MEASURING THE VALUE OF ELECTRONIC WORD OF MOUTH AND ITS IMPACT IN CONSUMER COMMUNITIES

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Marketing practitioners have recognized a need to measure customer-generated media in addition to the traditional marketing metrics. Message boards, chat rooms, blogs, and virtual brand communities have become important venues for customer-generated media. These communities can be modeled as two distinct, albeit connected, networks: social and informational. These networks change over time under the influence of online word of mouth. This study introduces *adapted PageRank* (APR), a new metric for measuring the value a community assigns each word-of-mouth instance and the value the community assigns to the members that create them. That metric is used to empirically support a model explaining how highly-valued information builds the social network. These communities are egalitarian in assigning value to informational content, without regard to the status of its source, and highly-valued content explains 10% of social network growth.

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"There go the people. I must follow them, for I am their leader."

—Alexandre Ledru-Rollin

Jim Nail (2005) of Forrester Research recently reported that VNU, a large market and media research company, purchased a stake in BuzzMetrics, a word-of-mouth measurement startup. He interpreted this move as a signal that the measurement of *consumer*[1]*-generated media* (refer to the Appendix for a glossary of italicized terms) was becoming as important as traditional market research methods. BuzzMetrics recently expanded its practice by offering a research service that monitors the millions of TV viewers who converse over the internet in virtual communities such as chat rooms, message boards, and *blogs* (or, *weblogs*). BuzzMetrics performs both a qualitative and quantitative analysis of this online word of mouth because they believe it provides a more complete understanding of viewer *involvement* than any alternative research method. The Advertising Research Foundation, American Association of Advertising Agencies, and Association of National Advertisers seem to recognize that existing ways of inferring product involvement are inadequate as they have announced a joint-venture to define a "consumer engagement" metric to complement traditional exposure metrics (such as Nielsen ratings). Academic research, such as Wang and Fesenmaier (2003) and Richins et al. (1992), supports the BuzzMetrics approach of inferring "consumer engagement" by measuring word of mouth.

Even though the Internet abounds in customer-generated media, most of it receives little attention. Current measures of word of mouth focus on quantity; there is a need for quantitative measures of impact or importance. This paper addresses this issue. Word of mouth is a network phenomenon: People create ties to other people with the exchange of units of discourse (that is, messages) that link to create an *information network* while the people create a *social network* (Figure 1). As a result, this paper proposes a metric for word-of-mouth importance and investigates the impact of highly valued discourse on the evolution of online community social networks.

[1] Although the term "consumer" is used throughout the paper, the term "customer," as used in a B2B context, could be substituted as the principles are equally applicable.

THEORETICAL BACKGROUND

General Network Typology

Newman (2003) lists four types of networks: social, informational, technological, and biological. He defines a social network as a set of people or groups with some pattern of contact or interaction between them. Social networks have been heavily studied by sociologists and marketing scholars. Most of these studies are like the Reingen et al. (1984) exploration of brand use commonality in a sorority: The sample size is small, the data are qualitative, and the network is analyzed as a static snapshot of its state at one particular time. More extensive studies include a study by Ebel et al. (2002) of email communications between 5,000 students at Keil University and an examination by Holme et al. (2004) of an online dating community. Holme et al. (2004) performed one of the few analyses documenting how a social network structure changes over time.

Informational networks are a way of modeling how separate pieces of related information fit together. The most often cited example of such a network is the citation network of scientific papers as examined by Price (1965) where the nodes of the network are journal articles and the ties between nodes indicate that one paper cited another. Burnett (2000) pointed out that virtual communities are both social and informational networks. Not only do units of discourse create an information network while people create a social network, but the content of community messages can be classified as informational, social, or indeed both.

Brand and Virtual Communities as Social Networks

Boorstin (1974) described invisible communities of consumption evolving after the industrial revolution. He observed that community, once exclusively based on geographic, political, or religious similarity, began to be based on commonalities in product use. Schouten and McAlexander (1995) described a more visible *subculture of consumption* in their immersive study of

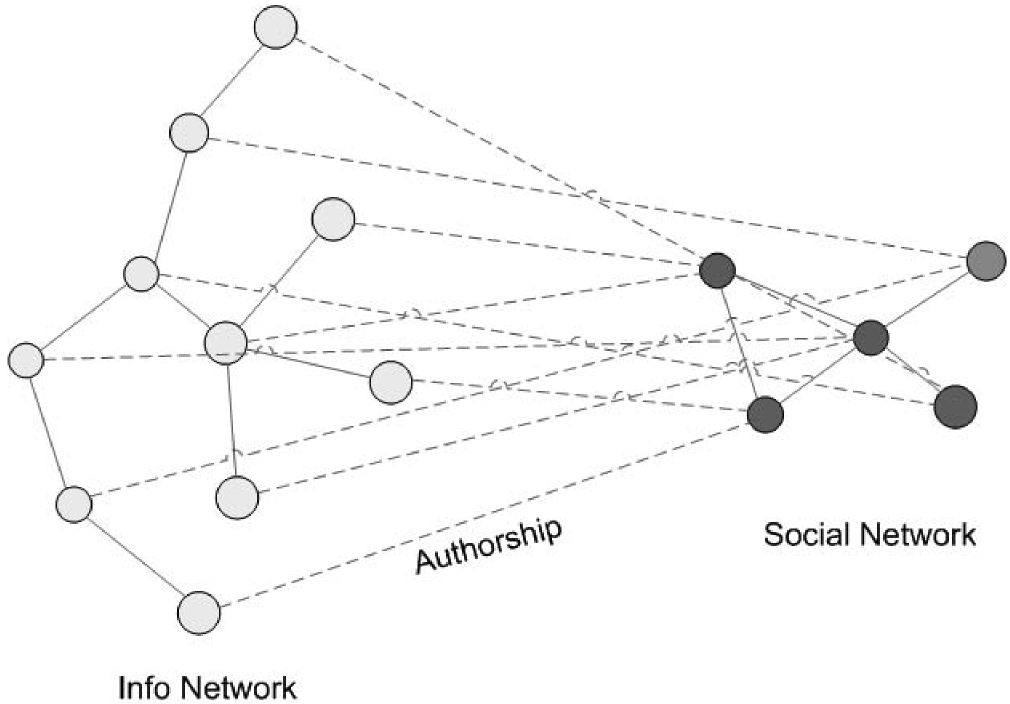

FIGURE 1
Virtual Community as a Dual Network

Harley-Davidson owners. Even though Reingen et al. (1984) did the first study of commonalities in brand use within a social network, Muniz and O'Guinn (2001) suggested the first model of a consumer or *brand community* that was also a social network.

Rheingold (1993) introduced the idea of a virtual community in his discourse about his activities with the WELL, a pioneering computer conferencing system that allowed people from around the world to participate in public conversations and exchange electronic mail. Wellman and Gulia (1999) performed the first social network analysis of a virtual community. Dholakia et al. (2004) recognized virtual communities as consumer groups of varying sizes that connect and interact online for the purpose of meeting personal and shared goals. A brief perusal of the virtual communities hosted by Yahoo! reveals that many of these communities thrive exclusively on the discussion of specific products or product types and are thus both brand and general consumption communities.

Involvement

This study embraces prior research that found word of mouth to be motivated by involvement; however, it does not seek to prove any such relationship. I adopted Zaichkowsky's (1985) definition of involvement as "a person's perceived relevance of the object based on inherent needs, values, and interests." She created the highly used Personal Involvement Inventory, a 20-item scale to measure an individual's involvement with a product, advertisement, or purchase decision. She found that a measure of high involvement on her scale correlated with an interest in reading more about the product, a process of detailed product comparison before purchase, and the eventual purchase of a product.

