Moment or Momentum? An Empirical Study on Users’ Continuous Participation in Online Weight-loss Communities

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Abstract

Patient-centric online platforms for seeking peer support and engaging in health activities become increasingly popular among patients. Although online healthcare communities are found to be helpful, the effectiveness of such communities in improving patients’ long-term health management has been overlooked. In this study, we examine users’ continuous participation in online healthcare communities, which is particularly important for those with chronic conditions. Through analyzing users’ activities in a weight-loss community over a 3-year period, we find that those who continuously participate are more likely to self-monitor their lifestyle, which implies that online healthcare communities are an effective means for patients’ lifelong disease management. Our analysis results also show that, although users are attracted to the massive amounts of information available in online communities, it is the opportunity to participate in behavior change that leads to their continuous participation. Surprisingly, our results indicate that the exchange of social support among users is not effective in ensuring their continuous participation, a finding that is different from that of prior studies on the short-term effect of social support. Because users need to actively engage in health behaviors to derive long-term benefits, and online healthcare communities need to have enough social resources to be sustainable, our findings are useful for both users with chronic conditions and service providers.

Keywords: online healthcare communities, chronic disease, continuous participation, social support, vector autoregression (VAR) models
1 Introduction

Healthcare-related social media platforms have become a widely used resource for health education and patient involvement. Among the various ways to promote health and healthcare, patient-centric online healthcare communities are particularly attractive, as they allow patients to actively engage in their own health and healthcare management. These virtual platforms not only provide convenient tools to help individuals monitor and keep track of their health progress but also offer opportunities for participants to meet and exchange information, share opinions, and support each other in a timely manner. This trend toward the use of such communities is increasing; a recent survey revealed that almost 80% of U.S. adults have searched for health-related information online (Fox and Duggan 2013), as compared to 61% in 2001. Among users who stated they went online to research health topics, 26% had read others’ comments about their health experiences, and 18% were particularly looking for others with similar health concerns.

Online healthcare communities have become an important component of Health 2.0. Accordingly, there is a significant interest in understanding the function and value of these patient-centric applications. Prior research has provided extensive evidence that online healthcare communities can help individuals to better engage in their disease management, improve self-care outcomes, and, consequently, enhance healthcare systems (Goh et al. 2016, Hartzler and Pratt 2011, Lefebvre and Bornkessel 2013, Smith and Christakis 2008, Yan and Tan 2014).

Researchers also have observed that patients with chronic health problems are more likely to post health-related questions to online platforms and to share personal health experiences with others (Fox 2014). Thus, it is conceivable that online healthcare communities can play an important role in chronic disease management. Whereas the findings of many studies have suggested that online healthcare communities are helpful in disease recovery, less attention has been paid to individuals’ use of online healthcare communities for treating chronic conditions or, especially, for long-term disease management. For example, do patients regularly participate in online healthcare communities over time? Do they behave differently regarding short-term and long-term engagement? And what are the features of online
platforms that encourage continuous participation? Notably, better understanding of the value brought by online healthcare communities to chronic disease management has benefits for the design of these platforms to meet users’ needs, which, in many cases, can lead to more affordable services (Greenwald 2013).

In this study, we are therefore interested in examining the following questions: (1) Do new and returning users exhibit different participation patterns in online healthcare communities? On the one hand, new users, who are attracted to an online healthcare community for its various resources, may more actively engage in exchanging social support. On the other hand, returning users, who are more experienced, may be active in self-management activities. It remains unclear whether there are any systematic differences among new and experienced users and their received benefits. (2) What factors encourage users to adhere to long-term disease management and to continue active participation in these platforms? This is an important question for patients’ long-term disease management and for user retention in online healthcare communities.

To differentiate long-term participations from short-term engagement, we refer to new users as curious explorers, as they are at the exploration stage in regard to their degree of participation, and to returning users as continuing participants, those who continue to engage in healthier behavior and monitor their health. It is conceivable, however, that such behavior would cease if they stopped participating.

To understand how online healthcare communities can contribute to long-term chronic disease management, we explore the role played by online healthcare communities in patients’ chronic disease management. We focus on overweight and obesity issues and highlight the importance of mechanisms such as self-monitoring, structured programs for behavior change, and social support that underpin the benefits that users contribute and receive from their activities in the online environment. We use data collected from a popular Health 2.0 platform that allows individuals who are interested in weight-management to meet and communicate. Specifically, we implement vector autoregression (VAR) models to investigate the dynamic nature of users’ online activities in this context.
The results of our analysis suggest that curious explorers and continuing participants behave differently in the online environment. First, curious explorers are more active in recording their weight-loss progress, whereas continuing participants are more active in recording in their journals outcomes other than weight-loss outcomes in regard to their weight management. Second, although mechanisms such as self-monitoring of weigh-in and participating in challenges for behavior treatment are effective acquisition means to get more curious explorers, weigh-in does not cause them to continue to participate. Third, social support does not exhibit direct influence on users’ participation. In particular, forum discussion posts, whereby social support is commonly exchanged, do not attract users to participate and become absorbed into the ecosystem of the online community. This finding is in sharp contrast to that of prior studies on the short-term effect of social support (Hwang et al. 2010, Poncela-Casasnovas et al. 2015, Yan 2018).

Understanding users’ participation patterns and their associated factors is important for online healthcare communities concerned with management of chronic diseases, which, in this study, is obesity. Obesity is a chronic and progressive disease that increases medical illness and imposes a significant economic burden on the healthcare system (Mauro et al. 2008). It is directly linked to over 300,000 deaths each year in the United States. Although there is a growing effort, as related to policies and programs, to encourage people adopt healthier lifestyles and short-term treatment, the findings on long-term weight management is not encouraging. Given that overweight and obesity are chronic diseases, and maintaining a healthy weight requires long-term effort, it is important to understand how users utilize resources provided by the online environment and what mechanisms can be used to encourage their continuing participation in weight-loss management and engaging in lifelong healthy behaviors.

Our work thus contributes to the emerging area of patient-centric models in the healthcare literature. Adding to the extant studies on social support and health, our findings extend the understanding of how available social support influences users’ online activities, how different forms of social support and services influence users’ continuous participation, and the relationship between new and returning users. Although self-monitoring and social support are effective for short-term health outcomes, it is the
opportunity to work together on behavior change that encourage users to adhere to long-term health management.

Understanding the long-term benefits brought about by online healthcare communities also can contribute to the improvement of these virtual platforms and better meets users’ needs. Our findings can inform online intervention design and can help system designers to improve services provided by health- and healthcare-focused online communities. Our findings suggest that service providers need to encourage the use of challenges to “work together” to increase retention of users and that attracting new users includes promoting self-monitoring tools, offering a structured program for health management, and providing dietary guidance. Finally, there is a need to promote the use of social support for long-term effectiveness.

