marketing and word-of-mouth or diffusion of innovations. Kaikati and Kaikati (2004) consider viral marketing as one type of six different stealth marketing techniques (others being brand pushers, celebrity marketing, bait-and-tease marketing, marketing in video games, and marketing in pop and rap music), whereas Phelps et al. (2004) have defined viral marketing as "the process of encouraging honest communication among consumer networks" (p. 334). While all these definitions share the notion that viral marketing is a consumer-to-consumer process, and that it is related to word-of-mouth communication, they differ in all other aspects (see Table 1). The definitions of Phelps et al. (2004) resembles the common definition of word-of-mouth (see e.g. Arndt 1967), whereas Montgomery (2001) links viral marketing with advertising. As advertising can be defined as any paid form of non-personal presentation of ideas, goods, or services by an identified sponsor (Alexander 1964), it can be argued that it is a different concept from word-of-mouth. This is also supported by Hogan, Lemon, and Libai (2004) who have proposed that word-of-mouth "often complements and extends the effects of advertising" (p. 271). On the other hand, Rosen's (2000) definition of buzz marketing is similar to the definition of viral marketing by Phelps et al. (2004), as Rosen defines buzz as: "...the word of mouth about a brand. It's the aggregate of all person-to-person communication about a particular product, service, or company at any point in time" (p. 6).

Table 1. Comparison of Definitions of Viral Marketing

	Definition	Consumer-to-consumer	Advertising	Word-of-mouth	Network Externalities	Networks	CMC[2]
Rosen (2000)	"the word of mouth about a brand. It's the aggregate of all person-to-person communication about a particular product, service, or company at any point in time". [1]	x		X			
Modzelewski (2000)	"true viral marketing differs from word-of-mouth in that the value of the virus to the original consumer is directly related to the number of other users it attracts"	x		X	x		
Montgomery (2001)	"a type of marketing that infects its customers with an advertising message, which passes from one customer to the next like a rampant flu virus"	x	x	X			
Subramani and Rajagopalan (2002)	"viral marketing, sometimes described as word of mouse publicity, is a tactic that leverages the considerable power of individuals to influence others in their online social networks using computer aided communication media such as email, instant messaging and online chat"	x		X		x	x
Phelps et al. (2004)	"the process of encouraging honest communication among consumer networks"	x		X		x	
De Bruyn and Lilien (2004)	"goal of electronic referral marketing is to use consumer-to-consumer (or peer-to-peer) communications, as opposed to company-to-consumer communications, to disseminate information about a product or service, hence leading to its rapid and cost effective market adoption"	x		X			

[1] Definition of buzz marketing
[2] Computer-mediated communications

If viral marketing is actually all about word-of-mouth, what is word-of-mouth then, and is computer-mediated word-of-mouth different from traditional face-to-face word-of-mouth? Word-of-mouth is often characterized as oral, person-to-person communication between a receiver and a communicator which the receiver perceives as a non-commercial message, regarding a brand, product, or service (Arndt 1967). However, Buttle (1998) has noted that word-of-mouth need not necessarily be brand, product, or service-focused, but can also be in regard to an organization. Word-of-mouth has typically been considered as spoken face-to-face communication (see e.g. Rogers 2003), but today, according to Buttle (1998), computer-mediated communication like blogs, message boards, and emails can also be included in the definition. This notion is embedded in the definition by Hennig-Thurau et al. (2004) of electronic word-of-mouth communication, as they define electronic word-of-mouth as "any positive or negative statement made by potential, actual, or former customers about a product or company, which is made available to a multitude of people and institutions via the Internet" (p. 39).

Modzelewski's (2000) proposition that viral marketing differs from traditional word-of-mouth due to the positive network externalities is interesting, as it integrates word-of-mouth with network effect theories. Network effects are believed to occur when "the buyer of the last unit of a good has a higher benefit than the buyer of the first because the sale of the earlier units has created some benefits in a related dimension" (Economides 1991, p. 41), and they can significantly influence the adoption and hence the diffusion of goods and services (Church and Gandal 1993; Katz and Shapiro 1985; Witt 1997). However, it has been proposed that under network effects the rate of adoption of interactive innovations does not take off in the familiar S-shape curve until a critical mass of adopters has been reached (Mahler and Rogers 1999). This is due to the fact that in the early phase of the diffusion the network does not seem attractive to potential adopters, because there are only a few users, which does not create enough utility for a potential adopter to join the network. Only after a critical mass is reached the interactive innovation is then perceived as valuable by potential adopters (Mahler and Rogers 1999). A comparison of innovations with and without network effects has shown that the latter is seen to diffuse more slowly until a critical mass of adopters is reached (see Schoder 2000). Thus network effect theories argue that innovations with network effects will diffuse slower than innovations without network effects (at least in the early phase of their life cycle). This is contrary to propositions in viral marketing research where viral marketing is believed to be positively related with network effects, which are believed to lead towards increased peer-to-peer communication, which according to diffusion theory should lead towards early adoption and thus faster diffusion. However, it has been noted that viral marketing has not been successful for all products (Subramani and Rajagopalan 2002). Hotmail and Skype provide examples of successful viral marketing cases. They both represent information and communication technology innovations with strong positive network externalities (i.e. the value for the adopter is higher the larger the installed base of an innovation is, making the adopters active marketers of the innovation), whose adoption is free of costs, and which have low risks of adoption. Thus, it may be that viral marketing works best for innovations with certain characteristics.