This research adopts a broader focus than Zaichkowsky (1985), which was primarily on the purchase decision. I suggest that the resources of an online community can be used by prospective buyers not only to facilitate information gathering but also to connect with a community of users to enhance their enjoyment after purchasing and using a product. A central premise of this study is that community participation is directly correlated to involvement; this is consistent with Zaichkowsky's (1985) findings in that high prepurchase community participation is the online representation of the information search process she described.

Involvement and Word of Mouth

Holmes and Lett (1977) found that product usage and purchase intention, both signs of product involvement, resulted in word-of-mouth behavior. Houston and Rothschild (1978) were the first to distinguish between *enduring involvement* and the *situational involvement* that surround a purchase. They also found that the highly involved excitement of a purchase dissipates over time. Their findings have been generally supported, albeit with some modification, by the work of later researchers such as Richins et al. (1992). Word of mouth is a common example of an *involvement response*.

Houston and Rothschild (1978) stated that external stimuli (for example, a new dishwasher was sought because the old one was beyond repair) cause situational involvement, and internal factors (such as a high linkage between product use and personal happiness) cause enduring involvement. Wang and Fesenmaier (2003) found that enduring involvement was the major reason for online community participation. Wang and Fesenmaier (2003) found the secondary motives of seeking benefits for oneself (for example, information) and offering help to others to be the other important precursors of community word of mouth.

Network Dynamics

Holme et al. (2004) demonstrated that network dynamics can be observed by doing a time series analysis of the metrics used to measure static networks. The models that explain how networks change are of two types: growth and destruction.

Price (1965) and Barabasi and Albert (1999) presented variations on a *preferential attachment* model, the principal explanation for how networks grow. In this model, network nodes that already have a lot of ties are the most likely attachment points for new network members. It is a "rich get richer" model of network growth. Lazarsfeld and Merton (1954) defined a secondary dynamic: *homophily,* which means like nodes will be attracted and create ties. The two dynamics have been combined to suggest that highly connected nodes are attracted to highly connected nodes. The chief limitation to these models is that they do not explain network decay.

Destruction models seek to explain how a network can be weakened by the deletion of nodes to the point of making communication through the network impossible. Albert et al. (2000) found that removing important nodes had a devastating effect on communication flow. Holme et al. (2002) expanded this area of study by looking at how the removal of key ties also can have a devastating effect. Newman (2003) pointed out that this research has been directed at assessing the resilience of the Internet to the failure of the computers that are its nodes. Carley et al. (2001) applied the destruction research to terrorist networks, speculating that the leaders of the decentralized terrorist networks would not be found by looking for the people with the most ties; rather, they would be the individuals with "high cognitive load," who emerge as leaders because they delegate tasks and are more likely to have *expert power*.

Unlike terrorist and technological networks, consumer networks are not subject to attack. They do, however, exhibit decay, possibly due to the dissipation of involvement. This phenomenon was noticed by Holme (2003) in his study of dating networks. He noticed that ties decay exponentially as time goes on because of decreasing contact.

Centrality, Prestige, and PageRank. Wasserman and Faust (1994) define two measures of network node importance: *centrality* and *prestige*. Centrality can be simply defined as the number of nodes to which a given node is connected. Prestige is a variant of centrality where a node has many incoming ties but is very selective in initiating ties with others. In a virtual community network a member gains prestige by posting messages that inspire others to post replies, thus creating incoming ties.

Burnett (2000) recommends using content analysis to determine the importance of the text messages posted to online communities. However, he admits that it is extremely difficult to specify a criterion for importance. Google, the Internet search engine, was faced with a similar problem when they wrestled with the problem of listing Web pages returned from a search in order of decreasing importance. They decided to adopt a very populist criterion for importance: the Web pages that were linked to the most were the most important. This PageRank algorithm also factors in the concept of prestige, where page importance is decreased in proportion to the number of links to other pages, and inheritance effects, where some of the importance of incoming links increases the importance of the page being assessed.

According to Bianchini et al. (2005), the PageRank (x_p) of page p is computed by taking into account the set of pages (pa[p]) pointing to p

$$x_p = d \sum_{q \in pa[p]} \frac{x_q}{h_q} + (1 - d) \tag{1}$$

where $d \in (0,1)$ is a proportioning factor and h_q is the *outdegree* of q, the number of links coming out from page q. The proportioning factor determines the amount of importance added to p by the pages linking to it. Page p has an inherent importance of $1 - d$. The outdegree parameter addresses the prestige issue, reducing the inherited importance of pages that link to other pages.

When PageRank is applied to information and social networks, outdegree is very difficult to assess. We do not know if the author of a message drew on the expertise of another person when composing its content. If a message is a reply to another message, it can be assumed that the original message provided some inspiration for the content of the reply. However, if a message begins a new topic of discourse, then this study assumes the source of its ideas to be the author alone. In this study the outdegree parameter is set at two (2) in the case of a reply and unity (1) otherwise. Since Google does not reveal the value it assigns to the proportioning factor, this study arbitrarily uses $d = 0.15$ in its adaptation of PageRank.

Applying this adapted PageRank (APR) to the information network recognizes that the value, or *knowledge capital*, of a message or information node is not only a function of its own inherent value but also the value of information nodes derived from or inspired by it. The sum of the individual message APRs yields a measure of the whole community's knowledge capital. Similarly, in the social network, APR measures both collective and individual *social capital* by aggregating the importance of members' personal contributions and the effect of having important associates.

Figure 2 vividly shows how centrality-based (that is, the number of immediate connections) measures of

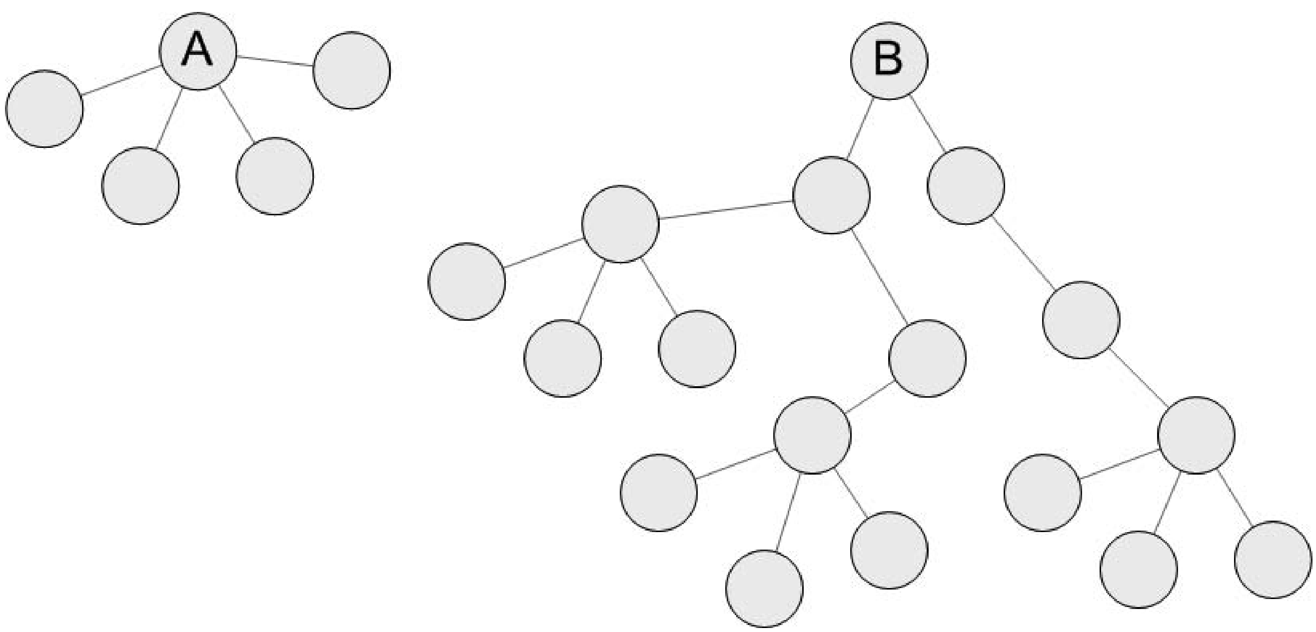

FIGURE 2
Centrality versus APR

importance are conceptually inferior to the APR metric. Using centrality, informational node A would be ranked twice as important as node B even though node B is the basis for a much larger information network.

