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Digital health communities: The effect of their motivation mechanisms

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ABSTRACT

Health-related online social networks are starting to play a role in many people's daily lives by enabling them to monitor their diet and motivating them to change their lifestyles. These social networks provide different motivation mechanisms. However, little research has been done on the effectiveness of these motivation mechanisms. This research analyzes data collected from a digital health community to examine what mechanisms can help motivate people. The results suggest that there is a high level of correlation between users' exercise activities and their participation in these digital health communities. This research benefits the digital health communities by providing insights into the design of motivation mechanisms.

1. Introduction

Healthcare is one of the most important industries in the U.S. With the development of electronic commerce, we have seen incredible transformations in banking, music, travel, and many other industries. The healthcare industry, however, still mostly runs on paper [21]. But in recent years, there has been a big push by the government, major healthcare organizations, and consumer advocacy groups to invest more in healthcare-related information technology and to move healthcare online. The federal government has invested a lot of money to encourage hospitals and physicians to automate their processes. Implementing modern information systems is expected to improve the efficiencies of hospitals and physicians' offices. It can also significantly improve the quality of healthcare.

With the growing popularity of web 2.0 technologies such as blogs, podcasts, and wikis, many healthcare organizations and professionals are embracing social media. Social media refer to blogs, social networks, and other media for social interaction. The use of social network software and its ability to promote the connection between patients and the rest of the medical industry has been dubbed "Health 2.0," and the number of organizations adopting Health 2.0 is growing. The Centers for Disease Control and CIGNA, for example, have active pilots in virtual worlds, such as Second Life, to test whether social media can help spread the word about issues like nutrition awareness, cancer screening, and infectious-disease prevention. American Red Cross uses Twitter to update information on natural disasters. Medscape, a social network for doctors, offers specialists, primary care physicians, and other health professionals integrated medical information and educational tools, and allows them to discuss, post, and answer questions about diseases and treatments.

The social-networking revolution is also coming to healthcare on the consumer side. The Internet technology and social media are making it easier than ever for consumers to find timely, personalized healthcare information online. Previously connected mainly through email discussion groups and chat rooms, now patients are able to build more sophisticated virtual communities that enable them to share information about treatments and support, and build online personal networks of friends. Patientslikeme.com is a platform that enables people to share information that can improve the lives of patients diagnosed with life-changing diseases. Patients can chat on the website, blog about their illness, and support each other with recommendations. DailyBurn and myfitnesspal.com, on the other hand, focus on fitness and healthy lifestyles instead of diseases. Registered members can update their health information and the websites provide suggestions tailored to the user's particular health/fitness needs, such as daily calorie intake and customized exercise plans. People can exercise together with their friends and participate in various fitness challenges.

Researchers have started to investigate the benefits of these health-related online social networks from different perspectives. Ni and Sun [30] study why doctors are willing to participate in online information platforms and how they benefit through participation. Kane and Ransbotham [22] analyze how people work together to create peer-produced medical information in social media platforms. Yan and Tan [51] propose an inhomogeneous Partially Observed Markov Decision Process model to study the helpfulness of an online healthcare community to patients' health condition dynamics. Xiao et al. [50] examine factors that influence patients' online health information search and find that perceived health status could affect patients' online health search frequency as well as diversity. The privacy concern, trust and information sensitivity are factors that have an impact on people's decision on providing their health information online [4].

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Decades of research indicate that physical activity is an important behavior for health promotion and disease prevention [18,42]. Despite widespread dissemination of information supporting the health benefits of physical activities, the percentage of sedentary American adults reaches almost 35% [3], and over half do not exercise regularly [33]. Therefore, it is important to study what motivation mechanisms really work. According to the new physical activity guidelines announced by the U.S. Department of Health and Human services in 2008, two and a half hours a week of moderate aerobic physical activity can help adults gain substantial health benefits, and children can benefit from an hour or more of physical activity a day. The National Prevention and Health Promotion Strategy, developed by the Surgeon General's National Prevention and Health Promotion Council, is shifting the nation from a focus on sickness and disease to one based on prevention of disease and promotion of wellness, which will help lead to longer, healthier, and more productive lives for all Americans.

Many digital health communities have emerged to do exactly that: promoting a healthy lifestyle and encouraging people to exercise more. They provide different motivation mechanisms to help achieve the goal. However, little research has been done on whether these motivation mechanisms are effective. The objective of this study is to analyze the effect of health-related social networks and their motivation mechanisms using data collected from a digital health community. Our two main research questions are:

- Does active participation in health-related online social networking motivate people to exercise more?
- What motivation mechanisms used in digital health websites motivate their users to exercise more?

The rest of the paper is organized as follows. In Section 2, we review the literature on motivation theory in sports and the relationship between social networking and health. Data and regression results are provided in Section 3. Section 4 concludes the paper with future research directions.

