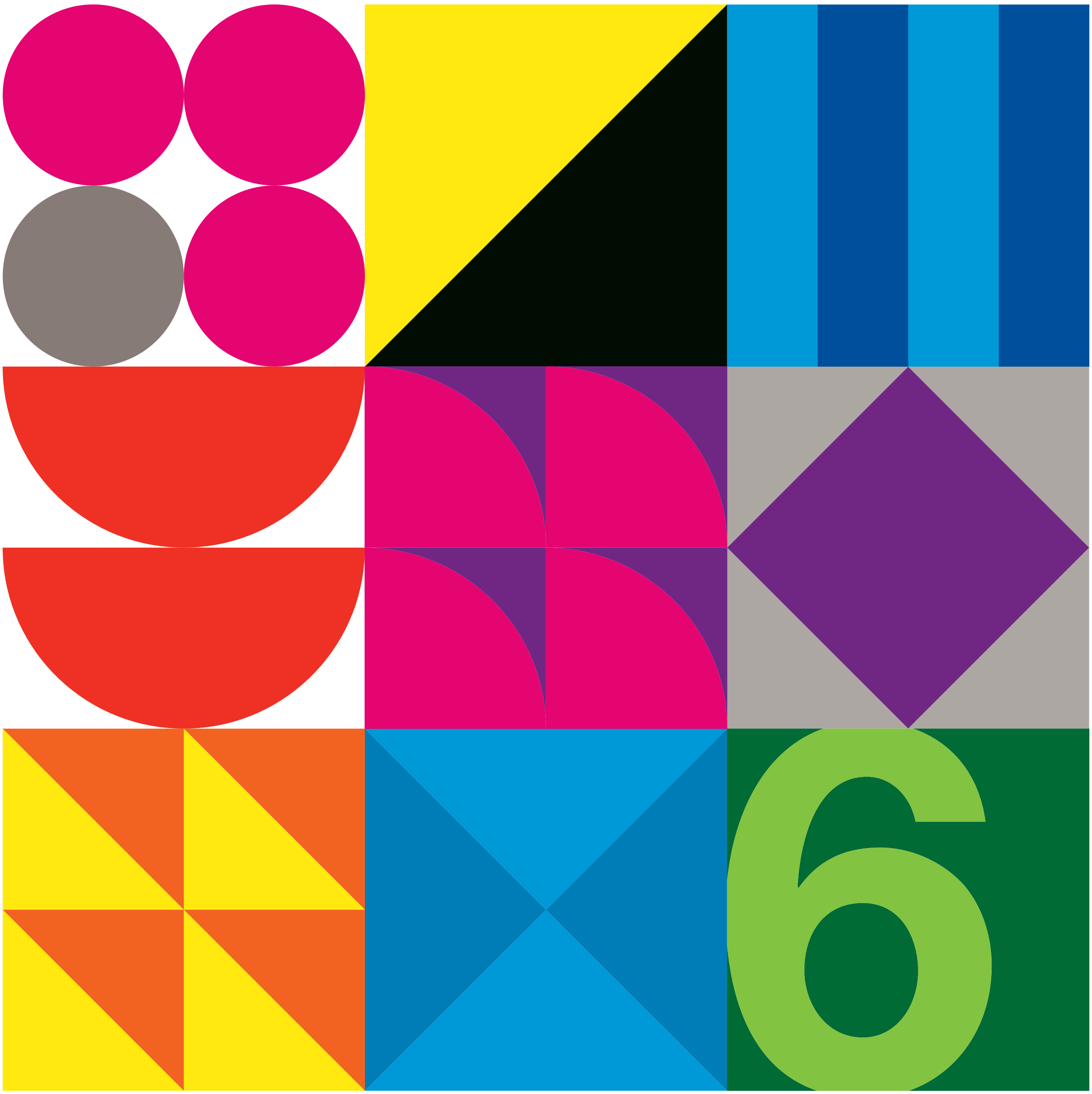
Lithium

Community Health Index
for Online Communities



Lithium

Community Health Index
for Online Communities

Contents

Lithium

Community Health Index
for Online Communities

Executive Summary

In the current economic climate, companies are discovering that their online communities have become a powerful and cost-effective vehicle for interacting with customers. For example, a consumer electronics community that runs on the Lithium platform recently reported 1.4 million deflected support calls, resulting in an annual estimated savings of $10 million.

Savings like these have clearly transformed online customer communities into vital enterprise assets, which makes monitoring their health increasingly important to corporate wellbeing. However, until now there has been no simple, common way to do so effectively, no standard by which to evaluate or take action on the myriad of metrics used to capture every aspect of community activity and performance. Imagine a discussion of credit-worthiness before the introduction of the FICO® score.

Lithium, the leading provider of Social Customer solutions that deliver real business results, offers a solution. Lithium has recently completed a detailed, time-series analysis of up to a decade's worth of proprietary data that represents billions of actions, millions of users, and scores of communities. This research, coupled with our acknowledged expertise in planning, deploying, and managing customer communities, enabled us to identify and calculate key factors that contribute to a new standard for measuring community health: the Community Health Index.