Based on the discussion above, we define viral marketing as word-of-mouth communication in situations where positive network effects prevail and where the role of the influencer is active due to positive network effects. This definition is in line with Subramani and Rajagopalan's (2002) framework of behavioral mechanisms underlying knowledge sharing, influence, and compliance in online social networks. Subramani and Rajagopalan (2002) label consumers who are active in knowledge dissemination and who perceive positive network effects as ‘motivated evangelists', who can create a bandwagon effect and accelerate adoption. However, our definition differs from Subramani and Rajagopalan's (2002) in that we do not restrict viral marketing to online or computer-mediated environments, although we admit that viral marketing can be more efficient in some cases due to the special characteristics of online environments [e.g. anonymity of the source (Gelb and Sundaram 2002) and reduction in the effort needed to reach out to others (Subramani and Rajagopalan 2002)], and that the effectiveness of viral marketing may also depend on the product type, i.e. it may be more effective for innovations that can be distributed online (like software). For example, Bellman, Lohse, and Johnson (1999) found that looking for product information on the Internet was the most important predictor of online buying behavior. This was also supported by Rogers (2003) when he noted that for certain innovations diffusion via the Internet greatly speeds up the rate of adoption of an innovation. The definition differs from Schiffman and Kanuk's (1997) view as they have noted that in word-of-mouth, the source of the information generally has nothing to gain from the receiver's subsequent actions.

NETWORK STRUCTURE AND ITS EFFECTS ON INNOVATION ADOPTION BEHAVIOR IN ONLINE ENVIRONMENTS

Analysis of the Network Structure

The study of networks helps to illuminate the communication structure, the differentiated elements that can be recognized in the patterned communication flows in a system. Networks have a certain degree of structure (Rogers 2003), and the focus of network analysis is on understanding how the structural properties of a network affect behavior (Wellman 1983). Networks consist of members (actors) and relational ties that link the members. Several network measures have been developed for analyzing network structures. In marketing, common network measures are density, clique, and centrality (Webster and Morrison 2004).

Density. Density is the most common measure of network cohesion (Webster and Morrison 2004). It measures the extent to which all possible ties are present for any one network. Dense networks are thought to encourage cooperation and collaboration among the actors (Webster and Morrison 2004), and density is associated with higher pressure to conform to group expectations but also with high social support and solidarity (e.g. Burt 1998).

Clique. Network subgroup detection has been a continuing interest in marketing (Webster and Morrison 2004). Clique (Luce and Perry 1949) has been used to describe potential subgroups. Webster and Morrison (2004) define a clique as "a subset of actors who all have direct connections to one another and no additional network member can be added who also has direct connections to everyone in the subset" (p. 13). Typical networks consist of a relatively large number of cliques that are small in size with a fair amount of overlap in membership (see e.g. Brown and Reingen 1987; Reingen and Kernan 1986).

The general notion of classifying network links on the basis of the degree to which they convey information is based on Granovetter's (1973) theory of the strength-of-weak-ties. Granovetter has suggested a special significance for weak ties, which have a bridging function (see also Reingen and Kernan 1986). This function of weak ties enables referrals to proceed from one subgroup (like one virtual community) to another segment (other communities) of the broader social system. Weak ties occur with individuals only marginally included in the current network, and connect an individual's small clique of intimate friends with another, distant clique. Thus, weak ties are often bridge links connecting two or more cliques. Reingen and his colleagues were the first to use formal network measures to test hypotheses related to the strength-of-weak-ties theory within a service marketing environment (see Brown and Reingen 1987; Reingen and Kernan 1986). They found support for the general notion that weak ties advance the flow of information throughout a network by acting as bridges between dense subgroups, but noticed also that strong ties were more numerous and more influential as information sources, but were less likely to be actively sought out.

Centrality. The idea of centrality as applied to human communication was introduced by Bavelas in 1948, and has also attracted research in marketing for some time (Webster and Morrison 2004). A centralized structure has been defined as one in which interactions are mediated by a supervisor. A decentralized structure, at the extreme, is one that is fully connected and allows immediate feedback (Tushman 1979). Degree centrality is a basic centrality measure and indicates the activity level, and is often related to early adoption behavior.