2. Background and theoretical foundation

Although the links between physical exercise and well-being are well documented [24,31], almost half of American adults are not active enough to accrue health benefits. Understanding what motivates people to engage in physical activity and how to facilitate adherence to regular exercise has been a central research topic in sports and exercise science [11,12,26,35]. Deci and Ryan [11,12] propose a multidimensional conceptualization of motivation which categorizes motivation into two types: extrinsic motivation and intrinsic motivation. Extrinsic motivation refers to external means that regulate behaviors, such as monetary rewards or grades, or threat of punishment. Intrinsic motivation is the happiness and satisfaction derived simply from exercising. There are three types of intrinsic motivation: intrinsic motivation to know, to accomplish things, and to experience stimulation. Vallerand and Losier [43] propose a motivational sequence that integrates much of the intrinsic and extrinsic motivation literature in sports. This sequence starts from social factors, leads to psychological mediators and types of motivation, and ends with consequences. They argue that the type of motivation that underlies athletes' behavior is determined in a large part by various social factors.

Given the fact that the motivation for engaging in a certain activity is a function of both intrinsic and extrinsic motivating factors [14,46], self-determination theory provides a unique framework for studying and understanding motivations in the adoption of exercise, or physical activity. Self-determination theory argues that a critical issue in the effects of goal pursuit and attainment concerns the degree to which people are able to satisfy their basic psychological needs as they pursue and attain their valued outcomes [13]. The theory has been extensively used in sports motivation research. Wankel [45], for example, views intrinsic motivation as a key factor in exercise adherence. He states that social motives, although extrinsic to the activity, may contribute to adherence because social interaction can add to one's enjoyment—an intrinsic motivation—in participating in the exercise activities. A study by Ryan et al. [35] reveals that adherence to exercise was associated with motives focused on enjoyment and social interaction. Based on self-determination theory, Li [26] develops and validates a multidimensional Exercise Motivation Scale to assess motivational tendencies in the exercise context. One dimension in the scale is the social dimension.

Allen [2] analyzes motivation from a social orientation perspective and identifies three sources of motivation: social validation of oneself, affiliation experience, and perceptions of belonging. Social validation of oneself is about getting recognition from others, in the form of social approval, social acceptance, and social status. Affiliation experience and perceptions of belonging, on the other hand, motivate people to exercise because they want to make friends and be part of a social group which shares the same interests.

In studies by McCullagh et al. [28] and Passer [32], participants report social reasons for engaging in physical activity. These reasons include affiliation, being part of a team, and social status. Positive effects come from social sources such as friendship opportunities, social recognition, and parental pressure [37]. Scanlan et al. [38] point out that individuals' motivation in sports may be related not only to a desire to develop physical ability, but also to develop social networks.

Social networks are the social connections that surround an individual. An individual can get social support, such as emotional, instrumental, and financial aid, from his social network. Social support has been linked to a number of health outcomes, and appears to be an important determinant of success in changing health habit [36]. Berkman [5] examines in detail the evidence linking social networks and social supports to health outcomes, and finds that social networks seem to have a remarkable relationship with disease states.

There are six functions of social relationships [47]. They are intimacy, social integration, opportunity for nurturant behavior, reassurance of worth, assistance, guidance and advice, and access to new contacts and diverse information. Intimacy is an emotional climate in which individuals can express their feelings freely and without self-consciousness. Social integration means that participants share their experience and ideas through their relationships because of similar situations or similar objectives. Opportunity for nurturant behavior emphasizes the value to self of obligations and duties toward others. Many people in different relationships provide assistance to each other. Network members may provide valuable advice and guidance to help other members to handle their problems. Social ties can also help members to find new sources of information and new contacts that may be helpful in the future.

One way social networks can help healthcare is through access to new information, advice, and contacts. Through this “pro-medical care” process, individuals learn how to get relevant information and how to utilize the information; therefore, they get better health care and improve their physical health. In addition, social networks can also exert social control and peer pressure. Individuals in a network may feel that they should behave in the way that their peers behave. People who have connections with people who exercise regularly may follow the patterns of their group simply to maintain their group identity.

Social network websites are part of our daily life now. Several studies exist that take Facebook networks as a stand-in for the “real” social networks of individuals. Traud et al. [40] and Lewis et al. [25], both using Facebook data, assert that Facebook networks are a reliable proxy for the physical networks of active ties. Mayer and Puller [27] report that only 0.4% of the Facebook friendships they studied appeared to reflect “merely online interactions.” Ellison et al. [17] support this finding, stating that Facebook is used primarily to maintain or reinforce existing offline relationships rather than to meet new people. Online social networks are in many ways similar to social networks in the physical world. Participants are primarily communicating with people who are already a part of their extended

social network [7]. In addition, the online social networks are primarily organized around people, with the individual at the center of their own community. This more accurately mirrors unmediated social structures, where "the world is composed of networks, not groups" [48]. Therefore, based on the sports motivation literature and social network literature discussed above, we hypothesize the following:

H1. Online social networking activities are positively associated with users' fitness activity accomplishments.

