Original Article

A diffusion model for measuring electronic community growth and value

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ABSTRACT Marketing practitioners have pursued understanding, support and leverage of virtual communities, given their potential for aggregating people/consumers with shared interests, fostering connections and relationships, and influencing behavior. A challenge for practitioners in building successful virtual communities has been understanding the dynamics of an online community with respect to growth, and, in turn, predicting the potential equity of an electronic community. Organizations armed with this predictive ability could better decide in which communities to be a first/early entrant and where they can build valuable customer relationships. We address this issue by developing and proposing a diffusion model of electronic community growth and value, based on a respected diffusion model, with modifications and adjustments to fit the special characteristics of electronic communities. This should help organizations to better understand how to build or identify valuable virtual communities, and better invest

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marketing dollars in community-related activities such as promotions and customer relationship building.

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INTRODUCTION

Marketing practitioners have pursued the understanding, support and leverage of virtual communities,¹ given their potential for aggregating people/consumers with shared interests,^{1–5} fostering connections and relationships (for example, Horrigan⁶), and influencing behavior.^{7–10} Indeed, many online communities are structured around consumption and marketing interests¹¹ and can play a strategic role for organizations.^{3,4,12}

Product/service providers and advertisers are keen about virtual communities¹³ because, for example, they facilitate the aggregation of a large target-rich environment and, correspondingly, simplify the process of finding target consumers, make expenditures more efficient (that is, greater likelihood of marketing effort reaching interested consumers) and, in spirit, carry out marketing tasks through mechanisms such as *word of web*,¹⁴ which can positively impact consumers' behaviors, such as making a purchase.

Some electronic communities have proven to be very successful.¹⁵ For example, eBay (a community of individuals and businesses who come together for exchange in its online marketplace), Edmunds.com (where people meet to learn about and discuss all things automotive) and BabyCenter.com (where new and expectant parents find information and support they need during pregnancy and in caring for a baby, toddler or child) have created communities that help them carry out their business objectives by building brand loyalty, increasing sales and fostering goodwill with customers.¹⁵ Few organizations have created truly sustainable virtual communities. However, there have been studies that have found general benefits of virtual communities in selected industries – for example, in the banking industry.¹⁶

Three key elements that are related to the success of a virtual community are membership size, member activity and interaction, and content quality,¹¹ as well as the motivation the members have to join.¹⁷ The problem for practitioners in building successful virtual communities has not so much been lack of awareness of these key factors; it has been understanding how these factors interact in determining the value of an online community, and, in turn, predicting the *potential* equity of an online community. Organizations armed with this predictive ability could better decide in which communities to be a first/early entrant and where they can build valuable customer relationships.

In this article, we address this issue by proposing a diffusion model of electronic community growth and value. First, we review relevant literature about electronic communities and examine a two-stage diffusion model by Kalish¹⁸ upon which we draw and adapt when building our model. We then describe our diffusion model and apply it using an illustration. Finally, we discuss the implications and some limitations of this model, and provide suggestions for future research.

LITERATURE REVIEW

Electronic communities

'Virtual communities are social aggregations that emerge from the Net when enough people carry on those public discussions long enough, with sufficient human feeling, to form webs of personal relationships in cyberspace' (p. 5).¹ These relationships may have been initiated offline (for example, high-school graduating cohort or friends) and the Internet may have been used to supplement them,⁵ or they may have been initiated online with interactions

occurring primarily online,⁴ or, in the case of *e2f* (that is, electronic-to-face) communities,¹⁹ for the purpose of interacting/socializing offline (for example, Meetup.com). Five basic structural types of online communities exist:⁸ bulletin boards, webpages and web rings, list(serv)s, multi-user dungeons and chat rooms.