The rest of this paper is organized as follows. In Section 2, we review the related literature and describe the research context. In Section 3, we explain the empirical setting, data, and variables. In Section 4, we describe the model setup, specification tests, and model estimation. We present the main findings, which are based on impulse response functions (IRFs), in Section 5. Finally, in Section 6, we conclude and discuss managerial implications.

2 Research Background and Related Literature

Compared with offline programs, online healthcare communities offer notable advantages to individuals with chronic health conditions. The first and most important benefit of online healthcare communities is the availability of enormous amounts of information and access to social support (Eysenbach 2008, Lefebvre and Bornkessel 2013, Yan and Tan 2017). The second benefit is the affordability of the services provided by online healthcare communities, compared to offline behavior treatments, which are associated with significant barriers, including financial, geographic, and temporal. Moreover, chronic diseases, such as diabetes and obesity, require lifelong support and help, which may not always be available from patients’ immediate social contacts. Further, online healthcare communities offer a more comfort environment for patients to openly express their problems and issues (Ballantine and Stephenson
2011, Hwang et al. 2010), and, thus, people are more willing to reveal their difficulties, without fear of social discrimination or isolation, in the online environment. Finally, online healthcare communities empower individuals to communicate with others with whom they are not required to be interpersonally close. Taken together, online healthcare communities are uniquely suited to fit the dynamic needs of patients who live with chronic health conditions and to help them to engage in long-term behavior change.

In the remainder of this section, we first provide a short discussion on online weight-loss communities and then review literature that are related to this study.

2.1 Obesity and Online Healthcare Communities for Weight Loss

In this paper, we focus on online weight-loss communities that help individuals lose weight and better engage in their weight management. In contrast to acknowledged chronic diseases, such as diabetes and depression, the chronicity and severity of obesity is under-recognized. Obesity is a global health problem that affects all ages. According to the Centers for Disease Control and Prevention (Ogden et al. 2015), two-thirds of U.S. adults and one-third of children are either overweight or obese. There are many adverse health conditions associated with obesity, including type-2 diabetes, hypertension, stoke, coronary heart disease, sleep apnea, and many other comorbidities (Khaylis et al. 2010, Kopelman 2000). More importantly, once obesity is established, people seldom succeed in achieving or maintaining a healthy weight, especially in the long term (Mauro et al. 2008). As a result, obesity is considered one of the most prevalent health problems and a leading risk factor of morbidity.

Treating obesity is difficult, and maintaining weight loss over a long period of time is even more difficult (Elfhag and Rossner 2005). Observations and experimental studies reveal that behavior interventions for weight loss are effective in promoting short-term outcomes. Long-term lifestyle changes, however, demand consistent self-monitoring activities and a strong support network, and, thus, in clinical practice, achieving or maintaining a healthy weight in the long term is very difficult (Mauro et al. 2008).

Online healthcare communities for weight management can be promising in providing a lifelong intervention. First, online weight-loss communities can directly support weight-loss management by creating spaces where users can interact with others with similar concerns, which influences behavior
change and increases adherence to a weight management plan (Coiera 2013). Second, these communities provide access to information and shared experience, and participants can acquire personalized advice or tips and receive encouragement from someone who has similar health problems. Because individuals can remain anonymous in online weight-loss communities, the environment is nonthreatening, enabling them to disclose and discuss issues that surround weight loss. Third, online weight-loss communities provide convenient tools to help users better engage in weight management, including monitoring their weight-loss effort and progress. These tools have been found to be comparable to face-to-face interventions in achieving weight-loss outcomes in a timely and cost-efficient manner (Johnson and Wardle 2011, Khaylis et al. 2010). All of these benefits make online weight-loss communities affordable for users to engage in weight-loss, consequently be effective in influencing long-term management of their chronic health conditions.

It is important to note that the effectiveness of these opportunities for long-term health benefits depends on users’ continuous participation in online healthcare communities, as these platforms rely on the collective content of individual users. It is common, however, in health-related social media applications, for a substantial proportion of users to drop out or stop using the application before completing a behavior treatment, and it is believed that the high dropout rate may be a typical feature of these kinds of platforms (Eysenbach 2008). Notably, the discontinuity of participation in online healthcare communities may prevent users from receiving long-term health benefits. Thus, understanding users’ participation patterns and driving forces behind continuous participation are important to the extant literature.

2.2 Related Literature

This research is related to several streams of literature, including patient-generated content, health information processing, and online healthcare communities. Online healthcare communities are social media-based platforms, where users, such as patients and caregivers, can look for health information, share personal experiences, exchange opinions on various health-related issues or topics, and provide empathy or support to each other. Given the recent advances in web technologies and user interface,
online healthcare communities have greatly changed the way health information is obtained and how personal health is managed. As a result, patient-centered and patient-driven healthcare models have become increasingly important in improving healthcare delivery (Eysenbach 2008). Several studies have empirically examined the impact of online healthcare communities. In a field study, Wicks et al. (2010) found that, in such a setting, it is easy for patients to find another patient who has a similar health condition and to learn from the other patient’s experience in treatment. Likewise, Yan et al. (2015) examined online activities among users with a mental disorder and found that they were more likely to form social relationships with individuals who shared symptoms or who had undergone a similar treatment. Hwang et al. (2010) found that users discuss weight-loss topics in online weight-loss communities, sharing motivation and encouragement. Finally, opportunities to interact with other users in online healthcare communities helps to alleviate rural-urban health disparities (Goh et al. 2016).

A related stream of literature concerns online reviews and ratings to improve healthcare services. There are several studies that focus on reviews generated by patients and the impact in the healthcare context. For example, Gao et al. (2015) examined how patients’ opinions about physicians are affected by online reviews. They found that ratings accumulated in online platforms are more toward the positive end of the spectrum, while those physicians who are viewed as low quality are less likely to be rated online. Yan and Tan (2017) examined characteristics of ratings of treatment and found that patients pay more attention to the consensus of treatment experience and that the impact of treatment consensus is mediated by factors such as patients’ own health experience and knowledge. Our work is related to this stream by considering the social value brought by users’ participation in online healthcare communities, and examine an issue which is not discussed yet, users’ continuous participation and the impact associated with their dynamic behavior patterns.