The Effect of the Internet on Network Structure

Network theories have been applied to a wide range of marketing issues, such as word-of-mouth communication (Duhan et al. 1997; Goldenberg, Libai, and Muller 2001) and diffusion and adoption of innovations (Midgley, Morrison, and Roberts 1992; Morrison, Roberts, and Midgley 2000; Rogers 1995). However, according to Webster and Morrison (2004), relatively few marketing studies have employed the formal network quantitative techniques that are associated with network theories. What is also missing is an analysis of word-of-mouth referral behavior in online social networks (Subramani and Rajagopalan 2003). Prior studies on the diffusion of innovations have viewed interpersonal influence as occurring largely in face-to-face interaction (Bansal and Voyers 2000). However, as Subramani and Rajogopalan (2003) highlight, "interpersonal influence in viral marketing [or word-of-mouse] occurs in computer-mediated settings and is significantly different from that occurring in conventional contexts in several ways" (p. 301).

First, the scale and scope of influence is considerably expanded (Subramani and Rajagopalan 2003) by electronic communication as it enables a larger number of individuals to be connected by informational linkages than through face-to-face contact. Second, computer mediated communication media provide the opportunity to connect individuals asynchronously, for example via email. This enables influencers to stay connected to each other around-the-clock (Subramani and Rajagopalan 2003), which further improves the consumer-to-consumer communication possibilities. Third, the growth in computer-mediated and networked communications can facilitate information exchange among people of various backgrounds (Van Alstyne and Brynjolfsson 2005).

Internet and Density. As mentioned above, density measures the extent to which all possible ties are present for any one network. The features of electronic communication may have a strong effect on the structure of the communication network, as the ability to reach other individuals increases considerably (Subramani and Rajagopalan 2003). In the Internet environment, for instance, the effort in sending an email message to multiple contacts is only marginally greater than the effort in sending the message to just one recipient. As the Internet enables consumers to communicate even with strangers (Dellarocas 2003), the density of consumers' communication networks may increase. On the other hand, opposite effects have also been recently proposed, as Van Alstyne and Brynjolfsson (2005) have noted that "separation in virtual knowledge space can divide special interest groups...[where]... people must choose some information contacts over others" (p. 851). On the basis of the above discussion, the following proposition can be presented:

> **P1:** Network structure related to electronic word-of-mouth communication is a loose-knit network.

Internet and Clique. Van Alstyne and Brynjolfsson (2005) proposed that due to the growth in computer-mediated communications, a global village, i.e. a virtual community of neighbors freed of geographical constraints, could emerge. The identification of subgroups and how they are connected to one another through bridges or overlapping members is essential in the examination of microflows of referral information and macro aspects of flow. Frenzen and Nakamoto (1993) have found that individuals tend to allow valued information that has the potential to provide limited positive benefits to flow through strong ties only. As information becomes inexpensive and benefits are permitted to become common, weak ties are developed. As the information and communication is basically free in electronic online environments (Dellarocas 2003), we can assume that in electronic word-of-mouth behavior the role of the tie strength becomes less important. Thus, we propose:

> **P2:** There are relatively few cliques in electronic word-of-mouth communication networks.

Internet and Centrality. Bavelas (1948) proposed that a message originating in the most central position in a network would spread throughout the entire network in minimum time. However, the effect of computer-mediated communications on the network structure is not yet known. It has been proposed that the improved communication access (like electronic word-of-mouth communication) can in some circumstances lead to more fragmented intellectual and social interaction (Van Alstyne and Brynjolfsson 2005), and that email and the Internet are unable to sustain broadly-based, multiplex relations (for review see Garton and Wellman 1995, and Wellman et al. 1996). Garton, Haythornthwaite, and Wellman (1997) note that the "tendency toward specialization is counter-balanced by the ease of forwarding online communication to multiple others". According to Wellman and Gulia (1999), Internet participants can sustain broad, multiplex, and supportive relationships. Thus, it seems that online electronic networks resemble more a decentralized communication structure than a centralized structure of communication networks. Thus, the following proposition is presented:

> **P3:** Electronic word-of-mouth communication networks are rather decentralized.

The Effect of Network Structure on Adoption Behavior in Online Environments

Interaction among the members is the engine that fosters the growth of virtual communities (Pitta and Fowler 2005). The most fundamental difference between real world communities and virtual communities is the communication mode: in the real world communication is often face-to-face, whereas in virtual environments it is not (Pitta and Fowler 2005). The term computer-mediated communication (CMC) refers to a type of interpersonal communication which operates in computer-mediated environments. Empirical studies have found that computer-mediated communication is more task-oriented, less emotional, and less personal than face-to-face communication (Hiltz, Johnson, and Turoff 1986). Actually, in virtual communities the communicating consumers may not know each other, as the use of pseudonyms is a common habit. Thus, it can be assumed that word-of-mouth behavior in electronic virtual environments is somewhat different from traditional face-to-face word-of-mouth.