The Role of Trust. Even the limited sample of communities used in this study highlights the diversity of subject matter around which online communities form. Some of the content posted to these communities may form the basis for consumer decisions, such as product purchases, or may involve the revelation of personal information—all acts that entail risk. Bart et al. (2005) note that community features are a factor driving trust in Web sites, especially those characterized by information risk (the risk associated with revealing personal information). They propose that "shared consciousness and a sense of moral responsibility and affinity enhance the consumer's level of trust" and may make consumers more confident in acting on information gained from online communities. While beyond the scope of this study, it would be interesting to know whether the APR estimations of knowledge and social capital reflect the level of trust readers place in contributing members and their content. It would also be interesting to assess the role of trust as another mechanism of preferential attachment.

Another factor that might influence trust-building is the appearance of the online community Web site. Schlosser et al. (2006) found that consumers trust the information contained on Web sites that look like they required a high degree of investment to create. While their study did not specifically involve community Web sites, it is possible that the effect they observed is a general phenomenon that is transferable. The people contributing information to an online community may be granted credibility by the appearance of the Web site even though they have no connection to the company that hosts the community. It is also reasonable to speculate that a community Web site that looks like it required a high level of investment may keep people involved in the community longer, opposing the process of decay.

PURPOSE

Based on the theoretical background presented here, this study proposes the model of Figure 3 to explain some of the dynamics of network growth and decay. The first phase of this study strives to validate the APR metric. I have described how the APR metric is a conceptually superior measure of information and social network importance compared to the prevalent metric of centrality (counting immediate connections). This study is designed to demonstrate a practical difference between the two metrics by showing how they answer a question concerning the central influence in preferential attachment: Is preferential attachment (network members deliberately creating ties with each other) driven by homophily (a desire to be associated with similar people) or expert power (a desire to be associated with experts)? In so doing, this study tests the hypothesis that the APR metric is merely a reflection of authored message volume and longevity of community participation rather than a measure of the community's appreciation of that participation. The second phase of this study uses the APR as a measure of knowledge capital to determine the role highly valued content in the informational network has in opposing decay (loss of members) in the social network.

DATA

The archives (October 1998 to February 2006) of 10 product-oriented Yahoo! groups (Table 1) were used to construct the social and informational networks studied. The data are therefore observational rather than experimental. In each case the entire population of data for each group is used. Figure 4 includes a sample

TABLE 1 Data Sources

GROUP	TYPE	MEMBERS	MESSAGES
1ALL_ROSWELL	TV – Roswell	2227	27960
2004-Prius	Brand – Automobile	2517	42419
7th_heaven	TV – 7th Heaven	912	6311
burningman-bcwa	Brand – Annual Event	789	18291
cb-750	Brand – Motorcycle	4541	93134
jumptheshark	TV – Generic	1124	53514
SimWatch	Brand – Computer Game	4303	40944
sportsterowners	Brand – Motorcycle	1630	36900
TheWestWing	TV – The West Wing	1160	12887
x-files	TV – X Files	1655	28844
Total		**20858**	**361204**

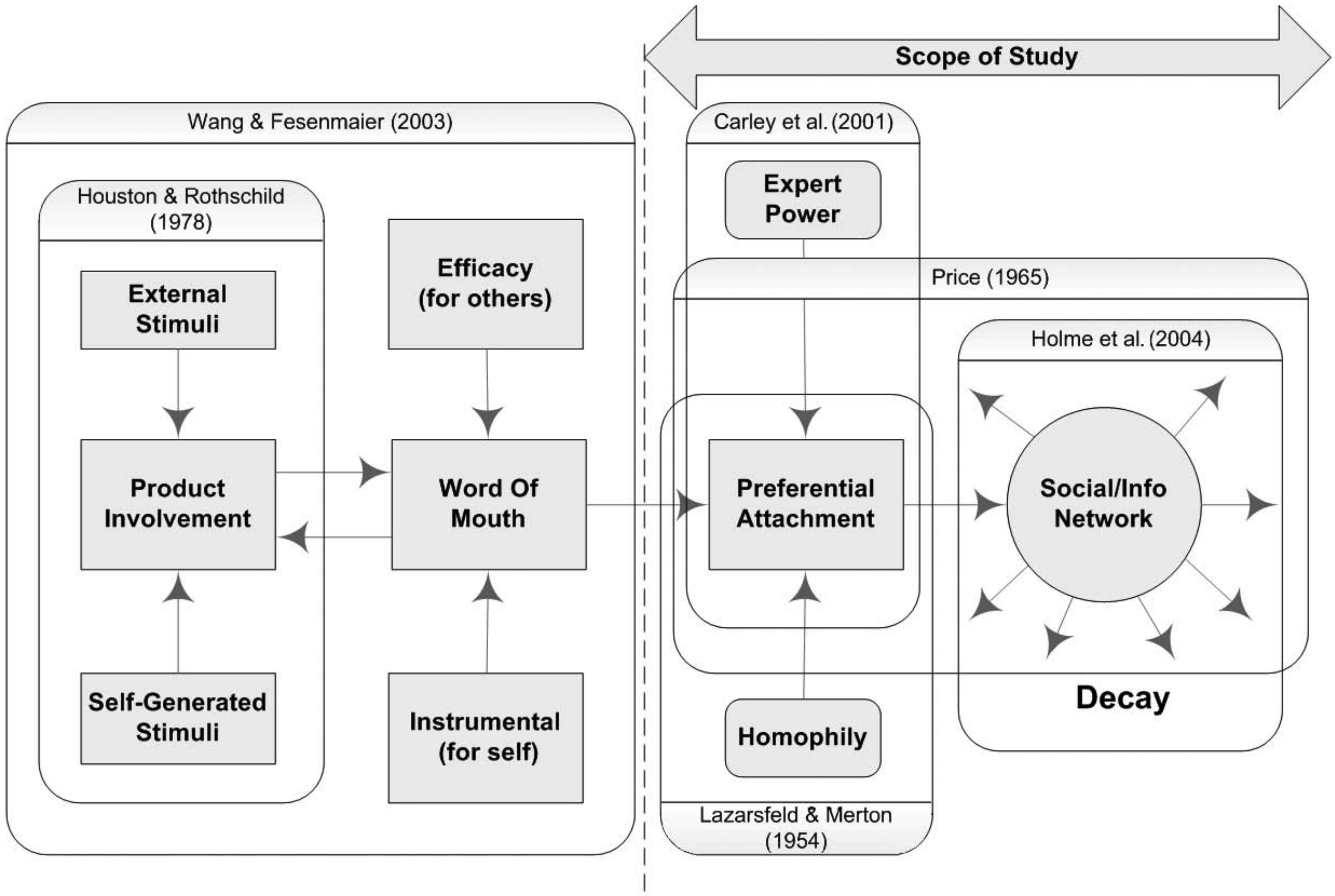

FIGURE 3
Conceptual Model of Consumer Network Dynamic

screen shot from the Yahoo! archives that indicates the author of each message, the date posted, and the thread hierarchy of messages and their replies (for example, message 18370 is a reply to message 17870). This allows a knowledge network for each group to be constructed in addition to a social network between authors. These groups were selected in a purposive manner to allow a study of large, highly active groups with wide diversity in their underlying subject matter and large volumes of messages.