By analyzing hundreds of metrics from communities of varying types, sizes, and ages, we identified the diagnostic and predictive metrics that most accurately represent key attributes of a healthy community: growth, useful content, popularity, responsiveness, interactivity, and liveliness. Although we uncovered other metrics that proved to be even more predictive of community health, the ones we selected as the basis for calculating the Community Health Index are readily available for most online communities across the industry.

Smoothed and normalized for community purpose, size, and age, the Community Health Index provides a single representation of community health. Deconstructed, its constituent health factors enable community managers to take specific action and measure the results. This paper describes these health factors and explains how to use them to calculate a Community Health Index. Although the source community data is proprietary, Lithium freely offers the results of our research toward a common standard for the industry.

Lithium

Community Health Index
for Online Communities

Introduction

Online customer communities have come a long way in the thirty years since a handful of hobbyists posted messages on the first public bulletin boards. For an increasing number of companies, they have become an important tool for engaging with their customers and driving sales.

In a recent study published in the Harvard Business Review, researchers found that community participants at an online auction site both bought and sold more, generating on average 56% more in sales than non-community users. This increased activity translated into several million dollars in profit over the course of a year. Likewise, a community running on the Lithium platform recently reported both a 41% increase in sales by community members and an $8 million savings in support costs.

Results such as these demonstrate the return on investment for healthy and successful communities: customers are getting what they need from the communities, which, in turn, allows the communities to meet the goals of the companies that sponsor them. The ROI that online communities are capable of delivering makes it all the more essential that companies be able to measure the health of their communities and take action to keep them healthy.

Measurement, however, has proved to be a challenge because of the missing component: a single industry standard—like the FICO score, Body-Mass Index, or standardized test scores, for example—that allows communities to gauge their health in absolute objective terms. As the result of a massive data analysis project, Lithium has developed such a standard, the Community Health Index. The development of the Community Health Index is based on data aggregated from a wide range of communities representing more than 15 billion actions and 6 million users. In order to make it universally applicable, the Community Health Index is normalized for community purpose, size, and age.

Like a low FICO score or high BMI, a low Community Health Index value points to the need for a change in behavior. And, like the components of standardized tests, deconstruction of the Community Health Index into specific health factors points to specific areas within the community that require corrective action. This deconstruction even extends to different levels within a community, where we can identify the less healthy subdivisions and the conditions that are affecting their health. With information such as this, a company can target its efforts and resources to make the specific changes most likely to further improve the community's health.

In the spirit of Mr. Fair and Mr. Isaac, the National Institutes of Health, and generations of high school English teachers, we offer the Community Health Index as an open measurement for community health.

Lithium

Community Health Index
for Online Communities

Defining Health Factors for Online Communities

Good health and good sense are two of life's greatest blessings.
-Publius Syrus, Maxim 827

Health in an online customer community, like health in an individual, is spread across a broad spectrum. And as Charles Atlas and the 97-pound weakling illustrate, some communities are stronger and healthier than others. But, no matter how good we look or how robust we feel at the moment, there is always room for improvement.

Humans enjoy the benefit of sophisticated diagnostic and preventive medicine, which tells us where we need to improve. In order to get the most out of online communities, we need similar diagnostics to help us make better use of the data currently available for measuring community activity and performance. Armed with the right data and with standards that allow us to evaluate that data objectively, we can then formulate a plan for improving community health.

Based on our continuous engagement with successful online communities, we were able to identify a common set of characteristics shared by healthy communities of all types, sizes, and ages: they are growing, useful, popular, responsive, interactive, lively, and positive. Furthermore, analysis of the vast body of data available to us allowed us to then define specific health factors that most accurately represent each characteristic.

The characteristics of healthy communities and their corresponding health factors are:

> Growing = Members. After an initial surge of registrations characteristic of a newly-launched community, membership in a healthy community continues to grow. Although mature communities typically experience a slower rate of growth, they still add new members as the company's customer base grows. The traditional method for measuring membership is the registration count.[1]
>
> Useful = Content. A critical mass of content posted on an online community is clearly one of its strongest attractions to both members and casual visitors. In support communities, the content enables participants to arrive at a general understanding or get answers to specific questions. In engagement (enthusiast or marketing) communities, it serves as a magnet to attract and engage members. In listening communities, the content posted by community members gives the company valuable input from the customers who use their products or services.

A steady infusion of useful content, then, is essential to the health of a community.[2] The traditional metric for measuring content is number of posts. This metric alone, however, gives no indication of the usefulness of the content, especially in communities that do not use content rating or tagging. In order to model content usefulness instead of sheer bulk, we consider page views as a surrogate for marketplace demand, but then dampen their effect to reduce the likelihood of spurious inflation.

Popular = Traffic. Like membership, traffic in a community—page views or eyes on content—is one of the most frequently cited metrics for community health. In deriving the Traffic health factor, we started with the standard page view metric, but then mitigated the effect of robot crawlers in order to diminish their impact.