Diffusion of innovations can be considered as a social process that involves interpersonal communication relationships, and it is generally believed that the patterned aspect of networks provides predictability to human behavior (Rogers 1983). It has also been noted that not all members of the network communicate with all the members, since according to Abrahamson and Rosenkopf (1996) the flows of information are channeled by social networks only to certain individuals. The research on the diffusion of innovations suggests that referral behavior may take place primarily among actors who are similar to each other in beliefs, education, and occupation (Rogers 1983), thus encouraging adoption. However, Internet researchers have reported that computer-mediated communication reduces the impact of social cues, and supports a wider range of participants and participation (see e.g. Garton, Haythornthwaite, and Wellman 1997). This may imply that in computer-mediated environments (e.g. like in virtual online communities) the importance of referral behavior may increase as all the members in the network are considered as important sources of referral information, and as it is relatively easier to inform multiple others. Reingen and colleagues (Brown and Reingen 1987; Reingen and Kernan 1986) found support for the general notion that strong ties were more numerous and more influential as information sources but were less likely to be actively sought out. As electronic referrals are usually unsolicited (i.e. they are sent to recipients who are not looking for information) (De Bruyn and Lilien 2004), and as the structure of communication networks influences the order in which potential adopters receive information about an innovation and, therefore, the order in which they adopt (Abrahamson and Rosenkopf 1996), it can be proposed that:

> **P4:** The stronger the tie, the more rapidly the innovation is adopted.

Midgley, Morrison, and Roberts (1992) found evidence for the notion that network structure could have a substantial effect on the manner in which innovations diffuse. Abrahamson and Fombrun (1994) proposed a trickle-down process where adoptions by potential adopters in the core strata of social networks tended to trigger imitations by members in the peripheral strata of the networks. Czepiel (1974) applied the centrality measures in marketing in a study of the diffusion of a major technological innovation in industrial settings. He found that centrality was associated with early adoption behavior, although the relationship was not significant. Also Webster and Morrison (2004) have found a positive correlation between centrality and time of adoption. Thus, it is proposed that:

> **P5:** Centrality in an electronic communication network leads to early adoption.

METHOD

In order to study structural issues, information regarding the inter-relationships among network members was required. A who-told-whom network of information flow was traced for an Internet campaign which opposed a new copyright law established in Finland in 2005. The campaign started on the 23rd of September, 2005. Even though the campaign was continuous, its aim was to bring the disapproval of the legislation to the attention of the members of parliament to influence their vote on the new law on October 4th. For the present study the information flow was traced for a time span of 3 weeks in the end of September and early October 2005, to reflect the most important duration of the campaign. The studied innovation was an Internet banner to be downloaded to one's own website, through which the adopter could support the campaign. In this research, the nodes in the network are called actors, and they are mainly personal websites (but also virtual communities can adopt the innovation) and the relationships between these are the ties (or links). Although these links were the unit of analysis, the focus was on the whole structure within which the communication occurred.

Data Collection and Sample

Our data collection was a two-phase procedure. In the first phase we collected data from the innovation adopters (i.e. participants of the campaign). They sent us basic information on their websites and the means to contact them. The first phase data collection was actually part of the campaign and was done through a simple feedback form on the campaign website. If the supporter wanted to see her/his website in the campaign participants' list she/he had to supply the campaign manager with their website name and their own name. Once the campaign manager received a message through the feedback form from the participant, we could determine the time of adoption in hours. This gave us a relatively complete understanding of the whole population, but not a complete picture, as some participants may have abstained from sending the information.

Once the participants of the network were identified, a secondary data set was needed as it was not known how the messages had been sent in the initial network. Thus, we needed to create a referral network. The data for the second phase was collected via an email survey. An electronic questionnaire was sent to the adopters (N=360) in order to reveal the source of their message. The recipients were asked to return a filled questionnaire within eight days. Even though some researchers have argued (e.g. Reingen and Kernan 1986) that referral behavior is a social phenomenon and existing social links should be known to analyze the referral network properly, this is not the case in an online environment. This is because the actors are able to view different sources of information, for example websites, without previous social linkages to that source and therefore only basic node information is needed.

In the second data set, the participants were asked who they had learned about the campaign from, whom they had told of the campaign, and how close/credible they considered the source to be. After the eight days, 186 completed questionnaires were returned, yielding an effective response rate of 51.7%.

MEASURES

The network structure was measured with three network measures commonly used in marketing studies: density, clique, and centrality. These three parameters can be calculated with network analysis software (UCINET).

Density. Density is a measure of network cohesion. It indicates the ratio of the ties actually present with regard to the possible number of ties (see e.g. Knoke and Kuklinski 1982). Density is a very simple tool to analyze network cohesion and with regard to very large networks, such as the Internet, the measure is usually very small. It is an appropriate measure to understand the density of the messages in any given network and thus needed to be calculated to understand the communication flow.

Clique. To distinguish subgroups from larger networks, one can use cliques. A clique is a subset of nodes that all have direct connections to one another and no additional network member can be added who also has direct connections to everyone in the subset (Webster and Morrison 2004). Studying cliques is an effective way to understand connectedness in a network between certain nodes. In our research, it reflected the nature of connections in an online environment where different nodes could very easily create a link between one another by simply viewing a website. This emphasized the structure of the network and how innovations are adopted.