DIRECTED ACYCLIC GRAPHS

The analyses used in this study refer to the methodology of Glymour et al. (1987) for *directed acyclic graphs* (DAGs). This methodology uses the correlation between variables and any knowledge of temporal relationships to construct a diagram of nodes, representing variables, and arcs, representing causal dependency among the variables. These diagrams must then be compared with known theory as a litmus test for their validity. Once such a diagram has been accepted as theoretically correct, then the same techniques used to calculate parameter values and fit in *structural equation models* (SEM) can be used.

In both the DAG and SEM methodologies, the modeler examines past research to gain some insight into how the variables being studied interrelate. The DAG methodology uses artificial intelligence techniques to examine the data gathered and to propose relationships between variables. In addition to a correlation matrix, these artificial intelligence algorithms also accept *metadata* describing prior knowledge, such as what relationships must exist based on theory and how these variables relate

17870	Save Roswell	Robyn	Feb 28, 2001
18370	Save Roswell	Alexandra Aleman	Mar 7, 2001
25416	Save Roswell	Suzi	Jan 30, 2002
17878	Save Roswell **We Need a Season Three** Sign Peti	desha	Feb 28, 2001
17888	Tess haters - Tess Lovers / Something I noticed i	bartonc@...	Feb 28, 2001
17969	Re: Tess haters - Tess Lovers / Something I notic	bello@...	Feb 28, 2001
17889	help save roswell!!!!	~*~Lou Lou~*~	Feb 28, 2001

FIGURE 4

Sample Yahoo! Forum Screen Shot

temporally (that is, one variable changed before another it affects).

There is no universally accepted methodology for the artificial intelligence algorithms that underlie DAGs. This study uses one of the best-supported methodologies, proposed by Glymour et al. (1987). Their methodology begins by assuming no relationship between the variables in the model and then uses F-tests, a correlation matrix, and prior knowledge metadata to find the relationships supported by the data.

The DAG methodology is similar to *exploratory factor analysis* in that it can provide insight where prior theory is lacking or ambiguous. A full explanation of the DAG methodology is beyond the scope of this paper. Glymour et al. (1987) is a good introduction for the interested reader. This methodology is growing in use and is extremely powerful in its ability to provide insight.

TABLE 2 The Extent That Attaching to the Top 5% Explains New Message Attachment

FORUM	PERCENTAGE OF MESSAGES ATTACHING TO THE TOP 5%			
	APR		CENTRALITY	
	KN	SN	KN	SN
1ALL_ROSWELL	79.7	27.9	43.0	13.1
2004-Prius	55.0	12.9	30.8	25.3
7th-Heaven	71.3	13.7	23.1	19.6
burningman-bcwa	59.7	26.6	18.5	43.4
cb-750	68.7	21.9	17.9	32.3
jumptheshark	70.3	35.5	22.6	51.0
SimWatch	68.4	22.3	29.2	26.8
sportsterowners	71.0	17.1	25.1	48.3
TheWestWing	65.7	12.1	21.4	30.3
x-files	69.9	14.2	24.1	28.3
Mean	**68.0**	**20.4**	**25.6**	**31.8**

KN = Knowledge/Information network, SN = Social network.

METHOD AND DISCUSSION

Phase One: Validation of the APR

Is There a Difference? The first phase of this study was designed to validate the superiority of the APR algorithm in demonstrating preferential attachment compared to the prevalent centrality-based method. I calculated the APR and centrality for each message and its author and then ranked each message in turn by each of those four categories in descending order. These calculations were done using a PC with a 2.0 MHz AMD 64-bit processor and 1.5 gigabytes of RAM. It took approximately three (3) hours to perform these calculations for the 1ALL_ROSWELL community. I then took the messages in the top 5% of each ranking and found the percentage of all messages that got attached to them. Tables 2 and 3 summarize the results. T-tests were used to show where there are significant differences in the use of the two methodologies across the two networks (Table 3). Table 3a shows

TABLE 3 (a) and (b) Differences in Methods Across Networks

(a)	KN vs. SN	(b)	APR vs. CENTRALITY
APR	$t = 17.48, \rho < 0.01$	KN	$t = 17.39, \rho < 0.01$
Centrality	$t = -1.12, \rho = 0.29$	SN	$t = -3.06, \rho = 0.01$

that centrality is unable to detect a difference between attaching messages to the top 5% of the social network and attaching messages to the top of the knowledge network. Table 3b shows there is a significant difference between the ways the two methods measure attachment in the social and knowledge networks. The APR metric shows that message posters are drawn to reply to information of highest value to the group, regardless of who the author is, while centrality is unable to make any such distinction.

Volume, Duration, or Quality? When message APRs are converted to z-scores to remove the influence of network size every message that attains a top 5% APR fits a curve of the form presented in Figure 5 with an $R^2 > 0.8$. Observe how these messages attract comment early and quickly build their APR score.

As already described, an individual's social capital APR is a function of the number of messages authored, both new threads of discussion ("seeds") and contributions to existing threads ("replies"). It would be logical to suggest that social capital APR might also be a function of duration of participation. If social capital APR is a true representation of the quality of a member's contributions, then it is necessary to show that this metric is not purely a function of the volume of messages posted and length of community membership. Figure 6 shows how one individual's social capital