Second, our research also related to the literature on social support and health. Social support has become recognized as an important predictor of health (Barrera 2000, Shumaker and Brownell 1984, Uchino 2004). Numerous studies document that social support is one of the most important psychosocial factors that influence physical health outcomes (Berkman 1984, Cohen 2004, Uchino 2004) and that it
promotes health-related behaviors by providing information and assurance as well as encouraging adherence to medical regimes (Cohen and Wills 1985, Uchino 2006, Verheijden et al. 2005). As online healthcare communities become increasingly popular, there has been increasing use of the web as a platform to exchange social support. The possibility for anonymity and asynchronous communication, free from the limitations of time and space, and the opportunity to reach many others with similar health concerns facilitate the formation of intimate personal relationship and social support. Through a comparison of offline relationships (e.g., friends, family members) with those of social contacts in online healthcare communities, Wright et al. (2010) found that members of online healthcare communities provide appropriate support for health issues, access to diverse points of views and information that may not be otherwise available, and objective feedback as well as reduce the role of obligations and risk. In addition, it is documented that different situations call for different types of support (Cohen and Wills 1985). In a study on an online community focused on mental disorders, for example, Yan and Tan (2014) found that informational support was the most exchanged social support and was positively associated with health conditions. They also found that the emotional support is more prominent than informational support in improving users’ health conditions. Our paper not only examines the social support generated in this online setting but, more importantly, differentiate different types of activities and investigate the associated benefits to different types of users as well as for the entire community.

Third, our study is related to the emerging literature on users’ continuous participation in the online environment. The core value of social media-based applications is the collectives of user-generated content, which are mainly volunteer based (Chen et al. 2017). Thus, users’ motivations to contribute is an important consideration that has received extensive attention. Such motivation includes the perceived connectedness with the community network or a sense of belongingness to the community (Kim and Sundar 2014, Wasko and Faraj 2005); social needs, such as conformity, uniqueness, or the need to resolve normative conflict in the community (Sridhar and Srinivasan 2012); the impact of users’ characteristics in prior reviews on following reviews (Forman et al. 2008); and the incentive strategies that are implemented by knowledge-based communities (Chen et al. 2017).
It is also well-recognized that the “silent groups”, usually known as lurkers, comprise most community members. In particular, for a given collaborative environment such as sharing knowledge or exchanging information, only 1% of users actively create new content, 9% of users edit content, and 90% of users only view content. Likewise, online health-related platforms encounter similar challenges. It was reported in prior literature, when examining several digital health social networks across different health problems or concerns, that 1% users are active participants who created 73.6% of the content, the next 9% participants created 24.7% of content, while the remaining 90% of participants only contributed roughly 1.7% content (van Mierlo 2014). When examining the ways how patients participate and interact in online healthcare communities focusing on weight loss, Ballantine and Stephenson (2011) found that the benefits patients accrue differ significantly. While active participates receive informational and emotional support through their online activities, lurkers receive little social support and benefit the least. In this study, we consider both new users (curious explorers) and returning users (continuing participants) and their activities in online healthcare communities, and study what works and what does not work for engaging users’ continuous participation, a critical but underexplored issue when referring to the management of chronic health conditions.

3 Data and Variables

3.1 Focal Online Weight-loss Community

In this paper, we focus on a non-commercial online weight-loss community as our research context for two reasons. First, despite increasing awareness of negative medical consequences of obesity, fewer Americans than in the past believe that they are overweight, and fewer indicate that they want to lose weight (McCarthy 2015). Instead, more people turn to fresh food and living a healthier life. In contrast to the commercial weight-loss industry, which is facing a decline in sales (Fortune 2015, Franchise 2017), participation in online healthcare communities that focus on weight management is increasing. Second, as a chronic disease, obesity, and related weight-loss maintenance, requires a lifelong effort to adhere to a
healthy lifestyle, which involves consistent self-monitoring and social support. These needs can be accessed through an online healthcare community in a convenient and cost-efficient manner.

The focal community has been in operation since 2007 and provides free and easy-to-use apps, online tools, and support for people who want to lose weight in a healthy way. Specifically, it provides users with access to a database on nutrition and food, self-monitoring tools on weight loss, a structured program that promotes healthier behavior, and a supportive venue in which users are encouraged to engage in the weight-management process and to achieve their goals. In this weight-loss community, users can create their own profiles on the website, enter their weight-related information, participate in activities that facilitate behavior changes, and record the various efforts that they have made to manage their weight, including the associated data on exercise and diets. For example, on her profile, a user can record her weight as a weigh-in entry or thoughts related to weight management. With these self-reported data, she can keep a tailored weight history and compare her progress with that of other users in the community. The centralized food and nutrition database allows users to easily calculate calories and to adjust their dietary plan. Users also can post and share their recipes in the dietary channel.

The other important component of weight-loss management, i.e., social support, is also available on the focal platform. Similar to other patient-centric healthcare communities, the website is social-networking oriented, harnessing the collective contributions from its users and providing individuals with implementable recommendations and advice. The discussion forum is a general venue where registered users can post questions or concerns about weight loss. Sharing thoughts and opinions opens up users to receiving support from a wider group of users in the community. Likewise, these same users can provide advice or share personal experience in response to others’ thoughts or opinions. These social interactions encourage users to support each other.

3.2 Data and Variable Description

Our data include the weekly number of new users (curious explorers) and returning users (continuing participants), as well as data such as the total number of posts, recipes, challenges, weigh-ins, and journals contributed to the community on a weekly basis. The observation period lasted from January
2014 to December 2016, a total of 157 weeks. Overall, 2,429,471 unique users participated in the data-collection period. Most were relatively new to the platform, and the number of continuous participants decreased dramatically over the course of the study. Figure 1 provides a plot of this long-tail phenomenon. Variable definitions and descriptions are presented in Table 1.

![Figure 1 Number of users over time](image)

In this study, the self-monitoring component involved weight charts and journals that depict weight-loss progress. Displayed as a line chart, the weight-loss history concerns how well a user is doing and the trend of her weight-loss progress. The journal contains thoughts and notes related to the weight-management effort. Both of these self-monitoring aspects provide information that not only helps individuals to track weight management progress but can also be shared with other users in the community, becoming its social capital.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. New Users (Curious Explorers)</td>
<td>The number of curious users who participate in the community for the first time in the first month after registration</td>
</tr>
<tr>
<td>No. Returning Users (Continuing Participants)</td>
<td>The number of committed users who have participated at least once in the community in a given week but also in previous weeks</td>
</tr>
<tr>
<td>No. Posts</td>
<td>The total number of posts created by the community in a given week</td>
</tr>
<tr>
<td>No. Weigh-ins</td>
<td>The total number of weigh-ins obtained by the community in a given week</td>
</tr>
<tr>
<td>No. Journals</td>
<td>The total number of journals (excluding weigh-ins) created by the community in a given week</td>
</tr>
<tr>
<td>No. Challenges</td>
<td>The total number of behavior challenges that are in progress in a given week</td>
</tr>
<tr>
<td>No. Recipes</td>
<td>The total number of recipes posted in the community</td>
</tr>
</tbody>
</table>
The social-support component derives mainly through discussions in the forum and comments on one’s profile. The former is public oriented, as any registered community user can create posts to participate; whereas the latter is more private, as it is within one’s profile. In addition, the focal community offers a large database for food and nutrition and is a popular springboard for discussion of diets and recipes. We consider forum posts and shared recipes as effective forms of social support that can be harnessed in the community.