The five basic characteristics of a virtual community are well summarized by Bagozzi and Dholakia.²⁰ First, communities are defined as bringing people together around some (common) need(s), interest(s) or cause(s), such as finding travel bargains (for example, see, www.biddingfortravel.com) or buying, selling or caring for a car (for example, see, townhall-talk.edmunds.com). Second, members feel affiliated with each other, which can impact their willingness to 'return' to the community, share information/resources and support others. Third, they establish rituals, play social roles, follow norms, support community goals and use shared conventions and language. Fourth, members actively create content by chatting with one another and with community organizers about concerns, opinions or questions pertaining to their common interests. And fifth, communication content is extremely prominent in influencing a community's nature and makeup.

One key difference between virtual and traditional communities is that membership, participation frequency and involvement are volitional in the former, and may be involuntary in the latter, such as by birth or geography.²⁰ In addition, the hold of an online community may be relatively tenuous given the relative ease with which one can withdraw.

Clearly, the major constructs within an electronic community are its member-to-member communications, relationships and activity. These relationships are of considerable interest to marketers because customers' purchase decisions are routinely affected by other customers.^{21–25} A critical aspect of an online community is the creation of an environment in which member-generated content is encouraged, captured and disseminated.

Naturally, the value or equity of an electronic community will vary by the number of members,

membership loyalty and the associated amount of customer-to-customer interactions,²⁶ as well as the quality and associated usefulness of the member-generated content. Of course, it will also vary by the general topic. For example, for informal learning, online communities are not unlike open universities, and have been particularly successful.²⁷ Research indicates that the adoption process involves stages at which an Internet user becomes aware of a community, 'lurks' or browses through its content/environment, and then becomes active in the community by joining and interacting with others, which may be followed by more frequent interactions.⁸ Once the latter occurs, 'it is likely that they will become a recurrent member of one or more of the gatherings, and increasingly turn to them as a source of information and social interaction'.⁸

This adoption process has many similarities with that modeled by Kalish.¹⁸ Therefore, we examine this diffusion model in the next section.

The Kalish model

Kalish¹⁸ extended the well-known Bass model²⁸ in several ways. Most notably, he posited that the adoption process can be divided into two stages: (1) awareness of the innovation and (2) adoption of the innovation among those who are aware. Furthermore, in stage 1, he explicitly considers the level of advertising expenditure as one of the determinants of awareness (not a shock, obviously, as it is just about axiomatic that advertising generates awareness). In addition, in stage 2, he explicitly considers two factors as determinants of the number who adopt, by postulating that these affect the market potential for adoption (and at a fixed level of these two factors, there is a constant proportion of this market potential who will adopt). One of these factors is price (with the obvious proposition that consumers will buy/adopt a product if the value to the consumer exceeds the price he/she needs to pay for it). The other factor is the uncertainty about the performance of the product (with the reasonable proposition that market potential increases as this uncertainty decreases).

Typically, the uncertainty about product performance will decrease as the number of adopters increases.

Kalish's first stage (in discrete form) states, in words:

Proportion of the total population aware, at time $[t + 1] =$

$$I(t+1) = I(t) + (1 - I(t)) \cdot (a + b + c)$$

where a = advertising impact function, a function of advertising expenditure, on those not yet aware; b = impact of those already aware, but having not adopted, on those not yet aware; and c = impact of those who have already adopted, on those not yet aware.

In model terms,

$$I(t + 1) = I(t) + (1 - I(t)) \cdot [W(A) + k \cdot (I(t) - X(t)/N) + k' \cdot (X(t)/N)] \quad (1)$$

where A = advertising expenditure;
 $W(A)$ = advertising impact, a function of A (for those currently unaware), $0 \leq W(A) \leq 1$; k = conversion of non-aware to aware rate (impacted by those who are aware but have not adopted); k' = conversion of non-aware to aware rate (impacted by those who have already adopted); N = total potential population to become aware; and $X(t)$ = number who have adopted at (by) time t .