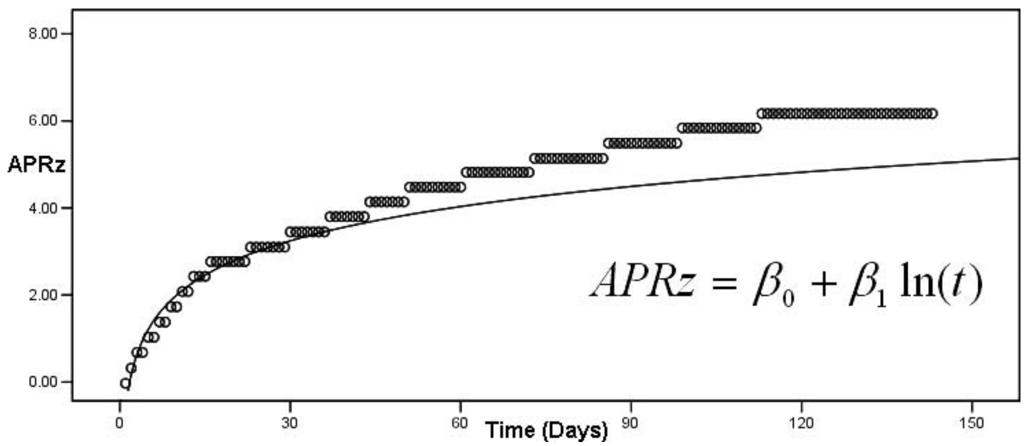

FIGURE 5

The Typical Pattern of Message Knowledge Capital Accrual

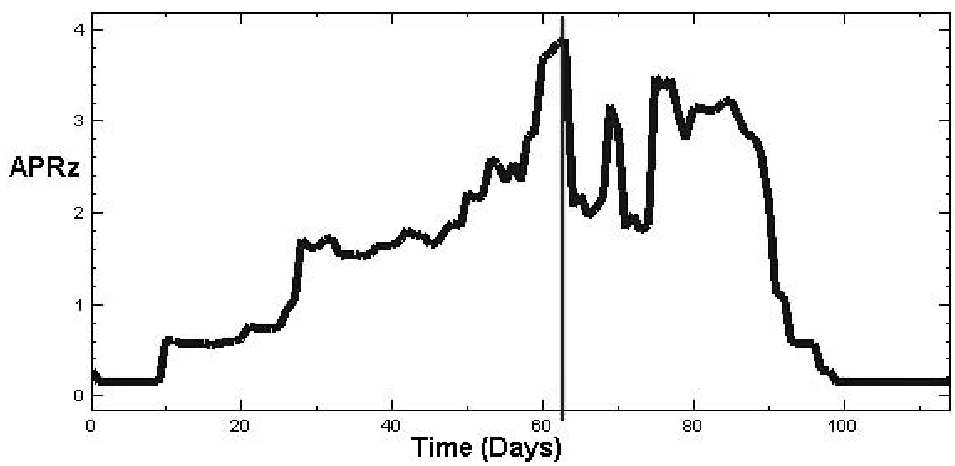

FIGURE 6

An Example of Individual Social Capital Development and Decay

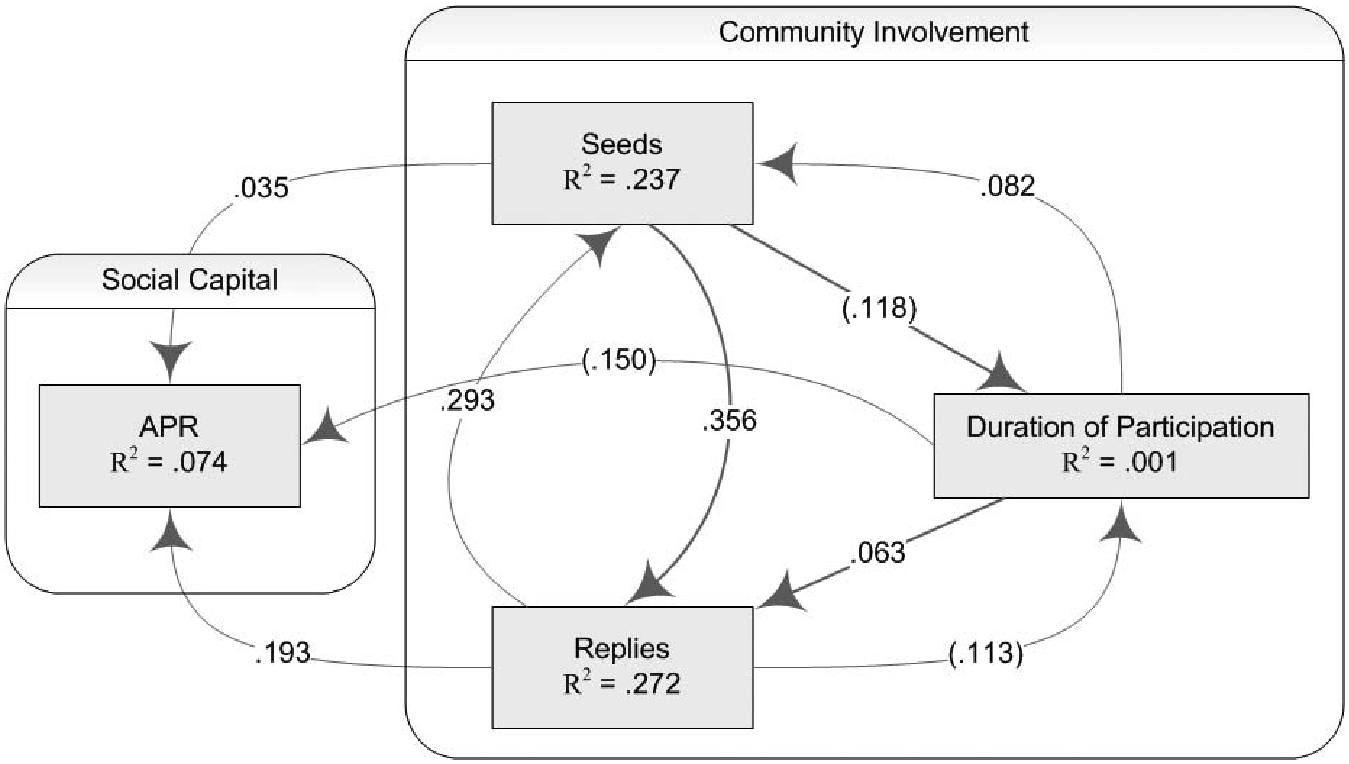

FIGURE 7

Effect of Message Volume and Duration on Social Capital

developed over time (in days). I have examined many such plots and found that there is no standard pattern that holds true for a majority of individuals except the general pattern of build-up and decay.

To show that social capital APR is a true representation of the quality of a member's contributions, rather than purely a function of the volume of messages posted and the length of community membership, I divided the contribution and longevity (in days) data for every community member at the time of their maximum APR (the vertical line in Figure 6) into two sets: prior and post. When these two data sets are processed using the Glymour et al. (1987) methodology, two DAGs, Figures 7 and 8, are significant at $\rho = .05$. The weights assigned to the arrows are the result of using maximum likelihood to estimate simultaneous linear equations with an *adjusted goodness-of-fit* (AGFI) equal to 1.00. Even though these findings are statistically significant, the explanatory power is weak. As a result, I conclude that the APR metric is not merely measuring the volume and longevity of activity.

Homophily or Expert Power? The second part of this phase was designed to discover the extent homophily, or tie creation between people of similar social capital, influences in the mechanism of preferential attachment. I reenacted the evolution of each forum beginning with its first message. As each subsequent message was added, I calculated the APR of every member of the community and converted it to a *z-score*. I then accumulated an average of the incoming and originating message authors' APR. The final averages are given in Table 4. The t-test shows that the two sets of averages are significantly different. Message originators come from the full spectrum of community membership, but the people who reply to these messages are usually possessed of greater social capital and by implication, greater expert power.

However, Table 5 shows that homophily is present as the density of ties between the top 5% of social capital holders is significantly greater than that of the community as a whole. I can conclude therefore that while homophily is present in most networks it is not an important driver of preferential attachment.