Responsiveness. The speed with which community members respond to each other's posts is another key metric for determining community health. Participants in support communities, for example, are only willing to wait for answers for a limited amount of time. The same is true for engagement and other types of communities. If there is too much of a lag between posts and responses, conversations peter off and members start looking elsewhere.

The traditional response time metric counts the number of minutes between the first post and the first reply. That first post might be anything—a question, a blog article, an idea, a status update. Because our analysis of community-member behavior has revealed the importance of subsequent responses, we have enhanced the traditional response time metric to account for all of the responses in a topic.

Interactive = Topic Interaction. Interaction between participants is one of the key reasons that online communities exist. The traditional metric for measuring interaction is thread depth[3] , where threads are topics of discussion and their depth is the average number of posts they contain. This way of looking at interaction, however, does not consider the number of individuals who are participating. As a result, a topic with six posts by the same participant would have the same depth as one with six different contributors. Because our experience with online communities has led us to understand that the number of participants in an interaction is even more important than the number of posts, we have added the dimension of unique contributors to our calculation of Topic Interaction.

Liveliness. Although most people would be hard-pressed to define it, they recognize and respond to liveliness or buzz when they encounter it. Research has shown that participants are not only attracted to but are also motivated to return and contribute in communities that feel animated and vibrant.[4]

We find that liveliness can be best measured by tracking a critical threshold of posting activity that experience and analysis have shown us characterizes healthy communities. In calculating the Liveliness factor, we look not only at the number of posts but also at their distribution within the community. We have identified the critical threshold at between five and ten posts per day in each community segment. Segments include discussion boards, forums, blogs, idea exchanges, and so forth. Lopsided distributions indicate a need to balance out the hot and cold spots in the community.

In addition to these key factors, a positive atmosphere, civil behavior, and a degree of trust among members is essential to the success of online communities. Abusive language and harassment have no place in any community—online or otherwise—particularly one sponsored by an enterprise.

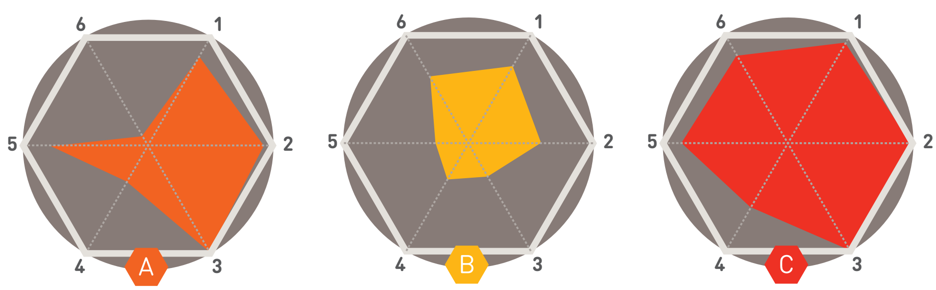
The opinions expressed by community members need not all be positive—in fact, one sign of a healthy community is the freedom members feel to express their opinions about a company or its products. More important to community health, however, is the way in which those opinions are expressed. In our experience and that of other community experts, healthy communities rely on moderators and active community members to maintain a positive atmosphere and keep the anti-social behavior at bay.[5] As a result, the Community Health Index is already normalized for moderator control of atmosphere.

Using Community Health Factors to Drive Action

Further examination of health factor data from scores of communities reveals strong correlations between two groups of factors. The first group consists of Members, Content, and Traffic, which are closely aligned to traditional registration, posting, and page view metrics. These factors are strongly affected by community size. We refer to them as diagnostic indicators because they reflect the current state of the community.

Fluctuations in a community's diagnostic factors typically correspond to specific events and serve as a record of their impact on the community. This correlation allows community managers to use diagnostic factors to gauge the effectiveness of tactics designed to boost registrations or page views, such as contests, participation incentives, or outreach campaigns. Activities such as these appear as inflection points in the community's diagnostic health factors.

The remaining group of factors—Responsiveness, Interaction, and Liveliness—are less susceptible to the effects of community size, more indicative of patterns of behavior within the community, and tend to be predictive indicators of community health. They are, in effect, an early warning system for aspects of community health that may require attention or intervention before their effects become apparent. Not only are the predictive factors interesting in and of themselves, but community managers can learn a great deal by looking at the interplay between predictive factors.