Now we 'have' $I(t + 1)$ and can consider adopters. Stage 2 of Kalish's model states that the number of adopters at time $[t + 1]$ depends (reasonably) on $I(t + 1)$, as well as the other factors discussed above. In words,

$$X(t + 1) = X(t) + \text{adoption rate} \cdot \{\text{market potential} - X(t)\}$$

where market potential depends on N , price and uncertainty about product performance. In model terms:

$$X(t + 1) = X(t) + C \cdot \{Q^* \cdot I(t + 1) - X(t)\} \quad (2)$$

where Q^* is a function of P and u ; that is, $Q^* = Q^*(P/u(X(t)/N))$, P = price; u = 'discount factor' or 'risk adjustment factor' of the product's value, associated with uncertainty about the product's performance, as a function of the proportion of the total potential population who have adopted, $X(t)/N$; $u(1) = 1$; Q^* = market potential for adoption, which varies with t , and P/u , and assumes full awareness of N ; and C = adoption rate (which could be a function of several other factors, such as distribution channels).

It can be noted that the Q^* function is decreasing in P and increasing in u ; and u is an increasing function of $X(t)$, and, by definition, $X(t) \leq N$. For durable products, Kalish suggests that the Q^* function is an exponential function with a negative exponent – ignoring various constants, $e^{-P/u}$ which, indeed, is increasing in u and decreasing in P .

In essence, our model is based on the Kalish model, with modifications and adjustments to fit the special characteristics of electronic communities. The Kalish model has been prominently cited as a useful model for the diffusion of innovation.²⁹

PROPOSED ELECTRONIC COMMUNITY DIFFUSION MODEL

Three conditions are necessary for diffusion processes to work: the population must be able to communicate freely, adopters must be able to communicate that they are adopters and the value of the innovation must be sufficiently high to encourage adoption. Most virtual communities certainly satisfy these conditions in that they enable individuals to communicate irrespective of location or other potential impediments (other than having access to the Internet, of course), tend to require membership in order to participate, and tend to be free.

As, in the majority of Internet communities, individuals can browse a community site at no cost (in monetary terms), it is assumed that the number of visitors, by itself, is not a sufficient indicator of community equity, as the ultimate value is closely tied to its assets, which include content and member expertise.^{10,30} Consider two online communities: one is relatively large with 100 000 registered members and the other is relatively small with 2000 members, and *each* has 1000 members who are active on a regular basis. As a primary online-advertising pricing mode is by exposures (for example, Cost per 1000 (exposures) (CPM)), it is reasonable to expect that the cost (or commission) of advertising to the larger community will be much higher. However, the potential 'profit' may warrant advertising to the smaller group and *not* to the larger group. Therefore, the proposed model implies the importance of using a media model that will charge advertisers according to not only exposures, but also *response* (that is, active membership). In addition, the proportion of active membership may serve as an indicator of the growth potential of a community.

Hence, it is assumed that in order to evaluate a community's equity, we need to recognize active members. Activism, which is a presumed driver of a community's equity and success potential,^{10,26,31,32} can be defined by the frequency of communication contacts within a community.

In our proposed model, activism in a community occurs in two stages. In the first stage, search engines and word-of-mouth/web communications generate an awareness of a community that spreads according to a simple epidemic model, leading individuals to browse the community's website. The second stage of being an active participant depends on both visits and consumer perceptions that the community has a sufficient risk-adjusted value.

Visiting (awareness) diffusion – Browsing the community site

Let N_0 be the relevant population size, $V(t)$ be the proportion of the population that visit (browse) the community site by time t and $X(t)$ be the number of active members by time t .

As noted before, individuals can browse the community site at no cost. Therefore, it seems reasonable to suggest that once somebody (from the relevant population) is aware of a site by using a search engine, clicking on a banner or by word-of-web, s/he will probably browse that site. In other words, we would expect him or her to 'lurk' (that is, unobtrusively read, but not write/post to) the site. Individuals who have not yet visited a community site can become aware of it by external influences, which include, primarily, search engines and their associated links.