Finally, to facilitate healthier behavior, the focal community offers structured programs and encourages users to participate in a variety of weight-management-related challenges. For example, a challenge could be to focus on a diet that contains “no processed foods/meats/beverages for 4 weeks” or “30-day low carb-30g carbs max per day.” A challenge can also focus on exercise such as “walking 30 minutes/1 hour every day for 5 weeks” or “planking for 20 seconds” that is increased by 5 seconds per day. There are also mixed approaches, such as “Daily HIIT & Eat Clean,” which utilizes 10 minutes of HITT daily (burst of intense exercise with period of rest between) and processed foods, drink water only. These various challenges enable users to participate in healthier behavior of their choice and to select accountability buddies to work together. Table 2 provides a summary of the descriptive statistics. Figure 2 presents the weekly data on the total number of posts, recipes, challenges, weigh-ins, and journals.

Table 2. Descriptive Statistics of the Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Std. Dev.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Curious Explorers</td>
<td>7,156.87</td>
<td>2,325.26</td>
<td>3,114</td>
<td>11,837</td>
</tr>
<tr>
<td>No. Continuing Participants</td>
<td>202,004.70</td>
<td>81,013.82</td>
<td>55,125</td>
<td>468,276</td>
</tr>
<tr>
<td>No. Posts</td>
<td>62,577.14</td>
<td>28,347.68</td>
<td>18,288</td>
<td>147,425</td>
</tr>
<tr>
<td>No. Weigh-ins</td>
<td>206,773.90</td>
<td>113,226.80</td>
<td>57,879</td>
<td>533,975</td>
</tr>
<tr>
<td>No. Journals</td>
<td>353,208.60</td>
<td>132,053.00</td>
<td>134,244</td>
<td>792,600</td>
</tr>
<tr>
<td>No. Challenges</td>
<td>600.60</td>
<td>206.04</td>
<td>305</td>
<td>1,090</td>
</tr>
<tr>
<td>No. Recipes</td>
<td>3,316.53</td>
<td>294.83</td>
<td>2,856</td>
<td>3,836</td>
</tr>
</tbody>
</table>

Whereas the data for weekly challenges in Figure 2(2) and weekly weigh-ins in Figure 2(3) exhibit similar patterns, i.e., more self-monitoring on weight changes in the first half the year with a decrease in the second half of the year, the other two plots (Figures 2(1) and 2(4)), which show the weekly posts and
weekly journals, follow this trend to a lesser extent. We used four weeks as the threshold to differentiate between new users and returning users and plotted their time trends in Figures 2(5) and 2(6). Not surprisingly, there are more curious explorers in the first half of the year, with the number’s dropping significantly in the second half of the year. This observation is consistent with what is seen in the weight management industry, with diet season’s typically starting in January and ending at the close of May. This pattern, however, is not observed among users who continue participate in the community. We also used alternative thresholds (1-week and 6-week) to conduct a robustness check (details are provided in Section 5.4). Figure 2(7) depicts the accumulative number of weekly recipes available in the community and Figure 2(8) is the weekly recipes after taking first difference.
To understand which mechanism works and which does not, we employed a time-series technique, a vector autoregression (VAR) model, to capture the interdependent evolution of patients’ online behaviors. There are several advantages to adopting this model. First, this approach allows us to track the dynamic evolution of each variable. In a VAR system, variables are explained by their own lag and that of other variables. Treating each variable as endogenous is particularly suitable for our study because, for example, it is likely that the number of curious explorers is associated with the number of continuing participants. It is also likely that the more community users there are, the more content (e.g., forum posts, recipes) will be created.
Second, in addition to capturing the potential endogeneity in the data, a VAR system also can account for other biases, such as auto correlation and reversed causality. For example, Granger causality tests can be conducted to investigate whether curious explorers “Granger-cause” the number of weigh-ins contributed to the community. If the test result returns positive (or negative) and significant, causality effect can be established, otherwise the causality cannot be concluded. Third, this approach can track not only the short-term impact but also the long-term cumulative impact of an increase in one variable on all of the other variables. Using simulation techniques to derive long-term impact can provide insights into persistence of communities, explaining what users are doing from both short- and long-term perspectives.

Fourth, a VAR model allows us to capture the dynamic feedback loop in users’ online activities. For example, an increase in curious explorers may lead to more forum posts, which may attract more continuing participants to respond, which then may attract more curious explorers to the site. Thus, a VAR model can be used to investigate the chained effects and to uncover the feedback loop in a complex system. Given these advantages, the VAR approach has been adopted by recent IS research (Adomavicius et al. 2012, Luo et al. 2013)

4.1 Model Specifications
In this study, we estimate a 7-equation VAR model in which endogenous variables are community users and their online activities. To correct for the distributional issues of these variables, we use the logged values for all of the time series in the model. In particular, \( LNR_t \) is the log value of the number of curious explorers at time \( t \); \( LRU_t \) is the log value of the number of continuing participants at time \( t \); \( LOW_t \) and \( LOJ_t \) are the log value of the number of weigh-ins and non-weight related online journals at time \( t \), respectively; and \( LOP_t \), \( LOR_t \), and \( LOC_t \) denote the number of forum posts, recipes, and challenges in the community at time \( t \). We also include a set of exogenous control variables, including a linear time trend and seasonal dummies. The VAR specification is given by the following:
where $\alpha$ is the intercept, $t$ is the deterministic-trend variable capturing the impact of omitted and gradually changing variables, and $Y_t$ and $S_{k,t}$ are the yearly and the seasonal dummies, respectively. In this model, we consider the number of recipes as the most exogenous variable because there are many well-known diet recipes in the weight management practice, and users can share what works for them with other members in the community. The next most exogenous variable is the number of challenges because every user can create her own challenge and invite other users to participate or create multiple challenges to enhance self-adherence to weight management. This is followed by the number of curious explorers and continuing participants, with the number of posts' (social support) being the most endogenous variable, and impose the following ordering of the variables: $LOR_t$, $LOC_t$, $LNU_t$, $LRU_t$, $LOW_t$, $LOJ_t$, and $LOP_t$. We also used an alternative ordering to conduct a robustness check, which is further explained in Section 5.4.