Centrality. Degree centrality is the most basic tool to analyze node activity and popularity. Centrality measures are used to describe and measure properties of actor location in a social network (Wasserman and Faust 1994). We applied Freeman's degree centrality figure, which measures the amount of incoming and outgoing links from and to each node.

Information Sources. The respondents were asked to identify all the information sources from which they had heard about the campaign (see e.g. Brown and Reingen 1987).

Information Targets. The respondents were also asked to identify each person they had told about the campaign, either by electronic means or interpersonal communication (see e.g. Reingen and Kernan 1986).

Tie Strength. To explore the impact of the strength of the tie on the adoption timing, the respondents were asked to rate the closeness/credibility of each information source from which they had heard about the campaign on a five point Likert scale (anchors varying from 1 (not at all close/credible) to 5 (extremely close/credible)).

Adoption Timing. Adoption timing was measured as hours from the beginning of the campaign.

ANALYSIS AND RESULTS

Analysis

The results of the e-mail questionnaire were coded into two matrices. The first was a binary matrix, with rows representing message sources and columns representing message targets. The value of 1 in the intersection of row A and column B indicates a communication link between A and B, where as a 0 indicates the lack of a link. The second was a value matrix where the intersection value denotes the closeness/credibility between the two actors. These matrices were used as input to the social network analysis software package UCINET (Borgatti, Everett, and Freeman 2005). UCINET was used to compute the different statistical data covered in this research. Visual network diagrams were drawn using the NetDraw (Borgatti 2005) software that also uses the matrices computed for UCINET.

Data Description

The number of information sources varied greatly; one respondent could not identify any source while one named 21 different information sources. On average, however, the respondents had heard about the campaign from only a few sources. The mean number of information sources was 1.97 (s.d. = 1.87), with 91.4% of the respondents having been informed about the campaign from up to three different sources.

Like the number of information sources, the number of targets also varied greatly: one actor named 61 different targets while 10.3% of the respondents had not told anyone about the campaign. The mean number of people to whom an actor had told about the campaign was 2.52 (s.d. = 4.84). Therefore, on average, the respondents told about the campaign to a larger number of actors than the number of sources where they had heard about if. However, the differences were not statistically significant.

The reported information sources were categorized into eight classes: personal web sites or blogs (reported by 66 respondents or 35.7%), mass-media like websites with editorial staff (46.9%), other web sites (31.9%), discussion forums (8.6%), real time chat and instant messaging applications (13.5%), e-mail (3.9%), other unspecified electronic sources (2.2%), and personal communication (9.7%) either face-to-face or by phone. On average, the respondents received messages about the campaign on 1.52 different communication channel types. Overall, the information sources were considered quite close or credible by the respondents. Of the total 115 source ratings, 93% were 3 or higher (meaning that the source of information was considered reliable), and the mean rating was 3.64 (s.d. = .958). Adoption times ranged from 1 to 479 hours, with a mean adoption time of 187.5 hours. (See Table 2)

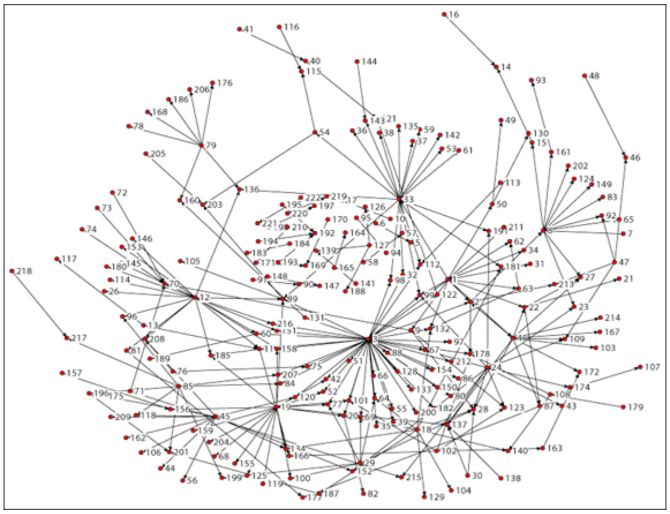
Table 2. Descriptives

Adoption time	
Minimum	1
Maximum	479
Mean	187.50
Information sources used	
Minimum	0
Maximum	21
Mean	1.97
Recipients	
Minimum	0
Maximum	61
Mean	2.52
Cliques	13

Network Structure

The first goal was to describe the communication network that emerged in the electronic word-of-mouth environment. Overall, 273 messages concerning the innovation were sent during the approximately 3 weeks covered by the data. Figure 1 presents a graph of the communication network for the 223 actors. The number of actors in the diagram is larger than the respondent size, because many actors gave sources that did not participate in the questionnaire. A visual exploration of the network structure revealed that the majority of the communication ties originated from only 5 nodes: 3, 19, 33, 12, and 1. Most of the remaining nodes created fewer than 12 ties, with 150 nodes creating no reported ties. Of the five most active nodes three can be considered to be mass media sources, i.e. news websites (nodes 3, 19 and 33). Node 1 was the founder of the campaign with 12 outgoing ties. Node 12 was a communication platform with 18 ties. The three mass media nodes adopted the innovation relatively early, as the times the news was published were 120, 157 and 126 hours, respectively. Node 1 was the innovation center (adoption time 0 hours), and for node 12 the adoption time cannot be calculated as the platform was used on a continuous base. This suggests a core-periphery structure to the network, with a certain node being a preferred communication partner or more important to the communication structure than others.