Let $E(t)$ be the mean rank/position of a (community) site averaged over different web search engines and related/relevant search keywords/expressions. For example, assume that an individual is looking for a community of new parents by using search engines such as Yahoo or Google. The keywords 'babies' and 'parents' may generate tens, or even hundreds, of links directing the searcher/customer to different communities such as babycenter.com, parentsoup.com, parents.com and so on, listed in a rank-order (whether it is explicitly stated or not that the order is, indeed, a rank-order). Each specific website can be ranked as first, second and so on, depending on its advertising budget and reputation. It is assumed that as time goes by the community site will be more recognized and, hence, its average position will improve on search engines (we are ignoring competition here and address this issue later); hence $E(t)$ is assumed to be a non-increasing function of time, as, in a search results listing, the lower the rank, the better the position. Let $f(E(t))$ be the impact of the search engine. We expect that $f(E(t))$ is *decreasing* with increasing $E(t)$, as the smaller the number of the mean rank/position, the higher the impact of the search engine on the proportion of the population that visits the community site by time t , $V(t)$. Our $f(E(t))$ is the analog of Kalish's $W(A)$.

Unaware individuals can also become aware of a particular community site by word-of-web. As individuals may browse many, perhaps hundreds of, community websites when searching for information, it is assumed that those who

just visit a site (without becoming an active participant) will have relatively less motivation to 'speak' than an active participant.⁸ In other words, 'visitors' will transmit information regarding the community site less effectively than active participants. Thus, in our visiting/awareness diffusion equation (3) below, building on equation (1), we expect that $k' > k$:

$$V(t+1) = V(t) + [1 - V(t)] \cdot \left\{ f(E(t)) + k \left[V(t) - \left(\frac{X}{N_0} \right) \right] + k' \left[\frac{X}{N_0} \right] \right\} \quad (3)$$

If we let $k'' = k' - k > 0$, (3) can be rewritten as:

$$V(t+1) = V(t) + [1 - V(t)] \cdot \left\{ f(E(t)) + k [V(t)] + k'' \left[\frac{X}{N_0} \right] \right\} \quad (4)$$

The model assumes that information diffusion among Internet users is homogeneous. This assumption seems to be a reasonable approximation in the context of the Internet because information tends to be relatively free, everybody has access to search engines, and, generally, there is no (monetary) cost for searching or entering online communities. Indeed, this assumption is less likely to be challenged in the context of the Internet than in offline scenarios, in which this assumption is frequently made. When we consider products or services that are *not* related to the Internet, the diffusion of information is actually *heterogeneous*. For example, the probability that a low-income individual would be informed about an expensive vacation by advertisement (such as direct mail, with its continually increasing targeting), or by word-of-mouth, is relatively low.

From a practical point of view, the number of registered members as the starting point for an evaluation of growth potential has an important advantage. Unlike awareness (in a variety of offline models), the number of registered members is more easily identifiable.

Market potential

As noted earlier, in the majority of cases, individuals can join a community website at no (monetary) cost. The 'price' that one has to pay for using the site stems from the time required, including navigation, information search/tracking, posting and so on. Consequently, we view the market potential in our model as a function of *Required-Time*, which we call '*T*'.

In addition, market potential for a product is typically influenced by perceived uncertainty in product performance. Here, this is represented by a member's uncertainty about the existence and quality of the desired information within the community. Of course, the time to actually access this information, of whatever quality (or find out that the information, indeed, does not exist), is part of the *T*, the Required-Time.

Community value – A network effect

Community equity is assumed to improve over time after introduction. The rationale behind this assumption is that an increase in the number of active participants increases member-generated content, which is central to the community's value. An increased number of active members implies that there will be more participants in chat areas, more exchange of information through bulletin board services and so on. The probability that one will find desired information will increase and the variety of information will be broader. Indeed, a larger number of participants in the group will increase the probability that somebody will provide content that addresses another member's informational needs. A post/message on an actual community, babycenter.com, is shown to illustrate members' belief in, and awareness of, this phenomenon:

I know this subject has nothing to do with our babies, but I need help and there are so many people on this board that I figure someone may have an answer.