### 4.2 Model Estimation

Following the standard procedure of VAR modeling discussed in Dekimpe and Hanssens (2004), our analysis approach consists of the following steps: (1) use unit-root tests to determine the stationarity of variables; (2) for nonstationary variables, use cointegration tests to determine the existence of long-term equilibrium among evolving variables; (3) determine VAR model specification (VAR in levels, VAR in difference, or error correction VEC) based on unit root and cointegration tests results; (4) derive impulse-response functions (IRFs) or cumulative impulse-response functions (CIRFs) for predicting long-term impact.

We first performed the augmented Dickey-Fuller (ADF) unit root test to check the univariate properties in time series data, e.g., stationarity versus evolution. A stationary time series process is the
assumption for basic VAR models. If this assumption is not met, other approaches, such as the vector error correction (VEC) model or VAR model of differences, need to be implemented. The test results, reported in Table 3, show that ADF statistics range from -10.774 to -6.194, all below the 5% critical value of -2.89, except for the variable $LOR_t$. For $LOR_t$, we took the first difference of the variable, and the ADF test suggests that its trend is stationary in the series. Therefore, we rejected the null hypotheses of unit root at the 5% confidence level for all variables. We also use the KPSS test to determine the hypotheses of stationarity. The KPSS test statistics ranged from 0.119 to 0.224, none of which is smaller than the 10% level critical value. Therefore, the null hypothesis of stationarity (i.e., no unit root) cannot be rejected at the 10% confidence level. Together, these results suggest that variables are stationary and do not cointegrate in the equilibrium (Dekimpe and Hanssens 2004). Therefore, we estimate the VAR model in levels with these endogenous variables.

Table 3. Summary of Unit Root Test Results

<table>
<thead>
<tr>
<th>Variable</th>
<th>ADF Test Statistics</th>
<th>5% level C.V.</th>
<th>KPS Test Statistics</th>
<th>10% level C.V.</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Curious Explorers</td>
<td>LNU -6.194</td>
<td>-2.89</td>
<td>0.215</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Continuing Participants</td>
<td>LRU -10.274</td>
<td>-2.89</td>
<td>0.150</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Posts</td>
<td>LOP -10.084</td>
<td>-2.89</td>
<td>0.189</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Weigh-ins</td>
<td>LOW -6.285</td>
<td>-2.89</td>
<td>0.224</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Journals</td>
<td>LOJ -10.774</td>
<td>-2.89</td>
<td>0.138</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Challenges</td>
<td>LOC -6.705</td>
<td>-2.89</td>
<td>0.222</td>
<td>0.119</td>
</tr>
<tr>
<td>No. Recipes a</td>
<td>LOR -11.353</td>
<td>-2.89</td>
<td>0.119</td>
<td>0.119</td>
</tr>
</tbody>
</table>

a. Number of recipes was first-differenced.

Given that our data are constructed on a weekly basis, the lag order in the VAR is selected by criteria AIC, the Hannan and Quinn information criterion (HQIC), and the final prediction error (FPE). The goal is to select the lag order with a minimized AIC, HQIC, and FPE (Adomavicius et al. 2012, Luo et al. 2013, Zhang et al. 2012). As shown in Table 4, the optimal lag length is 1, according to these criteria. Another assumption for the general VAR system is the whiteness of the residuals. To verify that this assumption holds, we conduct diagnostic tests to check the existence of autocorrelation, nonnormality, and white heteroscedasticity. We do not find evidence of violating these assumptions at the 5% confidence level.
Table 4. Lag Selection Criteria

<table>
<thead>
<tr>
<th>Lag</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>FPE</td>
<td>1.9e-12</td>
<td>1.0e-12</td>
<td>1.3e-12</td>
<td>1.9e-12</td>
<td>2.7e-12</td>
</tr>
<tr>
<td>HQIC</td>
<td>-7.0509</td>
<td>-7.2773*</td>
<td>-6.6259</td>
<td>-5.8988</td>
<td>-5.1470</td>
</tr>
</tbody>
</table>

On a related note, when testing the effectiveness of exogenous variables, we first include both the linear trend variable and a square term of the time variable. The square term, however, is removed as it does not improve the model fit value. Our test results also show that the seasonality patterns need to be controlled.

5 Findings

In contrast with standard empirical methods, the estimated coefficients of VAR regression are not as informative as an analysis of relationships among variables. The typical approach of implementing VAR modes is to conduct Granger causality tests and derive IRFs to depict the impact. In this section, we first report our analysis results and demonstrate the significant interrelationships among time series. Then, we discuss the short- and long-term impact based on IRF results.

5.1 Granger Causality Analysis

Statistics from the Granger causality test explain whether the lagged values of one variable are effective in predicting another variable in a VAR system. Specifically, in our context, if the number of weigh-ins does not help to predict the number of continuous participants, then the number of weigh-ins does not Granger-cause the number of continuous participants. A typical Granger causality test is conducted based on a pairwise comparison, indicating the significant influence of one variable on another in the system. Table 5 provides the Granger causality tests results.

The values reported in Table 5 are the $p$-values for the estimated VAR model. Because we are interested in identifying mechanisms that attract curious explorers and continuing participants, there are several significant Granger causality relationships identified in the estimated model. First, regarding the curious explorers (new users), LNU, we found that the self-monitoring tool that allows users to track their weight loss (LOW) Granger-causes the number of new users ($p < 0.05$). This make sense because curious
explorers who are getting into the weight-loss process are excited about checking how well they are doing. Moreover, the opportunity to adjust behaviors and to follow a healthy lifestyle (LOC) Granger-causes the curious explorers \((p < 0.01)\). Likewise, the opportunity to form a friendly “work out together” atmosphere creates a comfortable environment. It is also apparent that the number of curious explorers is influenced by its past value \((p < 0.01)\), but the number of new users (curious explorers) is not Granger-caused by the number of returning users (continuing participants). The results reveal that neither the number of continuing participants nor the number of posts attract curious explorers to the healthcare community, a finding that stands in contrast to that of other online content contributions (Zhang et al. 2012).