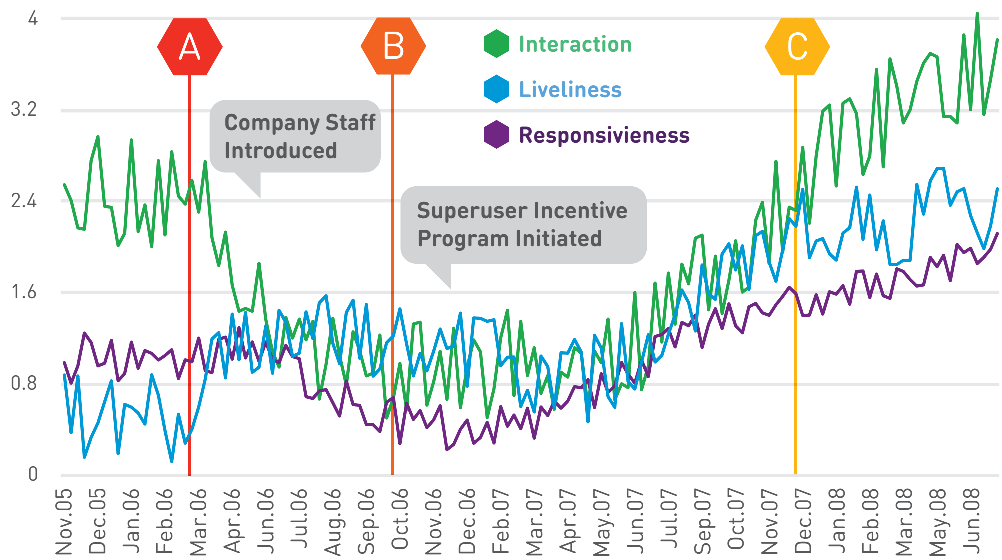


1.Members - 2.Content - 3.Traffic - 4.Liveliness - 5.Interaction - 6.Responsiveness

Take the case of a hypothetical software publisher based on communities that run on the Lithium platform. Concerned about the response rate in its support community, the company recruits staff experts to provide answers to members' questions. Although the Responsiveness health factor improves significantly as a result of this infusion, the Interaction factor, which is based in part on the number of unique participants in a thread or topic, begins to drop. Community members' questions are being answered, but the interactions between participants that give it the feel of a community fall off significantly, as does the Liveliness factor. Instead, community members begin to view their community as just another support channel. Armed with this information, community managers can take action: setting out to identify and encourage home-grown experts from within the community to replace the staff experts. Over time, this will lead to more participants, increased interaction levels, and ultimately to a renewed interest in the community.

Lithium

Community Health Index
for Online Communities



In addition to monitoring the community as a whole, community managers can correlate community health factors with usage metrics for specific community features to reveal the effects of these features on the community. Lithium customers, for example, can see the effects of critical engagement features such as Tagging, Kudos, Chat, or Accepted Solutions. This enables community managers to determine which features have the most positive impact on community health and to implement features or make other changes that have predictable effects on community health.

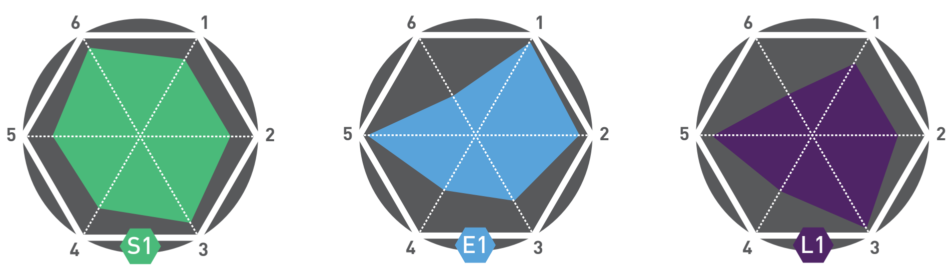
Using the Community Health Index as a Community Standard

As noted earlier, community health factors provide diagnostic and predictive information useful in measuring community health. Viewed either as a snapshot or mapped over time, these factors reveal a great deal about an online community. To account for factors such as community size, age, and volatility, we apply a series of smoothing and normalization algorithms to enable communities of all types to use a single formulation of the Community Health Index.

Community Health Index
for Online Communities

The three Community Health Index (CHI) compass diagrams below show healthy communities with the distinctly different profiles that are characteristic of support, engagement, and listening communities. Listening communities include both support and engagement elements. Although their profiles are different, all are healthy communities. These diagrams present a snapshot of health factors for a given period (in this case one week) as a relative percentage of the community's highest scores. For the purposes of illustration, the Predictive and Diagnostic factors are normalized separately to make the different profiles easier to identify.

The Community Health Index is on a scale of 0 to 1000. The higher the number, the healthier the community and the more likely it will accomplish the goals of the members and the company. Regardless of a community's score, there is always room for improvement and the individual health factors tell you exactly where to focus.



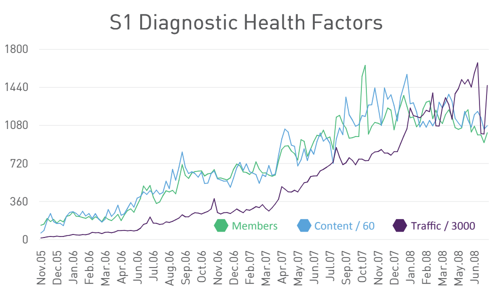
1.Members - 2.Content - 3.Traffic - 4.Liveliness - 5.Interaction - 6.Responsiveness

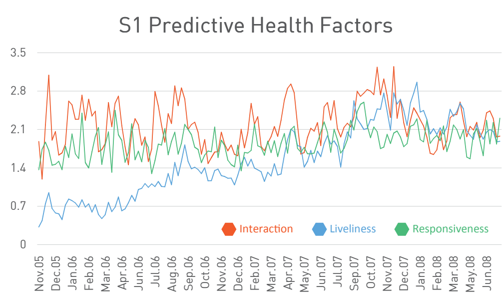
In the sample support community (S1), the three predictive factors—Responsiveness, Interaction, and Liveliness—are balanced. In the sample, engagement (E1) and listening (L1) communities, Interaction and Liveliness are characteristically higher than Responsiveness.