Moreover, the presence of a larger number of participants in the group will also extend the *variety* of answers, assuming that there will be more members in the community with

different experiences and different opinions. Another post/message from babycenter.com is used to illustrate this:

... I am glad to come to this board and know that there have to be many of you out there with the same problem as me and there are many others that can help me, offering many different opinions ...

Suppose that an individual has all the relevant information about a community, and thus s/he has no uncertainty about the 'quality' of information provided by members of this community. Let v be the value of the community for that individual. Let $F_v(v)$ be the proportion of individuals with valuation between v and $v + dv$. We suggest that someone will become an active member if the value of information in the community is more than the Required-Time (that is, price) to find/acquire the desired information, T , that is, if $T \leq v$. The market potential at Required-Time, T , under full information is, then, the sum of all individuals who value the community at T or more. Then,

$$N(T) = N_0 \bullet \int_{v \geq T} F_v(v) dv = N_0 \bullet \int_{v=T}^{\infty} F_v(v) dv$$

It is assumed that individuals will be active participants as long as the Required-Time is less than the value of the community's information. Hence, it is proposed that the market potential is a decreasing function of Required-Time. That is, when Required-Time is higher, there will be fewer people interested in becoming active participants in the community. Of course, $N(T) < N_0$, even when T heads to zero. For example, it is possible that an expectant or new parent with access to the Internet (which would comprise N_0), who, while trying to get information regarding some health issue, prefers to browse a health professional's medical website and not to look for answers from other parents in the babycenter.com community, even for a Required-Time of virtually zero.

Uncertainty

The discussion concerning the community value implies that there is uncertainty with regard to the existence and quality of information that an individual can receive, and hence, to the quality of the community in general. It was reasonably conjectured above that having a larger number of participants increases both the probability of finding desired information and the variety of answers/content. Thus, it seems reasonable to suggest that the level of uncertainty decreases as the number of active members increases.

Clearly, risk-averse individuals are willing to pay less for a risky choice, when they have the option of obtaining the expected value with certainty. Let CE be the Certainty Equivalent value of the uncertain community to the consumer. Define $u = CE/v$, that is, the ratio of the equity of the community with information value uncertain to the equity under certainty. This ratio can be written as a function of penetration as follows: $u = u[X/N_0]$, where $[our]$ $X(t)$ is the number of active members in the online community at time t . We expect u to be an increasing function of its argument, $0 < u \leq 1$.¹⁸

Therefore, the risk-adjusted potential at Required-Time, T , and ratio u is:

$$\begin{aligned} N(T, u) &= N_0 \bullet \int_{vu \geq T} F_v(v) dv \\ &= N_0 \bullet \int_{v=(T/u)}^{\infty} F_v(v) dv = N \left(\frac{T}{u} \right) \end{aligned}$$

Note how T and u appear (only) in ratio.

Required-Time

Recall that T refers to the Required-Time associated with being an active participant in a particular community. As with price (see, for example, Kalish¹⁸), it is assumed here that Required-Time can be written as a function of both uncertainty and penetration as follows: $T = f(u, X/N_0)$. As was indicated above, u itself is

Figure 1: Required-Time as a function of number of active members.

a function of X/N_0 , and thus we can write $T=f(X/N_0)$.

An important proposition of the proposed model is that as the community increases in size, the Required-Time will decrease until it reaches a certain point and then it will start to increase again³¹ (see Figure 1).

Required-Time can therefore be written as a function of the penetration following a U-shaped curve. The logic behind this assumption is that communities develop and transform according to their members' interests and preferences. Hence, it seems reasonable that the community structure is designed to improve over time after introduction. Consequently, these improvements will result in Required-Time decreasing over time. However, after reaching a certain critical point (t1 in Figure 1), the information density (that is, in essence, the community) becomes 'too crowded'. Participants with specific informational needs may find themselves more frequently browsing through topics of lesser interest, while searching for desired information (that is, the same needle in a now bigger haystack). Those with specific information needs will find that the community is becoming more time consuming (that is, *higher Required-Time*) per unit of 'value returned'.