Figure 1. Communication Network of the Adopters of the Case Innovation



The overall density for the communication network in our case was 0.6%, indicating an extremely loose-knit network, and giving support to our first proposition (P1) stating that the communication network structure related to electronic word-of-mouth communication is rather loose. This result is comparable to previous studies of online communication activity.

The methods of network analysis identify individuals in cliques on the basis of their communication proximity in network links, so that individuals who are less distant are assigned to the same clique. In order to study the second proposition (P2), which argued that in electronic word-of-mouth communication network there are relatively few cliques, the hierarchical clustering technique was applied (see Webster and Morrison (2004) for a similar procedure). In total 13 cliques were identified in the communication network. Node 1 was a member of 8 of the 13 cliques. A further proof of the loose-knit nature of the network was the fact that 188 nodes had no membership to any clique. Nodes 22 and 4 shared membership in 3 of the 13 cliques, as did nodes 1 and 3 (See Table 3). The hierarchical clustering of the clique co-membership, shown in Table 3, revealed the general subgroup structure for the entire network (Freeman 1978/1979). The nodes that did not belong to any of the cliques were discarded to keep the visualization relevant. There were 3 main subgroups, of which 2 were equal in size and the third was the largest, with two smaller subgroups inside it.

Table 3. Hierarchical Clustering of the Clique Overlap Matrix

```
      Node identification
                            1 1     1   1 2
      2   2 8 3       9 6 6 3 7 1 1 8 8 9 0
Level 2 4 7 7 3 2 1 3 9 2 3 2 8 1 2 5 5 6 1
----- - - - - - - - - - - - - - - - - - - -
3.000 XXX         XXX
2.000 XXX       XXXXX
1.000 XXXXX     XXXXXXX XXX     XXXXX XXXXX
0.679 XXXXX   XXXXXXXXX XXX     XXXXX XXXXX
0.667 XXXXX   XXXXXXXXX XXXXX   XXXXX XXXXX
0.400 XXXXXXX XXXXXXXXX XXXXX   XXXXX XXXXX
0.274 XXXXXXX XXXXXXXXX XXXXX   XXXXX XXXXX
0.103 XXXXXXX XXXXXXXXXXXXXXXXX XXXXX XXXXX
0.005 XXXXXXXXXXXXXXXXXXXXXXXXX XXXXX XXXXX
0.000 XXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXXX
```

The third proposition (P3) anticipated that electronic word-of-mouth communication networks would be rather decentralized. The centrality ranking differed for sent and received ties. The communication network (Figure 1) showed node 3 to be by far the most central when measured with the number of sent messages, creating 43 ties, whereas nodes 28 and 70 were the most popular nodes with 6 received ties. In the present study, the out-degree graph centralization was 19% and the in-degree graph centralization was 2%, indicating that there was a great amount of concentration in the whole network, which means that the power of individual nodes varied remarkably and that positional advantages were extremely unequally distributed in the network. These results are contrary to our proposition (P3), which argued that electronic word-of-mouth communications networks are rather decentralized.

Adoption Behavior

At the second stage of analysis, the last two propositions were tested using regression analysis, Mann-Whitney tests, and correlation coefficients. In order to test the effect of tie strength on adoption timing (P4), linear regression analysis was applied. However, the analysis did not provide satisfactory results (R2 = .009, ß = -.93, p = .209). Next, each respondent's average closeness/credibility rating was divided into two groups: strong ties (rating values 4 to 5) and weak ties (rating values 1 to 3). The Mann-Whitney test indicated a slight tendency towards information sources with stronger ties resulting in earlier adoption times, but the results were not statistically significant (p = .326). An analysis with each respondent's highest tie strength and adoption timing showed a similar relationship, but the results were not significant (p = .157) in this case, either. Table 4 presents the average adoption times for strong and weak ties. Information concerning the innovation from more trusted sources would seem to result in relatively earlier adoption. However, the results for P4 remained inconclusive.