Simple CHI trend analysis, coupled with the ability to drill down to the individual health factors, provides an early warning of potentially serious problems within a community. It is important to note that a single health factor, like a single metric, doesn't present the whole picture. Instead, community managers should consider the Community Health Index in conjunction with the individual health factors. As the graphs that follow show, a community can weather the decline in one or two health factors and remain healthy when the other factors are stable or improving.

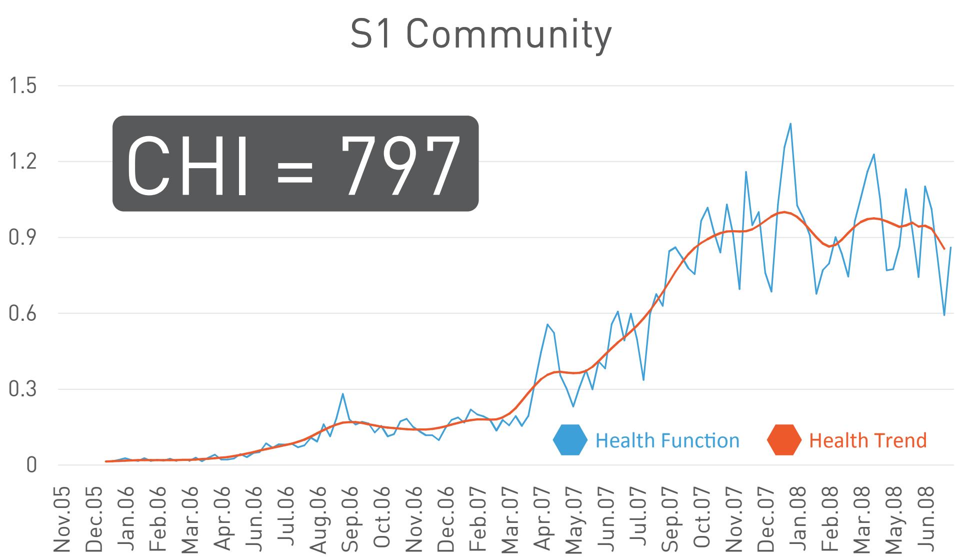
Community Health Index
for Online Communities

For example, the graphs below show diagnostic factors, predictive factors, and the health trend for a support community (S1).





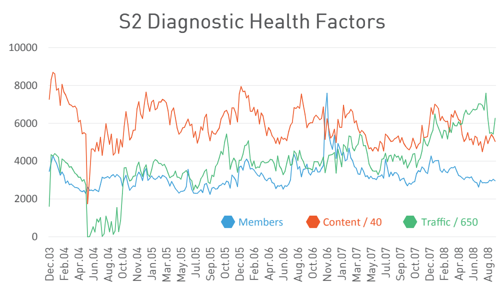
Graphs of the Diagnostic factors, Predictive factors, and the Health Trend for a health support community. To plot the Diagnostic factors in a single plot, we have down-scaled Content by 60 and Traffic by 3000.

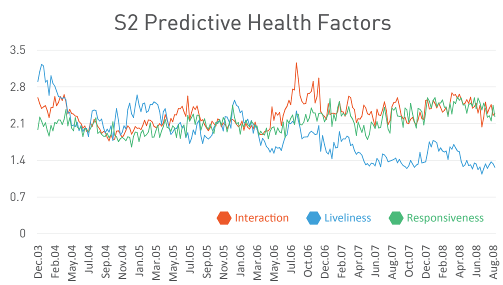


Our research has shown that support communities typically average between 1 and 4 interactions per topic. This community demonstrates a steady average Interaction of 2, which is considered healthy. Likewise, a Responsiveness of greater than 1, which reflects the community's ability to meet the expectations of most participants, is also healthy. A further indication of health is a Liveliness factor that shows improvement over time. Although the community's diagnostic factors reveal evidence of a plateau at the end of its second year, its high content usefulness indicates that community members continue to derive benefit from the content. Overall, as its CHI indicates, this is a healthy community.