We will use the evaluation of a hypothetical babycenter.com-like site as an example to illustrate this pattern. When the community was in the introduction stage, at t0, an individual who browsed the site to find information regarding, say, breast-feeding had to browse

extensively as, in this initial stage, the community site was not yet efficiently organized according to members' special needs. Hence, members had to 'dig out' a few words 'here and there' on this subject matter, thus needing to spend a significant amount of time finding the information. As t1 was approached, members' preferences and needs resulted in the development of a special bulletin board and chat room that specialized in breast-feeding. Thus, in this stage, the Required-Time searching for breast-feeding information decreased significantly. However, Required-Time for breast-feeding information increased again after a later point, say, t1, because eventually, when the number of members increased/evolved beyond a point, it also increased the *diversity* of needs, expectations and information on this topic, for example, for mothers that breast-feed *until the age of 6 months*, for *working* mothers that breast-feed and for *fathers* who find breast-feeding problematic. This evolution resulted in a plethora of bulletin boards and chat rooms, causing Required-Time to increase in order to (1) peruse the different bulletin boards to find the most useful information sources and (2) search through this larger number of information sources, once they were found/identified.

Another example that illustrates this pattern pertains to the different communities dedicated to *The X-Files* television series. Shortly after *The X-Files* debuted in September 1993, the first newsgroup, <alt.tv.x-files>, was formed as the first board, dedicated to general interest in the series, featuring participants primarily from the American market.³³ As Kozinets¹¹ notes, this was followed by <alt.tv.x-files.creative>, a board dedicated to creative expressions, such as fan stories, which utilized characters and themes drawn from the show. By 1999, a range of new newsgroups dedicated to *The X-Files* existed. For example, <alt.tv.x-files.analysis> was dedicated to an analysis of the series and its plot developments, while <alt.fan.david-duchovny> featured (predominantly female) fan activity related to the lead male star of the series. Fans in Italy, Poland, Russia and Germany, among other countries, had their own dedicated X-files

newsgroups (<it.fan.x-files>, <pl.rec.fantasyka.x-files>, <fido7.ru.video.x-files> and <de.rec.tv.akte-x>, respectively). Thus, as suggested by Clerc, 'the enormous amount of traffic on some newsgroups makes them impossible to follow regularly, and although fans value the multitude of voices and opinions on the large groups, they also seek out smaller circles to discuss their special interests' (p. 43).³³

Dynamics of activism

The total number of potential active participants at time t is the proportion of the relevant population who visit the community site, multiplied by the number of these individuals who find the (uncertainty-adjusted) Required-Time acceptable. Recall that $V(t)$, the proportion of the relevant population who visit/browse the community site by time, t , is given by (4). It is possible that past active members would not be active at the current Required-Time and uncertainty. This happens if T/u is higher than it was in the past. The 'net potential' number of active participants is the difference between the total potential of active participants and the number who are already active. Recalling that $X(t)$ is the number of active participants at time t , then, in discrete time-period terms, $X(t+1)$ is then determined by (5):

$$X(t+1) = X(t) + \left[N \left(\frac{T(X/N_0)}{u(X/N_0)} \right) \bullet V(t) - X(t) \right] \quad (5)$$

ESTIMATION

Initial estimates of model parameters can be constructed on the basis of information from various sources such as marketing research results or experience with different communities. Here, in an example, we construct estimates on the basis of research results reported in the literature and on some 'common knowledge'. For the visiting part of the model we need to estimate the number of visitors that have browsed

the community site, and the number of active members, up to time t . These numbers can often be easily provided by a community's organizers. The position of the site, $E(t)$, can be provided by services like www.submit-it.com. The service will report where the specific community website is currently ranked in the leading search engines for selected keywords. For simplicity, we will assume here that $f(E(t))$ is constant. Both k and k'' are parameters that need to be estimated. We repeat equation (4):

$$V(t+1) = V(t) + [1 - V] \bullet \left\{ f(E(t)) + k[V(t)] + k'' \left[\frac{X}{N_0} \right] \right\} \quad (6)$$

As an illustration, we set N_0 to be 100 000, $k=0.01$, $k''=0.01$, $f(E(t))=0.8$ (recall that we assumed for simplicity that this was constant), $X(t)=10\,000$ at time zero+, and $V(t)=0.5$ at time zero+. Figure 2 shows a graph of $V(t)$ versus t .