| Table 5. Summary of the Results of Granger Causality Tests |
|----------------------------------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|-----------------|
| Variable                  | LNU  | LRU  | LOP  | LOW  | LOJ  | LOC  | LOR  |
| No. Curious Explorers   | LNU  | 0.003** | 0.237 | 0.269 | 0.003** | 0.943 | 0.381 | 0.176 |
| No. Continuing Participants | LRU  | 0.932 | 0.051† | 0.793 | 0.413 | 0.013* | 0.305 | 0.985 |
| No. Posts                | LOP  | 0.145 | 0.753 | 0.095† | 0.465 | 0.235 | 0.631 | 0.201 |
| No. Weigh-ins            | LOW  | 0.037* | 0.727 | 0.267 | 0.006** | 0.013* | 0.591 | 0.418 |
| No. Journals             | LOJ  | 0.815 | 0.879 | 0.047* | 0.066† | 0.006** | 0.154 | 0.406 |
| No. Challenges           | LOC  | 0.001** | 0.078† | 0.535 | 0.137 | 0.390 | 0.000** | 0.066† |
| No. Recipes              | LOR  | 0.271 | 0.482 | 0.189 | 0.924 | 0.965 | 0.007** | 0.127 |

†\(p < 0.10\), *\(p < 0.05\), **\(p < 0.01\)

For continuing participants, LRU, we find these returning users behave differently in the online weight-loss community. First, the results indicate that the value of continuing participants is influenced by its past values \((p < 0.1)\). In addition, the number of challenges (LOC) Granger-cause the number of continuing participants \((p < 0.1)\), providing strong evidence that users are attracted by the challenge function to continuously participate and engage in weight management. The other mechanisms that are shown in prior studies to be beneficial and, thus, attract users to participate, however, are shown to be not effective in terms of users’ continuous participation. In particular, extant literature suggests that the availability of social support, e.g., forum discussions, is one of the most important incentives for users to participate in online healthcare communities (Khaylis et al. 2010, Yan 2018). Surprisingly, our results suggest that social support does not Granger-cause curious explorers or continuing participants. That is,
forum discussions do not necessarily lead to more new users or returning users to the online weight-loss community. Instead, the chance to “work out together,” i.e., participate in different challenges, attracts both curious explorers and continuing participants.

Because there are new challenges each week, as well as challenges that are ongoing or completed, we further split the types of challenge into starting and ongoing as well as ending categories and test whether these different challenges have a different influence on users’ participation. The results are reported in Table 6. Although challenges, in general, are effective in attracting both curious explorers and continuing participants, further results show that starting and ongoing challenges Granger-cause both curious explorers and continuing participants, as shown by the LOC_SO Granger-causes LNU ($p < 0.01$) and LOC_SO Granger-causes LRU ($p < 0.1$), whereas completing challenges attract only curious explorers LOC_E Granger-causes LNU ($p < 0.01$) but not Granger-causes LRU. It seems that curious explorers not only focus on engaging in healthier behaviors but also are interested to learn how other users are doing. In contrast, continuing participants are more focused on self-weight management. In short, these results demonstrate that “challenges” are an effective mechanism to get users to participate in online weight-loss communities. The platform needs to maintain the number of starting or ongoing challenges so that more users will join in or come back.

Table 6. Different Types of Challenges

<table>
<thead>
<tr>
<th>Variable</th>
<th>LNU</th>
<th>LRU</th>
<th>LOP</th>
<th>LOW</th>
<th>LOJ</th>
<th>LOC_E</th>
<th>LOC_SO</th>
<th>LOR</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. Curious Explorers</td>
<td>LNU</td>
<td>0.005**</td>
<td>0.205</td>
<td>0.228</td>
<td>0.004**</td>
<td>0.813</td>
<td>0.288</td>
<td>0.602</td>
</tr>
<tr>
<td>No. Continuing Participants</td>
<td>LRU</td>
<td>0.873</td>
<td>0.077†</td>
<td>0.751</td>
<td>0.421</td>
<td>0.011**</td>
<td>0.507</td>
<td>0.942</td>
</tr>
<tr>
<td>No. Posts</td>
<td>LOP</td>
<td>0.165</td>
<td>0.728</td>
<td>0.142</td>
<td>0.460</td>
<td>0.269</td>
<td>0.782</td>
<td>0.603</td>
</tr>
<tr>
<td>No. Weigh-ins</td>
<td>LOW</td>
<td>0.048*</td>
<td>0.685</td>
<td>0.241</td>
<td>0.009**</td>
<td>0.019*</td>
<td>0.606</td>
<td>0.442</td>
</tr>
<tr>
<td>No. Journals</td>
<td>LOJ</td>
<td>0.685</td>
<td>0.793</td>
<td>0.063†</td>
<td>0.071†</td>
<td>0.007**</td>
<td>0.167</td>
<td>0.598</td>
</tr>
<tr>
<td>No. Challenges Ended</td>
<td>LOC_E</td>
<td>0.000**</td>
<td>0.204</td>
<td>0.381</td>
<td>0.153</td>
<td>0.218</td>
<td>0.000**</td>
<td>0.962</td>
</tr>
<tr>
<td>No. Challenges Started/Ongoing</td>
<td>LOC_SO</td>
<td>0.004**</td>
<td>0.059†</td>
<td>0.640</td>
<td>0.149</td>
<td>0.485</td>
<td>0.858</td>
<td>0.001**</td>
</tr>
<tr>
<td>No. Recipes</td>
<td>LOR</td>
<td>0.241</td>
<td>0.450</td>
<td>0.213</td>
<td>0.938</td>
<td>0.886</td>
<td>0.883</td>
<td>0.118</td>
</tr>
</tbody>
</table>

†$p < 0.10$, *$p < 0.05$, **$p < 0.01$
Although Granger causality reveals that challenges are an effective way to engage both new and returning users, self-monitoring tools, such as keep record on weight-loss or document weight-loss related thoughts, for weight loss are effective only for attracting new users. To assess the magnitude of these mechanisms, we focus on IRFs and interpret the influence.

5.2 Findings on Curious Explorers and Continuing Participants

IFRs are commonly used to interpret VAR findings in the literature. Specifically, an IFR traces the change in the response variable when there is a one-unit shock to the impulse variable. In presenting the changes in current and future values of the response variable, the impulse variable returns to zero in subsequent periods, while all other variables remain at zero in the IFR. Thus, tracing changes over time can reveal the immediate (short-term) and long-term effects. For curious explorers and continuing participants, Figure 3 presents the 12 possible IRFs of interest for the estimated VAR, which also provides evidence to support the results of the Granger causality test. For example, in the IRFs that show the responses of continuous participants, expect week 2 of journal, none of the responses that result from posts, weight-ins, or journal shocks is significantly different from zero, as shown in Figure 3(8–10).

Consistent with the Granger causality results, we are interested in the following IRFs:

1. When the number of challenges is the impulse variable, and the number of curious explorers is the response variable, the IRF measures the additional users’ joining the community over time when there is an addition of a challenge. The positive and significant response of curious explorers is shown in Figure 3(1). The positive influence is continuing and significant almost until Week 10.