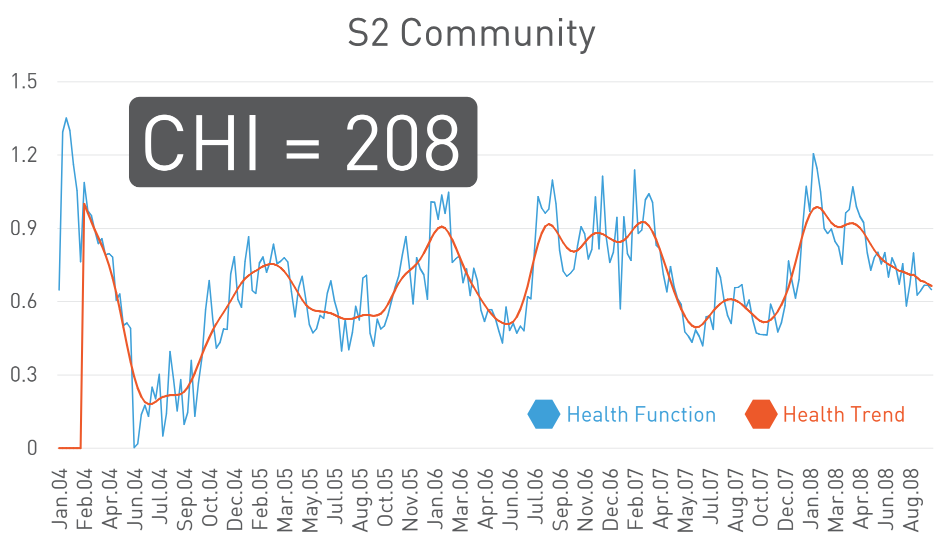
Lithium

Community Health Index
for Online Communities





Graphs of the Diagnostic factors, Predictive factors, and the Health Trend for a health support community. To plot the Diagnostic factors in a single plot, we have down-scaled Content by 40 and Traffic by 650.



The graphs above show health factors for an older and larger but less robust community. This community is more than 10 times the size of S1, but its diagnostic factors demonstrate wildly fluctuating yearly cycles with little actual improvement over time. The diagnostic factors show that the community experienced a spike in registrations toward the end of 2006, but was unable to capitalize on the infusion of new members. Responsiveness and Interaction are stable and within norms for support communities, but S2 shows a troubling decline in its Liveliness factor, which can often be remedied by adjusting the community’s structure, something that other large communities routinely do on an ongoing basis. Although still large, this community is stagnant, with a low CHI for its size.

Lithium

Community Health Index
for Online Communities

Conclusion

Although existing community metrics yield a tremendous amount of data, the industry has been unable until now to use that data to achieve a meaningful measure of community health. With the introduction of the Community Health Index, companies and community experts have a way to organize and compare this data against both the past performance of the community itself and against other similar communities.

In fact, we see communities using the Community Health Index in multiple ways: as a metric to objectively measure the health of a community, as a means to validate the perceptions of community moderators and other community experts, and as diagnostic and prescriptive drivers to help communities meet ROI and business objectives.

Companies have the data, and now they have a standard to compare it against.

References

[1]Butler, B. S. (2001). Membership Size, Communication Activity, and Sustainability: A Resource-Based Model of Online Social Structures. INFORMATION SYSTEMS RESEARCH, 12(4), 346-362.

[2]Soroka,V., & Rafaeli,S (2006). Invisible Participants: How Cultural Capital Relates to Lurking Behavior. Proceedings of the 15th international conference on World Wide Web (pp163-172).

[3]Preece, J. (2001). Sociability and usability in online communities: determining and measuring success. Behaviour and Information Technology, 347-356

[4]Ackerman, M. S., & Starr, B. (1995). Social activity indicators: interface components for CSCW systems. In Proceedings of the 8th annual ACM symposium on User interface and software technology (pp. 159-168).

[5]Cosley, D., Frankowski, D., Kiesler, S., Terveen, L., & Riedl, J. (2005). How oversight improves member-maintained communities. In Proceedings of the SIGCHI conference on Human factors in computing systems (pp. 11-20). Portland, Oregon, USA: ACM

Lithium

Community Health Index
for Online Communities

About Lithium

Your customers are everywhere. Lithium helps you find your social customers, understand their influence, and build lasting relationships. For market leaders such as Best Buy, AT&T, Research In Motion Limited (RIM), Univision, and PayPal, Lithium is the leading provider of social customer solutions that deliver real business results. The Lithium Social Customer Suite offers complete social monitoring, a comprehensive community platform, and actionable analytics across millions of blogs, forums, and social networking sites. Our technology is proven in high-volume, growth environments and provides security, open and custom APIs, and multi-language support. Founded in 2001, Lithium is privately held with headquarters in Emeryville, California. For more information, visit lithium.com. Or, engage with us on Twitter, Facebook, and our community – the Lithosphere.

Lithium

Community Health Index for Online Communities

Defining the CHI Health Factors

Our goal in introducing the Community Health Index (CHI) is to provide a standard of measurement that all online communities can use. To that end, this section describes the representation of the six health factors as well as a formula for combining them.

Members
The standard measure for Members is the registration metric that all communities track. In the formulas that follow, Members is represented by μ.