(To create Figure 2 and subsequent figures, we used the software package WINPP.)

For activism, we use the traditional decreasing exponential functional form as follows: $N(T) = N_0 e^{-dT}$ where N_0 is the market potential at (theoretically) zero Required-Time, and d is a constant. In addition, for the illustrative example that follows, we assume that $u(X/N_0) = (a + [X/N_0]^2)/(a+1)$, and a is a parameter to be estimated. This states that the 'risk adjustment factor' for uncertainty heads toward 1 in a nonlinear way; for example, with a very small (for example, 0.01), when $(X/N_0)=0.5$, indicating that 50 per cent of the potential market has adopted (that is, is an active member of the community), $u \approx 0.25$. Furthermore, we assume that $T = c \bullet (X(t) - m)^2 + c'$, where c and c' are positive constants, and m is the size of active membership (that is, the value of $X(t)$) that minimizes Required-Time – in essence, time t_1 on Figure 1. As noted earlier, Required-Time, T , decreases as the number of active members, $X(t)$, in the community increases until it reaches some

Figure 2: Visiting diffusion.

maximal number, m . At active membership above m , the community, as discussed earlier, becomes ‘too crowded’, thus increasing the amount of Required-Time.

$$X(t+1) = X(t) + \left[N_0 \exp \left(-\frac{d \cdot T \cdot (a+1)}{a + (X(t)/N_0)^2} \right) \cdot V(t) - X(t) \right] \quad (7)$$

Continuing our illustration, we additionally set $a=0.01$, $d=0.0001$ and $c=1$, $c'=0$. Recall that we earlier specified N_0 to be 100 000 and $k=0.01$ (to create Figure 2). We can now graph the key quantity, $X(t)$, as a function of various input parameters. The most impactful parameter appears to be the value of m – essentially the precise value of t_1 in Figure 1. Figure 3 graphs $X(t)$, as a function of t , for various values of m , (m and X in thousands):

Figure 3 clearly shows that Required-Time, and more specifically, m , is a key factor that influences activism diffusion. Of course, Figure 3 also reflects the uncertainty parameter chosen, a ,

the value of $X(t)$ at time zero, as well as the chosen values of the other parameters. It should be noted that m is a parameter that needs to be estimated for different categories of communities.

An analysis of Figure 3 for our specific numerical example suggests that when m is smaller than about 29 000 members, the community is small enough that ‘over-crowding’ has not yet set in, and thus the number of active members increases.

However, when m is above approximately 29 000, the community is (apparently) too crowded and the number of active members begins to decrease. Presumably, the community then splits into different, smaller communities that may be narrower in their focus.

Other parameters also impact $X(t)$. We show a graph of $X(t)$ versus t for various values of $f(E(t))$, still holding it constant (Figure 4), for $m=20$.

We also have $X(t)$ versus t for various values of k (Figure 5), and $X(t)$ versus t for various values of a (Figure 6). As can be seen, the impact of changing f or k or a is clearly evident, but much less than the impact of changing m , as shown earlier in Figure 3. Indeed, if we determined a ‘new Figure 3’ for each value of f in Figure 4

Figure 3: Active members (X) versus t (for various values of m).

Figure 4: $X(t)$ versus t (for various values of f).

(instead of the 0.8 used in the current Figure 3), all of these 'new Figure 3s' would be relatively similar. The same holds were we to produce 'new Figure 3s' for the values of k in Figure 5

(instead of the 0.01 used in the current Figure 3) or for the values of a in Figure 6 (instead of the 0.01 used in the current Figure 3). When $m \geq 29\,000$, that is, when the $X(t)$ versus t curve

Figure 5: $X(t)$ versus t For various values of k .