Table 4. Average Adoption Times for Strong and Weak Ties

		Strong ties	Weak ties
Adoption time (h)	Average tie strength	176.79 (N = 85, s.d. = 110.32)	198.33 (N = 99, s.d. = 120.02)
	Highest tie strength	177.92 (N = 114, s.d. = 109.78)	208.33 (N = 69, s.d. = 122.45)

In an attempt to replicate the findings of Czepiel (1974) and Webster and Morrison (2004) in an online environment, and to test P5 which proposed that centrality in electronic communication networks leads to early adoption, the correlation between adoption times and degree centrality was calculated. Webster and Morrison (2004) applied Pearson correlation coefficients, but since neither the in-degree nor the out-degree centrality measures followed normal distribution, in the present study the correlations were tested using Spearman's rho. As in Czepiel (1974), indegree centrality (number of ties received) was associated with early adoption. Unlike Czepiel (1974), however, in the present study the relationship was significant (rho = -.309, p < .01), supporting P5. The results were also in line with those in Webster and Morrison (2004). Webster and Morrison (2004) also found that outdegree centrality (number of outgoing ties) was associated with early adoption. Our results, however, did not confirm their findings. Instead, there was a slightly positive relationship between outdegree centrality and adoption times (for outdegree measure rho = .052), but the correlations were not significant (see Table 5). Multiple regression analysis was also applied to assess the relative impacts of normalized indegree and outdegree centrality (independent variables) on adoption timing (dependent variable). With the stepwise method the regression model produced a poor R2 value of .086, but the model was, nonetheless, statistically significant. The results were similar as in the correlation tests: higher indegree centrality values were associated with earlier adoption times. A summary of the results for this regression model is presented in Table 5. On the basis of the analyses, we concluded that centrality in electronic communication networks leads to early adoption, i.e. P5 is supported.

Table 5. Results of Regression Analysis on Degree Centrality and Adoption Timing

Variable	B	SE B	ß
(constant)	193.044***	8.706	–
Normalized indegree centrality	-46.389***	11.454	-.293

*** $p < 0.01$

DISCUSSION

Electronic Word-of-Mouth Behavior

The literature review on electronic word-of-mouth behavior revealed that the terminology for this relatively new phenomenon has not yet been established. For example, viral marketing and word-of-mouth are considered synonymous. Word-of-mouth is even regarded to be equivalent to advertising. Based on the review of previous literature we see viral marketing and word-of-mouth behavior as separate but related concepts, and define viral marketing as word-of-mouth communication in situations where positive network effects prevail and where the role of the influencer is active due to positive network effects.

Network Structure

The goal of the present paper was to study what kind of network structure would emerge in online environments. We assumed that the network structures in online environments would differ from non-online real life networks, and believed that the density of electronic referral networks would be low, there would be relatively few cliques and that the network structure would be rather decentralized than centralized.

Density

We found that the overall density of the network in the present study was 0.6%, which indicated an extremely loose-knit network. This is partially in line with Paccagnella (1998), who studied the communication structure of an Italian online computer community over the duration of 19 months, and reported a density value of only 3% for the communication network in the early stages of its life cycle. Cadeaux (1997) has cautioned that networks with low densities can be quite rigid and only those actors with sufficient status are able to negotiate their exchange relations. These extremely loose random referral networks may be difficult to manage for marketing purposes. Thus, their role resembles that of mass media as they seem to serve well for the need to get potential adopters informed about the innovation, but loose networks do not serve the important function of word-of-mouth in influencing potential adopters. This is supported by Ahuja and

Carley (1999) who proposed that the members of virtual communities may be active in providing information needed by other members because of the sense of a community. It has been argued that in virtual contexts the structure that will emerge will change in response to information/processing needs (c.f. Ahuja and Carley 1999). Thus it might be that a loose-knit network will appear in similar contexts where adopters witness network effects and the success of the innovation is highly dependent on the number of adopters and the speed of reaching the critical mass.

The analyzed network turned out to be a radial network, which consisted of a set of actors who were linked to a focal actor but did not interact with one another, and can thus be described as a less dense and more open network, allowing the focal actor to exchange information with a wider environment. Such radial networks are believed to be particularly important in the diffusion of innovations because the links reach out into the entire system. The people in a radial network are more likely to possess information that the focal individual does not already possess. This further supports our proposition on the role of online networks as important information channels for distributing innovation related information.

Clique

Typical networks consist of a relatively large number of cliques that are small in size with a fair amount of overlap in membership. However, in the present study on the network structure of an online communication environment, relatively few cliques were identified, indicating that the network structure in the online environment differs from traditional network structures. This result differs from results reported earlier in non-online environments (e.g. Brown and Reingen 1987; Reingen and Kernan 1986). The low number of cliques can be explained by the fact that it was the innovation (the campaign) itself that brought together a large amount of actors who did not know each other before, and thus the amount of interpersonal links and cohesion was limited in the network.

This further distinguishes electronic word-of-mouth from traditional face-to-face word-of-mouth. Electronic word-of-mouth behavior seems to have a huge potential in coverage, achieved through the Internet's low-cost, bidirectional capabilities, and people's willingness to communicate even with strangers (see Dellarocas 2003). Thus, although the online network structure is different, it is still possible that in online environments information concerning the innovation is rapidly diffused, despite the number of cliques.