Content
The two standard metrics that contribute to calculating content utility are posts and page views. Posts (represented by p) is the number of posts added to the community over a period of time. We use page views to represent consumer demand because we have found that page views provides an accurate reflection of the relative usefulness of the posts. However, we also observed that highly viewed pages tend to draw more random views, resulting in a snowball effect that could spuriously inflate the estimate of consumer demand. To dampen this effect, we take the $\log$ of page views as a surrogate for user demand, and thus the usefulness of the posts. We therefore express **Content Utility** (represented by U) as:

$$U = p \log_2 v_h \; . \tag{1}$$

Traffic
Traffic is typically measured using the standard page views metric. Because the page view metric can be heavily contaminated by robot crawlers, it is important to discount the effects of robots and use only human contributed page views when computing CHI. Traffic is represented by v_h.

Responsiveness
The traditional time-to-response metric is the starting point for calculating Responsiveness. Time-to-response is generally defined as the number of minutes between the first message in a message thread and the first response to that message. However, this metric does not consider the intervals between the first response and the second response, and so on. Therefore, we have defined a more robust health factor, called Responsiveness (denoted by R). This health factor is computed in three steps. First, we compute the average response time (denoted by t_R) by averaging the response time for all messages within a topic, and then averaging that over all topics. If Δt_k^θ denotes the response time for the k^{th} message posted in thread θ, then the average response time may be expressed as

Community Health Index
for Online Communities

$$t_R = \frac{1}{\Theta}\sum_{\theta=1}^{\Theta}\frac{1}{m_\theta - 1}\sum_{k=1}^{m_\theta - 1}\Delta t_k^\theta\,, \qquad (2)$$

where Θ is the total number of threads and m_θ is the number of messages in thread θ.

Unlike page views and registrations, which are purely numeric, t_R is a measure of time, so its value can change depending on the unit at which Δt_k^θ is measured. When measured in days, the response time for a hypothetical community may be $t_R = 1$ day. However, if it is measured in hours, $t_R = 24$, and if in minutes, $t_R = 1440$. Therefore, the second step involves converting t_R into a unit-less numeric value. This can be done by defining a constant, called the expected response time (t_e), which defines the time that a user would be willing to wait before receiving a response. Since it is another measure of time, it should have the same unit as t_R. Taking the ratio of t_R to t_e would then cancel out the units and render the ratio a unit-less measure of response time with an expected value of 1. Because we have found that response time is inversely related to community health, with a shorter response time typically pointing to a healthier community, the final step simply computes the inverse of the ratio t_R/t_e. Therefore Responsiveness can be written as:

$$R = \left[\frac{t_R}{t_e}\right]^{-1} = \left[\frac{1}{t_e\Theta}\sum_{\theta=1}^{\Theta}\frac{1}{m_\theta - 1}\sum_{k=1}^{m_\theta - 1}\Delta t_k^\theta\right]^{-1}. \qquad (3)$$

Community Health Index
for Online Communities

Interaction

The conventional metric for measuring interactivity is thread depth, the average number of messages in a topic. However, this number does not consider the number of participants. Therefore, we calculate Topic Interaction (denoted by I) as a function of two terms: the number of unique users participating in a thread (denoted by u_θ) and the number of messages in a thread, m_θ. The minimum unit of interaction is achieved when there are two messages between two distinct users. Furthermore, since we do not want the level of interaction to be biased by extremely long threads, we use the function to dampen their effect. Based on these requirements, Topic Interaction can be written as:

$$I = \frac{1}{\Theta} \sum_{\theta=1}^{\Theta} (u_\theta - 1) \log_2 m_\theta \, . \tag{4}$$

Liveliness

Although online communities furnish users with many activities, the most obvious action is posting. Therefore, we calculate the Liveliness of a community (represented by L) as a function of the average number of posts per forum or other community division.

$$L = \frac{\arctan[0.07 \cdot p/(p_e B)]}{\arctan(0.07)} , \tag{5}$$

where **B** is the total number of publicly accessible boards, and p_e is the expected number of posts per board (a constant explained later). The $\arctan$ function with the parameter 0.07 is used to give a linear behavior near the origin and a slow saturation as its argument increases. This prevents the indefinite inflation of liveliness by continuously reducing the number of forums or other community divisions.

Combining Health Factors

After defining the health factors, the next step is to derive the functional form of the health function, H_o, in terms of its factors. Since the factors are defined in such way that they are directly proportional to community health, combining the health factors simply requires multiplying them together. We also take the square root of the product to make the health function more robust against large fluctuations in any one health factor that is not correlated with the other factors. Therefore, the final form of the health function is:

$$H_o = \sqrt{\mu v_h URIL}$$

$$= \left[\frac{\frac{1}{\Theta} \sum_{\theta=1}^{\Theta} (u_\theta - 1) \log_2 m_\theta}{\frac{1}{t_e \Theta} \sum_{\theta=1}^{\Theta} \frac{1}{m_\theta - 1} \sum_{k=1}^{m_\theta - 1} \Delta t_k^\theta} \left\{ \frac{\arctan[0.07 \cdot p/(p_e B)]}{\arctan(0.07)} \right\} \mu v_h p \log_2(v_h) \right]^{1/2} . \tag{6}$$

Lithium

Community Health Index
for Online Communities

Computing the Community Health Index

Although equation (6) defines the health function (H_o), it does not describe how we actually compute it. This section fills in the technical details that make it possible. The basic steps are:

- Choose a window for data aggregation.
- Assign values to the free parameters.
- Smooth the health function to more easily see the trend.
- Normalize the health function for community size, age, and type for comparison purposes.