2. When the number of weigh-ins is the impulse variable, and the number of curious explorers is the response variable, the IRF measures the additional users’ joining the community over time when there is an addition of a weigh-in record contributed to the community. As shown in Figure 3(3), there is a peak at Week 1, suggesting that a new weigh-in entry added to the community has a positive influence on the consequent new user enrollment. This positive influence also has lasting effect, as shown in the figure.

3. When the number of curious explorers is the impulse variable, and the number of curious explorers is the response variable, the IRF measures the additional users’ joining the community over
time when there is an addition of a new user. The positive impact shown in Figure 3(6) suggests that there is a social influence effect in new-user acquisition. When more users know about the online healthcare community and are interested to explore it, the chance of acquiring more users increases, albeit this influence quickly diminishes over time.

Consistent with the Granger causality test results, when the number of posts, or the number of journals, is the impulse variables, and the number of curious explorers is the response variable, the IRFs show that neither posts nor journals would have significant impact leading to more curious explorers, as shown in Figures 3(2) and 3(4).

(4) When the number of challenges is the impulse variable, and the continuing participants is the response variable, the IRF measures the additional returning users’ participating in the community over time when there is an addition of a challenge. Corroborating the findings in the Granger causality test, the evidence in Figure 3(7) implies that challenges are an effective means to retain community users. Interestingly, the convenient self-monitoring tools, such as weigh-ins for tracking weight loss history and journals that reflect one’s effort in weight management, are found to be insignificant in continuing users’ long-term online activities. This is evident in Figure 3(9), in which the effect is insignificant for all weeks, while, in Figure 3(10), only Week 2 is significant.

(5) When the number of continuing participants is the impulse variable, and the number of continuing participants is the response variable, the IRF measures the additional returning users’ participating in the community over time when there is an addition of a continuous participant. Figure 3(11) shows that there is a positive effect. However, the effect quickly decreases.

Although the more curious explorers, the better chance that some of them will be converted into continuing participants, as shown in Figure 3(12), there is no evidence to suggest a causal effect because the influence is not significantly different from zero. Similarly, having more continuing participants does not necessarily attract more curious explorers, as shown in Figure 3(5).
Figure 3 Impulse Response Plots

5.3 Short-term and Long-term Behavior Adjustment

The value of online weight-loss communities depends on the repository of users’ creative input, such as their knowledge, experience, and willingness to engage in social support. Because new and returning users participate in the focal online weight-loss community through different mechanisms, it is conceivable that their contributions to the community vary as well. Below, we first explore the contribution of curious explorers, followed by that of continuing participants, reflecting their journey of behavior adjustment in weight-loss management.

Our results suggest that curious explorers are active in self-monitoring, as seen by their recording their weigh-ins, but they are not necessarily creating more posts that indicate that they are developing
knowledge of weight loss or engaging in social support activities. As seen in Figures 4(1) to 4(3), only LNU→LOW is statistically different from zero, whereas LNU→LOP and LNU→LOJ are not. In addition, curious explorers may create challenges for the first two weeks, as shown in Figure 4(4). The positive impact is significant for these first two weeks, reaching a peak in Week 1, and then the impact decreases and becomes insignificant. Curious explorers, however, do not contribute to the sharing of diet recipes (Figure 4(5)), which is reasonable, as they are new to weight management and might not have enough experience with recipes to know what works well.

In contrast, continuing participants will produce more journals related to their weight-loss management. Figure 4(8) shows that one more continuing participant can lead to 0.01 more journals. Like curious explorers, however, statistically, these returning users do engage more in forum posts or weigh-ins, as seen in Figures 4(6) and 4(7). There is also no evidence to suggest that continuing participants necessarily create more structured challenges or contribute to the community, as shown in Figure 4(9).

These findings suggest that there is a disconnection in the ecosystem of an online platform. Although the structured programs, i.e., challenges, are an effective means to attract returning users to continuously
participate, neither new nor returning users are creating more challenges in the community, which is in the service of self-sustainability. Additional interventions, for example, challenges initiated by the system rather than by users, are needed. Further, social support, i.e., forum posts and recipes, becomes an absorbed component in the ecosystem of the focal community, suggesting that the availability of social support does not add value to the entire community over the long run. This finding is in contrast to social support as effective means for health benefits in the short run (Yan 2018). Figure 5 summaries the ecosystem of the focal weight-loss platform. In Figure 5, challenges is the structured behavior change program, denoted in green; whereas weigh-ins and journals are self-monitoring activities, which are in blue; lastly, social support is denoted in light orange, includes forum posts and recipes posted to the community.

Figure 5 Ecosystem of the Community

5.4 Robustness Check

In the main analysis, a 4-week time window is used to classify a user as a curious explorer or a continuing participant. It could be argued that new users might not need much time to explore the community or that one month is not enough time for one to commit to weight management. Thus, in this section, we discuss the implementation of alternative thresholds, that is, 1 week and 6 weeks, to conduct robustness checks. Figure 6 provides a plot of curious explorers and continuing participants based on the 1- and 6-week criteria.
Based on these alternative definitions, VAR models are revised and analyzed. We first use 1 week as the criterion to differentiate curious explorers and continuing participants and conduct a VAR analysis. The unit root tests suggest the stationarity of the time series. Likewise, we use 6 weeks as the criterion to differentiate community users. The statistics from unit root tests also suggest that the VAR model can be estimated in levels with these endogenous variables. Tables 7 and 8 present the results from Granger causality tests. These testing results are consistent with the main findings, reported in Section 5.1.

![Figure 6(a) Time Series Plot of Weekly Curious Explorers (1-week)](image)

![Figure 6(b) Time Series Plot of Weekly Continuing Participants (1-week)](image)

| Table 7. Summary of the Results of Granger Causality Tests (Threshold: 1 Week) |
|---------------------------------|-----|-----|-----|-----|-----|-----|-----|
|                                | LNU | LRU | LOP | LOW | LOJ | LOC | LOR |
| No. Curious Explorers          | LNU | 0.002** | 0.182 | 0.303 | 0.002** | 0.982 | 0.415 | 0.117 |
| No. Continuing Participants    | LRU | 0.950 | 0.039* | 0.920 | 0.429 | 0.014* | 0.245 | 0.883 |
| No. Posts                      | LOP | 0.100 | 0.980 | 0.081† | 0.526 | 0.268 | 0.673 | 0.213 |
| No. Weigh-ins                  | LOW | 0.023* | 0.734 | 0.286 | 0.017* | 0.004** | 0.624 | 0.396 |
| No. Journals                   | LOJ | 0.802 | 0.735 | 0.051† | 0.070† | 0.006** | 0.156 | 0.425 |
| No. Challenges                 | LOC | 0.001** | 0.040* | 0.602 | 0.155 | 0.444 | 0.000** | 0.069† |
| No. Recipes                    | LOR | 0.389 | 0.522 | 0.188 | 0.896 | 0.950 | 0.009** | 0.154 |

†p < 0.10, *p < 0.05, **p < 0.01
There also could be a different ordering in the VAR system. For example, it is possible that curious explorers are less exogenous than are continuing participants, while the number of weigh-ins may be more endogenous than is the number of non-weight related journals. Hence, we formulate a different ordering among the variables in VAR systems, but our findings remain consistent.