Centrality

The analysis of the network structure revealed that there was a great amount of concentration in the whole network. As the power of individual nodes varied remarkably, the positional advantages were extremely unequally distributed in the network. The mass media nodes (e.g. news sites) had a large audience, and thus, created a lot of ties and referral communications. As actors in highly central positions "have access to more resources and typically are able to control the flow of resources, to a large extent, throughout the network" (Webster and Morrison 2004, p.14), reaching these nodes in online environments is equally - or even more - important for ‘online marketers'. The present study highlighted the role of online news sites and personal blogs in information sharing. This is actually in line with the traditional diffusion theory which states that early adopters are influenced by external (mass media) information sources, whereas internal (personal) information sources are applied only later in the diffusion process (Rogers 2003). These results also support Wellman and Gulia's (1999) notion of Internet participants having rather broad and open relationships instead of close and specified ones.

Adoption Behavior

Previous studies (e.g. Midgley, Morrison, and Roberts1992) have found evidence that the network structure can have a substantial effect on the manner in which innovations diffuse, since the structure of communication networks influences the order in which potential adopters receive information about an innovation and, therefore, the order in which they adopt (Abrahamson and Rosenkopf 1996). Thus, it was proposed that network structure characteristics (namely the tie strength and centrality) would affect the innovation adoption behavior (i.e. timing/earliness of adoption). Partial support was found for the proposed positive relationship between the tie strength and early adoption behavior. We assumed that strong ties, which are believed to be more trustworthy and credible, would result in relatively earlier adoption. This was not fully supported by our data as only partial support was found, indicating that tie strength was not related to adoption behavior. This was an interesting result, implicating that all connections in virtual electronic environments are equal in their effectiveness and persuasiveness. Similar findings are proposed to be related to online feedback mechanisms, as Guernsey (2000) noted that people now increasingly rely on opinions posted on such systems [online feedback mechanisms] to make a variety of decisions ranging from what movie to watch to what stocks to invest in. This has an important implication for today's organizations as they need to understand and even manage these conversations. For example, for high technology innovations it might be of utmost importance to manage the preannouncement strategy in order to create positive buzz about the new innovation (Mohr, Sengupta, and Slater 2005), and thus prevent potential adopters from buying competing products already launched by competitors.

As earlier empirical research (e.g. Czepiel 1974; Webster and Morrison 2004) reported a positive correlation between centrality and the time of adoption, it was important to study the robustness of this assumption also in the online context. The present study found empirical evidence for the proposed relationship between network centrality and adoption behavior. Also in online environments the network structure (i.e. network centrality) seems to affect adoption timing, as higher in-degree centrality values were associated with early adoption behavior. This result is in line with Webster and Morrison (2004) who studied the communication network of Australian laboratories and found a positive and significant relationship between network centrality and the time of adoption. This indicates that opinion leaders, whose most striking characteristic is their unique and influential position at the center of the communication network of their system (Rogers 2003), have a significant role in innovation diffusion also in online networks. The results of the analysis of the network structure also revealed that the innovation diffusion studied here resembles a decentralized diffusion system in which new ideas spread horizontally via peer networks in a relatively spontaneous fashion (see e.g. Rogers 2003).

LIMITATIONS AND FURTHER RESEARCH

Several things should be noted to put this research in proper perspective. Since the study concerned one specific innovation in one specific setting, it can be viewed as a micro-analytic case study with inherent limitations on generalization to other contexts.

It is generally accepted that social network analysis is intolerant to missing or incomplete data (Borgatti, Carley, and Krackhardt 2006). Borgatti, Carley, and Krackhardt (2006) have shown that lower response rates are detrimental for the calculation of certain network analysis measures, especially degree centrality. However, their analysis is based on randomly generated networks and therefore the results may not be applicable to actual social networks. On the other hand, Kossinets (in press) argues that certain data collection methods may be more tolerant to missing data. If the respondents are asked to identify those actors with whom they communicate, as in the present study, then "the non-response effect can be balanced out by reciprocal nominations" (Kossinets in press). We acknowledge that the response rate in the present study (51.7%) may be a limitation. However, in very large networks (like online networks) it is not feasible to study every node in the network (c.f. Webster and Morrison 2004).

Furthermore, tie strength was determined on the basis of a single, self-reported measure. Using multiple measures, objective as well as subjective, might have resulted in more robust findings. For example, Reingen and Kernan (1986) based their tie strength measure on the frequency and duration of the communication (objective measures) and the importance attached to the relationship (subjective measure).

The studied innovation was free (i.e. non-profit) and the messages concerning the innovation on the mass media websites were informational and not commercial. This might have had an effect on the results, and thus the results may be different in the case of commercial innovations with producer-originated marketing messages. Thus, further research should track the referral network of a commercial online innovation. Additionally, more research is needed on the role of different types of information sources (i.e. mass media versus peer-to-peer), and on how the participants in electronic communication networks perceive different types of information sources, and what characteristics affect their persuasiveness.

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