Figure 6: $X(t)$ versus t For various values of a .

is decreasing, the impact of f , k and a is virtually non-existent. We reiterate that, of course, all of the above discussion is for our specific example and rests on our assumed functional form for T ,

Required-Time and the other assumptions made. Yet, we have no reason to believe that our assumed parameter values are untypical, at least in relation to one another.

DISCUSSION

We have introduced a model for estimating electronic community growth and equity. We built our diffusion model based on electronic community theory, and were partly guided by Kalish's model.¹⁸ An important finding is the critical impact of Required-Time, the size of active membership and the optimal Required-Time given the number of active members on a community's growth and value/equity. Activism is indeed important in (creating) community value. However, managers need to understand that more information does not necessarily provide more value; it is critical to recognize – and integrate into the design of an evolving community (for example, through facilitating the creation of 'new' groups or subcommunities) – that information *and* the time devoted to finding useful information in the community are critical. Although the context and the problem are somewhat different, we believe that those in the search space (for example, Google) have, to a certain extent, discovered this general notion.

Nobody can deny that virtual/electronic (e-)communities and social networks are flourishing, and that marketing can greatly benefit from the analysis of their growth patterns (diffusion) and the potential value to be gained from them. Indeed, in Gartner's 'Hype Cycle for Emerging Technologies 2009', analysis of these communities arises from the 'Trough of Disillusionment', very close to the next stage of 'Slope of Enlightenment', which precedes his 'Plateau of Productivity'. It is estimated that reaching this 'plateau' will require a 3–5 year period.³⁴ In *Wikipedia*, the free encyclopedia, discussion of virtual/e-communities mentions the Bass Model (the basis of the Kalish Model, the latter, as noted above, having guided our model) as a source to study diffusion of these communities.³⁵

A key way in which a company's marketing program can benefit from knowledge of the growth/diffusion pattern of an electronic community is that the company can choose among potential e-communities and determine the one(s) that best align with its products/services

and achieve what is, essentially, a 'first-mover advantage'. For the purposes of investing marketing dollars/euros, it is clearly preferable to identify 'to be successful' electronic communities early, and 'partner' with them before they have become fully established. Of course, the way in which this partnership would occur depends on the organizational structure of the community. A partnering might have some of the same characteristics of partnering with associations or affiliation groups.³⁶

One challenge in this research is that diffusion (and value) will vary by type of community. Indeed, it also varies across cultures.³⁷ While we have detailed a case for one type of community, we do not provide optimal values that necessarily hold in the general case. However, we do provide some direction for managers deciding whether, or how, to invest in a particular community. We hope our proposed model is a first big step that leads to further work in examining, for both electronic communities and other Internet-related phenomena, the proposition that, with proper 'adjustment' these phenomena are subject to the same diffusion models that have been proposed for other products and product types in the past.

Testing the model as applied to an actual electronic community is beyond the scope of our article. However, there are methods proposed for testing the Bass and Kalish models¹⁸ that can be applied to our model. We would need various kinds of data that differ somewhat from that of Kalish, to complement the differences in our models. Core elements we would need from an electronic community would include the number of visitors that have browsed the community and the number of active members (however defined) for various periods of time; these should be able to be easily provided. Another core element would be the position of the site at various times $\{E(t)\}$, and this should be able to be provided by such services as www.submit-it.com; these services will report where an electronic communities' website is currently ranked in leading search engines. Various assumptions of our model can be examined, such as the exponential function representing activism over time. Data on 'Required-Time' would

likely have to be set up in an (time series) experimental framework, where selected tasks were chosen and Required-Time studied over a time frame. It is clear that more study needs to be conducted to achieve further specificity and fine-tune the testing process.

Marketing practitioners have recognized the need to generate metrics to measure customer-generated media, in addition to using traditional marketing metrics.³⁸ In general, we are undergoing an upheaval in marketing that is beginning to cede a certain portion of marketing control to electronic communities/social networks. Any step we can take to better understand their workings, growth/diffusion pattern and potential value is surely useful.

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