### 6 Discussion and Conclusions

Online healthcare communities are conduits for individuals to explore health issues, share anecdotal experiences, and fulfill their emotional needs in a timely and convenient manner. These key characteristics facilitate interactions that can support knowledge sharing and provide emotional support for individuals who are dealing with health-related questions or problems that affect themselves or other
people they care about (Eysenbach 2008). As these communities become an increasingly common way for individuals to seek information and share social support available on the Web, it is a natural extension for people turn to online healthcare communities for issues that surround weight loss. The role played by online healthcare communities in long-term chronic disease management, however, remains unexplored. Although intuition might suggest a clear, positive impact, the relationship between activities in online healthcare communities and their long-term effect on chronic disease management is nuanced.

In this research, we study the important role of an online weight-loss community in treating the issues associated with obesity. Obesity is a common problem that has become one of the most significant contributors to ill health. Despite the pressing need to reduce the prevalence and impact of obesity, few studies have been conducted with self-help weight-loss groups (Gearhardt et al. 2012). Our work, by examining the role played by online weight-loss programs in the obesity community, sheds light on how to increase the utilization rates of technology-based weight-loss interventions. By analyzing data collected from a real-world online weight-loss community, we are able to investigate users’ participation patterns and understand how users actively engage in these places. In response to the potential for social media to have a stronger role in the treatment of obesity, our findings can be used to improve system design and to better meet users’ need. In a broader sense, our work also contributes to understanding and improving weight-loss programs and to creating an effective and comfortable environment for individuals who seek to manage their weight.

Our results indicate that new users (curious explorers) and returning users (continuing participants) have different behavior patterns, consequently, the effectiveness of community modules varies. Specifically, although curious explorers are active in tracking their weight-loss outcomes, they do not Granger-cause journals to document their weight-loss management. In contrast, continuing participants are more focused on writing online diaries to engage with their weight-loss management but are not active in keeping track of their weight-loss performance. Although both types of users are operationalizing online healthcare communities for self-monitoring activities, their behaviors patterns have different emphases.
Online healthcare communities provide various tools and functions to engage users. The effective mechanisms, however, are different for new versus returning users. Although challenges and convenient tools to record weight loss are attractive to new users, only the opportunity to engage in behavior regulation, i.e., challenges, are attractive to returning users. Further, although curious explorers are attracted by starting, ongoing, and completing challenges, continuing participants are interested only in starting and ongoing challenges, as they are more self-focused on the adherence to behavior changes while less focused on the outcome they would achieve.

Our analysis also provided some surprising findings. Despite social support’s being widely believed to be a key benefit for online participants, our results suggest that neither curious explorers nor continuing participants are attracted by engaging social exchange or social support. Instead, the social support, forum discussion in particular, becomes an absorbed component in the ecosystem of the weight-loss community, as already shown in Figure 5. This result is in contrast to prior findings that weight-loss programs will have better outcomes if they are associated with social support. According to extant literature, it is indeed the opportunity to communicate with many other users that attracts more people to join online healthcare communities (Eysenbach 2008, O’Grady et al. 2008, Wicks et al. 2010). When considering the value of social support on a short-term basis, prior studies have found that social support is an effective means to attract users’ activities in online healthcare communities (Hwang et al. 2010, O’Grady et al. 2008, Yan and Tan 2014). However, when considering the value of social support from long-term perspective, especially for its effectiveness in attracting users’ continuous participation, our results do not provide evidence to support such direct impact.

In addition, it is worth to note that the diet management, i.e., recipes, is found to have causality effect on structured program for behavior change, i.e., challenges. However, it does not directly leads to users’ online activities. Unlike forum posts, which is more social oriented and empathizes the active engagement of social support, recipes is a form of social support that related to information sharing, which does not require active engagement. However, it is reported that users derive less value from passive participation, e.g., browsing content, than that from active participation (Ballantine and Stephenson 2011).
On the other hand, although there is no evidence to suggest that curious explorers or continuing participants Granger-cause forum posts, there are indirect paths. For example, continuing participants can Granger-cause more journals, while journals Granger-cause more posts. Likewise, curious explorers can indirectly cause more posts through Granger-cause weigh-ins, and weigh-ins Granger-cause journals, thus eventually creating more posts.

By understating what works and what does not, our findings also derive important implications in practice. A focus on the long-term continuous participation is important to health-service platforms, such as online healthcare communities. Investors are particularly interested in the role of patients’ sharing data in “peer-to-peer” social networks and online patient-centric platforms represent $3 trillion U.S. healthcare market (Greenwald 2013). Therefore, understanding what functions or community models are most effective provides actionable insights for healthcare practitioners, including how to increase user retention in the community as well as how to use users’ online activities to induce more contributions. First, like other forms of social media-based communities, the growth of these platforms depends on the collective content contributed by individual users. Although it is evident in our analysis that various functions provided by online healthcare communities are effective in attracting new users to explore its services, our findings also suggest that the current mechanisms are less effective in motivating them to continue to participate. Despite online platforms’ providing shared knowledge and social support, we find that these benefits do not guarantee users’ continuous participation. There is a need for the platform providers to analyze users’ needs, especially in regard to long-term engagement.

Second, users’ active engagement not only relates to their own benefits, but also indicates the social capital created and available in the community as a whole. That is, the more users participate and contribute, the more social resource will be available and accessible for other users. Given that a large number of participants does not imply more active participations or contributions, there is a need for the community to create an incentive strategy to encourage users’ active participation. For example, it is conceivable that if a user knows she can benefit more by making content, e.g., forum posts, to the community, she would be more motivated to contribute. That is, when a weight-loss community, for
example, can quantify users’ activities to show how they are benefited, it will keep its users coming back for more and create a positive loop for the ecosystem of the community. Knowing how much more they can get from their adherence to community modules, including self-monitoring and social support, can help users to remain as active participants and discourage users’ lurking behaviors, all of which has important managerial and practical value for healthcare services providing chronic disease management.

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