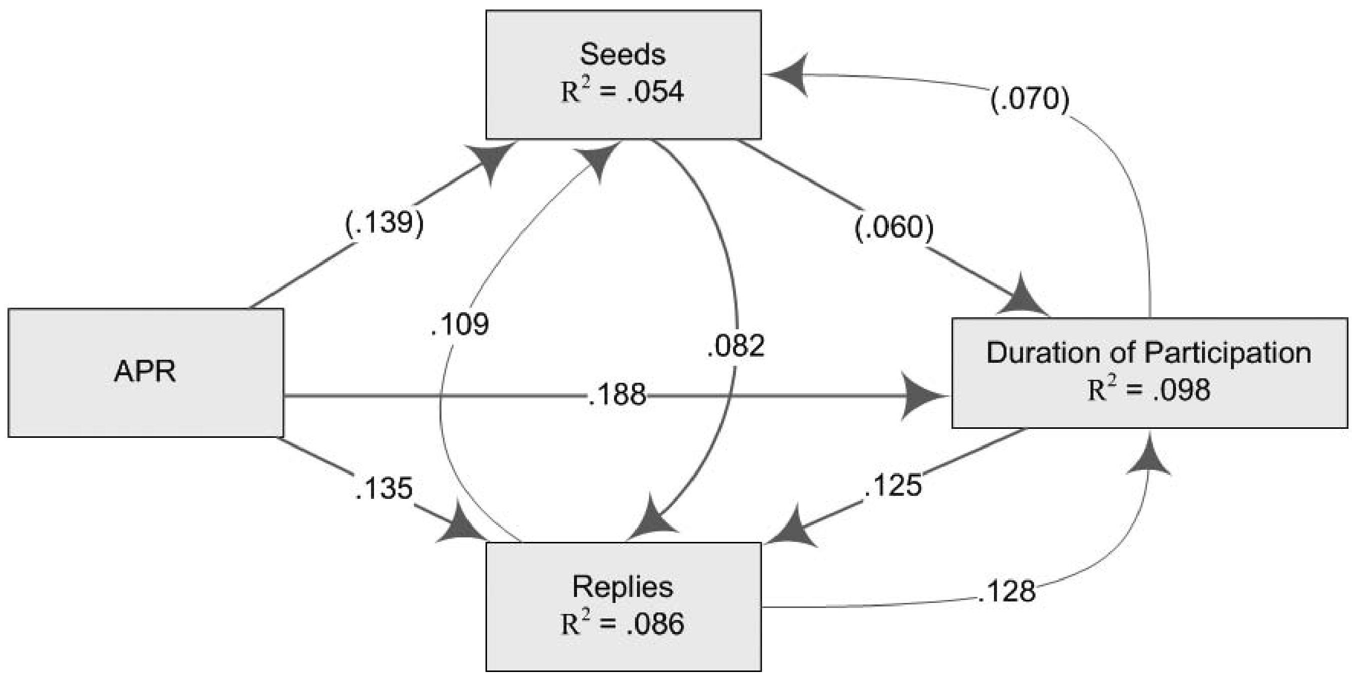

FIGURE 8
Effect of High Social Capital on Subsequent Community Involvement

TABLE 4 The Insignificant Role of Homophily in Preferential Attachment

FORUM	ORIGINATING AUTHOR'S AVERAGE APR *Z*-SCORE	REPLYING AUTHOR'S AVERAGE APR *Z*-SCORE
1ALL_ROSWELL	.24	1.07
2004-Prius	.64	1.00
7th_Heaven	.10	.72
burningman-bcwa	.33	.56
cb-750	.39	.98
jumptheshark	.30	.66
SimWatch	.39	1.07
sportsterowners	.38	.54
TheWestWing	.18	.78
x-files	.13	.88
Mean	**.31**	**.83**
t	-7.24	
p	$<.01$	

TABLE 5 The Presence of Homophily

FORUM	DENSITY OF TOP 5% IN SOCIAL NETWORK	OVERALL NETWORK DENSITY
1ALL_ROSWELL	11.9	2.4
2004-Prius	11.1	3.9
7th_Heaven	5.2	7.9
burningman-bcwa	35.6	12.7
cb-750	28.3	5.6
jumptheshark	24.8	18.1
SimWatch	25.4	4.3
sportsterowners	13.8	7.1
TheWestWing	8.2	8.8
x-files	2.7	6.1
Mean	**16.7**	**7.7**
t	2.81	
p	.02	

Phase Two: The Effect of Knowledge Capital on the Social Network

In the final part of this study, I quantified and investigated the interplay between preferential attachment and decay in the social network and changes in community knowledge capital over time. Table 6 summarizes some measurements of attachment and decay.

The Ongoing column contains the proportion of community membership that carries over from month to month. The Joiners column is the proportion of new members. The Leavers column is the proportion of members contributing their last message. Most of these series are stationary about a mean; however, the means vary considerably. When the source data for Table 6 is corrected for heteroskedasticity, it results in the Glymour et al. (1987) DAG model shown in Figure 9 ($\rho = .05$, AGFI = .97). The model shows a high degree of autoregressive interaction between the variables of interest. When autoregression is removed from the model it simplifies to the *contemporaneous model* of Figure 10 ($\rho = .05$, AGFI = 1.00).

TABLE 6 Attachment and Decay Measured

FORUM	AVERAGE PERCENTAGE		
	ONGOING	JOINERS	LEAVERS
1ALL_ROSWELL	59.2*	16.7*	23.2*
2004-Prius	49.6*	19.9*	28.1*
7th_Heaven	59.2*	17.8*	20.0*
burningman-bcwa	81.1*	14.9*	10.0
cb-750	67.1*	16.8*	16.1
jumptheshark	68.8*	15.9*	12.7*
SimWatch	69.3*	15.4*	19.6
sportsterowners	73.3*	15.1*	15.6
TheWestWing	69.4*	16.9*	20.0*
x-files	57.4	16.9*	19.7*
Mean	**65.4**	**16.6**	**18.5**
σ	9.1	1.5	5.2

*Satisfies the Dickey and Fuller (1981) test of *stationarity* with $t < -2.89$ (95% sig.).