Choosing a Window for Data Aggregation
The first step in computing the health function is to choose a window for data aggregation. The aggregation window gives context to the variable in the definition for the health factors. For example, it is understood that θ is the thread count within the period of one aggregation window, and B is the cumulative board count up to and including the current window of interest. The aggregation window is typically set to be one month or one week. It is not advisable to use windows smaller than one week, because online behaviors of community users show strong weekly cyclic variation. We used a one week aggregation window for all our calculations.

Assigning Values for Free Parameters
Grouping the messages via their post date into weekly windows, the health factors for each week can be computed using only data within and prior to the week of interest. Subsequently, all the health factors are plotted and examined over time. We usually discard the health factors for the first and the last window to avoid edge effects.

To compute the predictive health function, we need to choose a value for the expected response time (t_e) and the expected number of posts per board (p_e).Based on our analysis, we found healthy communities generally have an average response time of 1000 minutes or less. On average, they also have 50 posts per forum per week. Therefore, we set t_e equal to 1000 minutes and p_e equal to 50 posts per forum for a one week aggregation window. With these parameters, we can compute the health function for any community over time via equation (6). This will give us the whole history of the community's health.

Community Health Index
for Online Communities

Smoothing The Health Function to View a Trend
Once we have the health function (H_o), the remaining computations involve smoothing and normalizing the health function. These computations are not difficult, but they do involve certain mathematical literacy. Depending on the application, they may or may not be necessary. Smoothing is often desirable, because it removes extraneous noise in the data to give a better indication of the health progression for the community. Normalization is only necessary when comparing the health between different communities.

To accurately portray the health of a community, we require the smoothing algorithm to use the latest data effectively as they are most important for determining the current state of health. Although a moving average will use the most recent data efficiently, it introduces a lag that is undesirable. Kernel smoothing can track the trend in the bulk of the data very accurately, but performs poorly at the two ends of the data series because it does not use that data efficiently. We developed a hybrid approach that takes advantage of both types of smoothing algorithms by using a weighted average between the two algorithms. The latest data near the end of the series are smoothed primarily with a weighted moving average. Earlier data are smoothed primarily with kernel smoothing that uses a Hanning window as its kernel function. The smoothed health function is called the health trend (denoted by without any subscript).

Normalizing CHI for Comparisons
The health trend will give a good indication of the community's health throughout its history, so we can objectively compare the health condition of a community between any two points in time. However, the health trend is derived from the un-normalized health function, so we cannot directly compare the health between different communities. In applications, such as benchmark studies, that require comparison of health across communities, we must normalize the health function. There are many different ways to normalize the health function depending on what aspect of the communities we like to compare. For benchmark studies, we normalized the health function by the following steps:

1. First we compute the smoothed derivative of the health function to reveal all the positive and negative health trends throughout the history of the community. (This operation is mathematically equivalent to taking the derivative of the health trend, because the smoothing operator commutes with the differential operator).

2. We also weight the smoothed derivative with an exponential decay that has a decay time constant of 50 weeks. This will attenuate the effect of long past health trends on the community's current health condition.

Lithium

Community Health Index
for Online Communities

3. We compute the definite integral of the weighted derivative to obtain the "net health" of the community.

4. We take into account the volatility of CHI by dividing the net health by the square root of the weighted mean absolute deviation of the health function's derivative. The weighting function is the same as the one we used in step 2 of this normalization procedure.

5. Because the weighted net health has a very large range of values, we apply the "signed-logarithm" function to the weighted net health so that its value is more linear. Here, the signed-logarithm is defined by

6. Finally, to calibrate the result into a more commonly used scale, we shift the reference point by adding a constant C_o to the result from step 5 and then multiplied by a scaling constant, C_s. The result is the community health index (denoted by the Greek letter χ).

Mathematically , the sequence of operations for computing CHI can be written as where

$$\chi = C_s \cdot \left\{ \mathrm{signlog}\left(\left[\langle \frac{e^{-|t_o - t|/50}}{50} |dH_o(t)/dt - \langle dH_o(t)/dt \rangle_t | \rangle_t \right]^{-1/2} \cdot \int_{-\infty}^{t_o} \frac{dH(t)}{dt} \frac{e^{-|t_o - t|/50}}{50} dt \right) + C_o \right\}, \qquad (7)$$

H_o is the health function, H is the health trend, t represents time measured in weeks, and t_o is the current time in weeks. The notation $\langle \cdot \rangle_t$ represents the sample average that takes averages over the time variable, t.

© 2011 Lithium Technologies, Inc. All Rights Reserved.