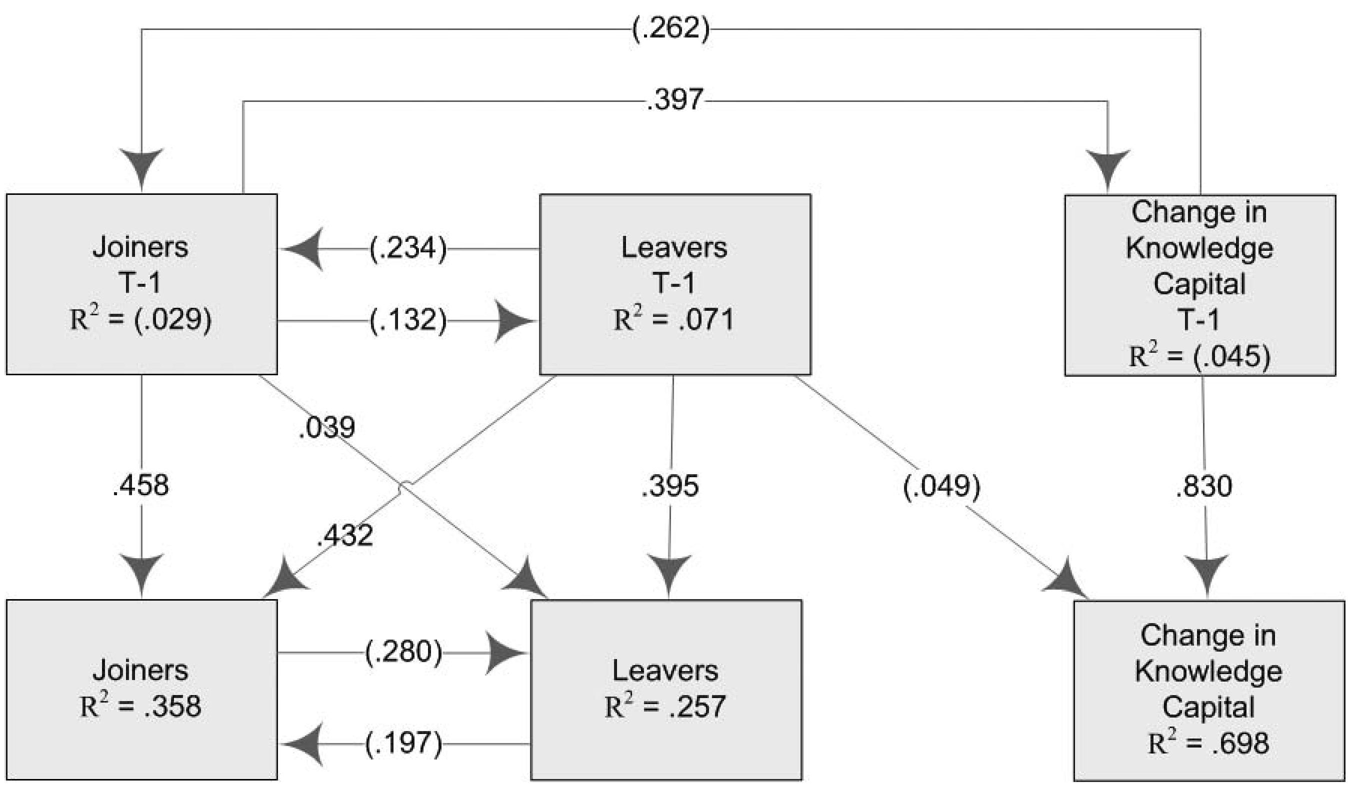

FIGURE 9
Dynamics of Knowledge Capital, Joiners and Leavers

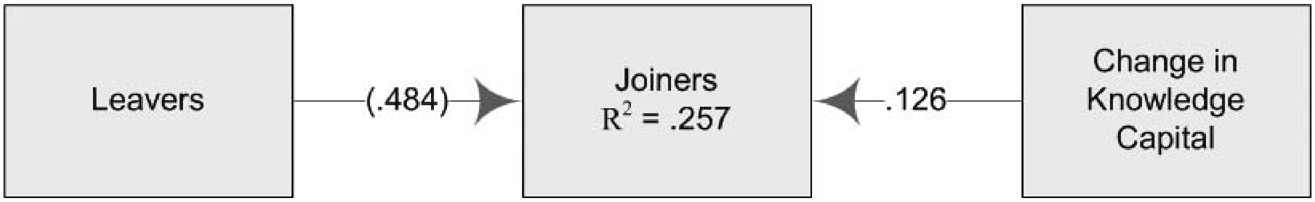

FIGURE 10
Effect of Changes in Knowledge Capital and Leavers on Joining

Here we see that changes in knowledge capital and Leavers are endogenous drivers of Joiners. The negative coefficient on the arrow reflects that Leavers are subtracted from the social network while Joiners and the knowledge network only change in a positive direction. Because Leavers actually could not be influencing Joiners, I interpret these causal relationships to mean that an unobserved effect causes members to join, the absence of which causes members to leave (Figure 11). Based on a survey of relevant theory, I suggest that this unobserved effect is product involvement.

Performing a common factor analysis on Leavers and Joiners finds the indicated result explaining 49% of the variance in Leavers and Joiners albeit with a miserable KMO of .5. An increase in high-value content seems to explain about 10% (58.6 – 49.0 = 9.6) of what causes people on the sidelines to join in on the discussion and become active members (that is, Joiners). Change in knowledge capital is Pearson correlated to this common factor at .091 ($\rho = .02$). If this common factor represents an underlying product involvement, it is consistent with this discussion that it should be positively correlated with changes in knowledge capital.

SUMMARY AND CONCLUSIONS

The PageRank-based algorithm is a superior basis for measuring importance in the informational and social networks compared to the prevalent centrality-based metrics (counting a node's immediate ties). Content of high value to the community attracts attention with little reference to who originated the content. Thus expert power, in whatever form, is respected by the

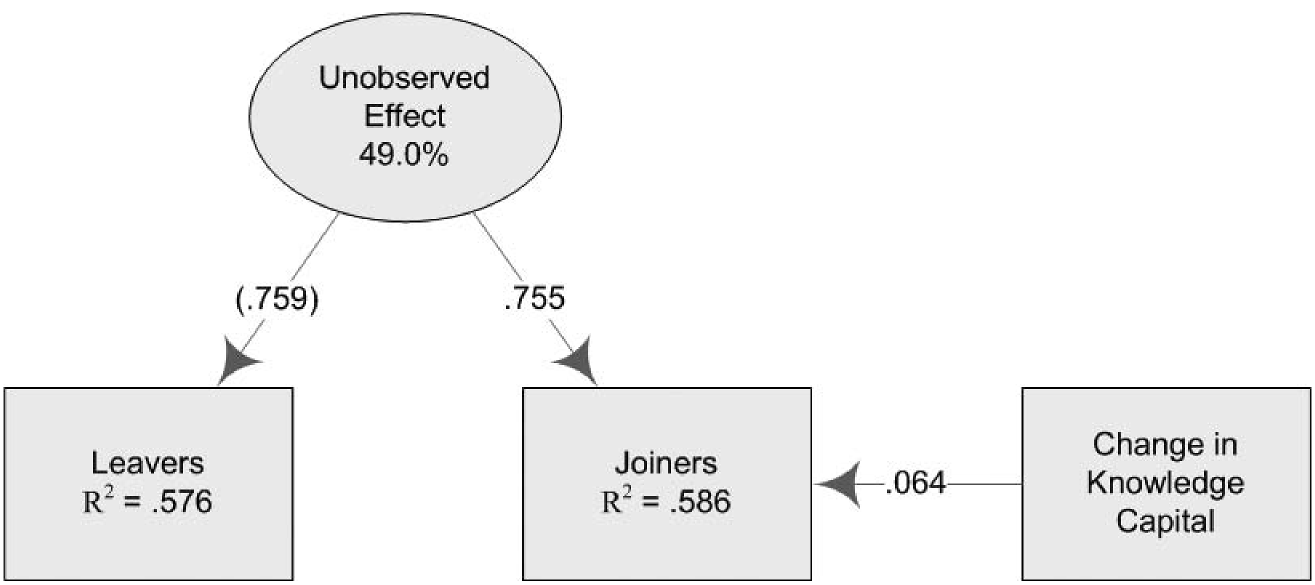

FIGURE 11
Unobserved Common Effect

community, is the prime influence in how the knowledge network causes the social network to evolve over time. High-value content in the knowledge network explains 10% of social network growth. Changes in people's enjoyment of the products they use may account for a large part of the network changes my model has not explained. Validating this supposition would be a logical avenue for further research.

As stated in the introduction, many companies have begun monitoring online communities of their customers as a source of feedback. They seem to be aware that community members are often the most fanatical of their customers and act as product evangelists. With the APR metric, companies can automate the process of filtering community message traffic to identify the information that attracted the most customer attention, as well as the members who typically provided that information. Since high quality content plays a significant role in building online community, companies who have products with large and active online communities should consider hosting a *blog* so they can play an active and visible role in injecting such content into their user community. Such efforts should be in the spirit of Alexandre Ledru-Rollin's lead-by-following philosophy, that is, the company must restrain itself from trying to control their consumer communities and let emergent forces among the consumers be the guiding influence. The effort a company applies to this mode of marketing communications should be rewarded by increased sales as the enthusiasm of consumer-evangelists is maintained and producers gain greater ability to create products their customers desire.

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APPENDIX GLOSSARY

Adjusted goodness-of-fit: The adjusted goodness-of-fit index (AGFI) is a measure of how well a proposed model fits a body of data corrected for the degrees of freedom (that is, number of data observations minus the number of variables) in the model. The closer the index is to 1.00, the better the fit.

Autoregression: When the current value of a variable is partially based on its previous value, or indeed the previous values of other variables, that variable is said to show *autoregression*. Sometimes it is useful to know to what extent a variable's current value is based on previous values; however, if you are trying primarily to determine the extent to which a current value is based on the present values of other variables, then you will want to remove the *autoregressive* portion so that it will not be a source of confusion.

Blog: An abbreviated form of *weblog* (see Weblog).

Centrality: In a network or a set of connected entities, *centrality* is a common way of denoting which entity or entities are most important. Centrality, expressed simply, is the number of direct ties connected to an entity by other entities in the same network. The more ties an entity has, the more "central" it is said to be. Centrality is often more specifically called *degree centrality*. Sometimes centrality is expressed as a percentage: If you know 30% of the people in a room—all members of a club (that is, in a network)—your centrality is 30%.

Consumer-generated media: The term "consumer-generated media" is used interchangeably with the "customer-generated media." It refers to online content that is produced by people who were hitherto assumed to be only users or consumers of online content. The phenomenon reflects the availability of affordable new tools for authoring content that can be easily disseminated through the Internet. Such content includes *blogs*, podcasts (an audio file, usually containing commentary or entertainment content), video, cellular phone photos, word of mouth, and wikis (a Web site that allows readers to edit the content and thus be a tool for collaborative authoring).

Contemporaneous: In the preceding definition of *autoregression*, I distinguish between past and present influences on a variable's current value. The present influences are said to be *contemporaneous*.

Decay: People come and go from social networks and communities, making the community subject to the opposing forces of growth and *decay*. People are motivated to stay in communities by satisfying social and tangible rewards (for example, information). When these rewards lessen, people leave. If this perception of lessened rewards becomes widespread, then the community will eventually disappear.

Directed acyclic graph (DAG): A DAG is a diagram showing how a group of variables affect each other's values. It is termed *acyclic* because it never depicts a variable as having its value determined by itself, either directly or through one or more other variables. A DAG is a type of *structural equation model* (defined below).

Endogenous: A situation in which a variable's value is fully determined or explained by the value of other variables that it is known to be in a relationship with. For example, in the basic equation for a straight line:

$$y = mx + b \tag{2}$$

The variable y is *endogenous* in that its value is fully determined by the values of variables m, x, and b.

Exogenous: *Exogenous* is the opposite of endogenous. In Equation 2, variables m, x, and b are termed exogenous because their value is determined by something other than any relationship defined by Equation 2.

Heteroskedasticity: Suppose that you are trying to determine how the weight of a calf increases over time as it grows. Let's say that you weigh the calf using the same scale every day for 100 days and then weigh it again for another 100 days using a different scale. It might seem reasonable that you could take all 200 values, plot a trend line, and thereby get a good estimate of how calves gain weight. However, because the two scales might vary in their accuracy, you have a potential for the introduction of error in your weight estimation due to *heteroskedasticity*. In this paper, data are gathered from a variety of different communities, all possessing unique levels of variance. When these data are merged to derive findings true of communities in general, heteroskedasticity must be removed. In this situation, all values are converted to z-scores (see definition below), removing the variance unique to a community.

Homophily: Suppose you, a prospective club member, enter a room filled with members of that club. One general theory that tries to explain what strategy you will employ to become integrated with the club (or network) is *homophily,* that is, you will look for people similar to you. In an online community, we become aware that a new member has joined when he or she posts a message. If the new member chooses to announce his or her presence by deliberately attaching a message to that of another member, then he or she has practiced homophily. The similarity of homophily can be expressed in almost unlimited ways.

Information network: When separate pieces of information are linked together and to other pieces of information because they have been judged to be thematically or semantically related, that collection of interrelated information can be called an *information network*. In this paper, I use this term interchangeably with knowledge network (see definition following). An online community's only tangible asset is the information contained in the messages members post to it. Members generally add their messages so they logically relate to those already there. As a result, these communities are informational networks.

Involvement: Involvement is a motivational state aroused by the personal relevance of some stimulus, object, or situation. In this study, the messages posted to online communities are seen to be a possible result and an arouser of involvement in the participants. Prior research distinguishes between situational (short-term, context-dependent) and enduring (long-term, lifestyle-related) involvement. Behavior that is motivated by involvement is called an involvement response. Prior research has identified word of mouth as an involvement response.

Knowledge capital: As in an informational network, an online community's only tangible asset is the messages posted to it. These messages, and the way they relate to each other, have value and increase in value as more content is added. This value is called *knowledge capital*. The adapted PageRank metric described in this paper is a way of expressing the value a community has assigned to all or part of its information network.

Knowledge network: As said in the definition of informational network, this paper uses *informational* and *knowledge network* interchangeably. Other writers in the marketing discipline define the term differently.

Metadata: This word literally means "data about data." The directed acyclic graph methodology (defined earlier) is able to take into account prior knowledge about the relationships between variables in a model. This prior knowledge is *metadata*.

Node: A network is composed of *nodes* connected by ties. Nodes refer to entities that belong to a network. The relationships that connect these entities are *ties.* A family is a common network. One example of a family might consist of a husband, wife, and two children. The four people are nodes, and the marital, parental, sibling, and familial relationships are all ties.

Outdegree: The term *outdegree* uses the word degree in a manner similar to its use in the phrase degree centrality. If you enter a room full of networked strangers and make 10 new friends, then your outdegree in that context is 10. A related term is *indegree,* the number of relationships others have initiated with you. These two terms are integrated in the concept of prestige (see definition).

Preferential attachment: If, when you join a network, you exercise a strategy for selecting specific members of the network for the creation of a relationship (such as friendship), then you have demonstrated *preferential attachment.* Homophily, defined above, is an example of preferential attachment strategy. In this paper, I discuss two preferential attachment strategies: homophily and expert power. *Expert power* refers to a strategy of creating ties with people who possess superior knowledge.

Prestige: *Prestige* is a type of centrality (defined earlier) where a node has a much larger number of incoming ties (indegree) than outgoing ties (outdegree). The implication is that others have sought you out for preferential attachment but that you are more self-sufficient and have not sought many ties with others.

Proportioning factor: When Google calculates a Web page's PageRank, it uses a portion of the PageRank of Web pages that it links to. The linking page inherits some of the importance of pages it references. This idea can be transferred to social networks: Your importance is partially based on the importance of the people you know. Google keeps secret the exact proportion it uses. This paper uses an arbitrary value of 15%.

Purposive selection: There are two ways to select a sample for a scientific study: randomly or purposively. Random sampling is commonly used in laboratory settings when you want to avoid introducing sources of bias or nonrandom variation. However, in a real-world setting, you can accomplish the same goal by deliberately looking for wide diversity in your test subjects. Even though many product-oriented online communities have been started, few are highly active. A random sampling of these communities would probably result in an attempt to derive conclusions from a small amount of data. As a result, I used *purposive selection,* purposely looking for large and active communities interested in a wide variety of product classes. While this might bias the findings toward attributes peculiar to large and active communities, I contend that this risk of bias does not impair my ability to meet the goals of this study.

Social capital: The value of your social network added to your own inherent worth (i.e., unique knowledge and skills) is your *social capital*. A whole network can also have social capital—the sum of the individual social capital of all its members. What constitutes value in a social network is very specific to its context. Theorists have proposed that expertise or knowledge is the core determinant of value. You have value because of what you know and the knowledge you can access through your friends.

Social network: When a group of people is linked together by any relationship or set of relationships, from casual acquaintance to immediate family, the group is said to be a *social network*. Members of the same online community may never have physically met; however, if they have communicated ideas to each other, they have met semantically and thereby become connected.

Stationarity: When some value is measured over time, it may exhibit an upward or downward trend; it may also fluctuate about some average value. In the latter situation, the value can be said to be *stationary* about a mean. There are ways of testing whether a series of values is stationary; this study uses the method proposed by Dickey and Fuller (1981).

Structural equation model (SEM): The relationships between a set of variables that affect each other's values can be expressed as a diagram such as that in Figure 9. Measured variables are depicted as boxes connected by arrows that denote directions of influence. The degree of influence is represented by a number on the arrow. SEMs can also depict the influence of latent variables (see Figure 11), that is, variables that have not been directly measured but whose value and influence can be inferred from the other variables in the model.

Weblog: A weblog, or *blog,* is a Web site where one or more regular authors initiate discussion on a topic of their choosing. The Web site allows comments to be added to the end of the blog author's entry thus allowing a two-way conversation between author and reader and a many-to-many conversation among the readers. A weblog is usually distinguished from a forum or message board by the presence of the blog entry, which is intended to control the subject of conversation.

***Z*-score:** A *z-score* or standard score is calculated using Equation 3:

$$z = \frac{X - \mu}{\sigma} \tag{3}$$

where X is a member of a set of values having a mean of μ and a standard deviation of σ. Z-scores are useful when comparing sets of values that differ in size and variance by placing the values on a common footing.