Social support appears to be an important determinant of success in changing health habits. Several weight-loss studies indicate that spousal support and participation in treatment enhances weight loss [15,34]. Social support includes family support, spousal support and friend support. To some degree, social support from family and friends has been shown to have a consistent and positive relationship with adult physical activity [19,41,44]. Eyler et al. [18] demonstrate that enhancing social support is an important aspect of interventions aimed at increasing physical activity in a population of sedentary women of various backgrounds.

Health-related social networking sites are starting to play a role in people's daily lives by allowing them to monitor their food intake and create challenges to motivate them to change their lifestyles. HealthyPlace.com, myfitnesspal.com and DailyBurn.com are examples of such health-related social networking sites. "A friend, not an apple, a day will help keep the doctor away" [16]. It shows the importance of social support as a good preventive and curative medicine. Evidence has supported the idea that social ties are related to good health and well-being [5]. Berkman and Breslow [6] find that "a social network provides a web that assures every person in it of receiving a certain amount of emotional and practical support." Therefore, our second hypothesis is about the social support provided by digital health communities:

H2. The support network of a user in a digital health community is positively associated with his/her fitness activity accomplishment.

The sociology of sports literature has maintained an interest in social and economic capital [23,29,49]. Social capital or social economic status is believed to play a very important role when people make their physical activity choices. The higher one's social status, the more one will participate in physical activity. Wilson [49] finds that people who are rich in cultural and economic capital are more likely to be involved in sports.

Subsequent research has examined the effect of cost. Cost of exercise can play an important role in motivating people to exercise. In many situations, exercise involves cost. For example, fitness centers require paid membership for usage. Paying money for the membership is a personal investment an individual makes to the exercise activity. Wankel [44] argues that rationally evaluating cost and benefit motivates people to exercise. Alexandris et al. [1] demonstrate that individuals who are willing to invest more money are less likely to drop out from exercising. Thus, we hypothesize that:

H3. People who pay for services in a digital health community are more likely to exercise compared to the ones with only a free membership.

3. Empirical analyses

3.1. The research context

Our research context is DailyBurn, one of the most popular fitness tracking social networks. Several prime media outlets have reported its success, such as the New York Times, the Washington Post, and TechCrunch. Allowing people to find workout programs, track food and nutrition, and join the community to get motivated to exercise, DailyBurn is an interactive, motivational tool to help people in their quest to lose weight, build body strength and achieve an overall healthy lifestyle. Launched in 2007, it already has nearly 5 million registered members and the number is increasing every month. Users can join DailyBurn for free or pay for a "Pro" or "Elite" membership that offers a more enhanced experience, including a personal trainer who can provide users customized exercise plans, advanced nutrition tracking, and a detailed meal plan to keep positive eating habits on track (Fig. 1).

Several types of online services are available for its registered members. Through nutrition tracking, a registered user can create a nutrition log to record the food they eat and compute how many calories, fat, or protein they take. Personalized training plans can be created based on users' health condition and their needs. These plans are step-by-step programs combined with videos to show how one should exercise to achieve one's goals. The training process can also be tracked online. DailyBurn also offers several mobile apps for the iPhone, such as the FoodScanner app and Push-up Wars app.

In addition to these online services, there are also social network functions on DailyBurn, one being the motivator network. Unlike the "follow" function on Twitter, the motivator relationship on DailyBurn is a two-way relationship and needs consent from both parties. A user can find motivators on DailyBurn who share the same fitness goals with him and build his motivator network online. Motivation groups, another motivation mechanism on DailyBurn, are formed by people who share the same value, have similar problems, or are located at the same places. Users can join different motivation groups. Another interesting feature offered by DailyBurn is the challenges created by registered users. Some of the popular ones are "lose 20 pounds," "1000 push-ups," etc. A user can join the challenges he likes and compete with others who join the same challenges. If he wants, he can create new challenges by himself and invite his friends to join. Posting is another social networking feature of DailyBurn. DailyBurn offers forums where people can share their exercise experience, ask specific questions about diet or exercise plans, comment on others' stories, and answer others' questions. Users can find kindred souls going through the same struggles and can help each other stay motivated [10]. Fig. A in the Appendix A is a screenshot of a conversation thread that highlights the social interactions among members and motivations members provide to each other.

With these social networking features, DailyBurn is transformed from an online fitness provider to a social community focusing on motivating people to exercise and achieve fitness goals. Unlike Facebook, where friends are often times friends in real life, motivators on DailyBurn may not know each other offline. However, they share common interests and fitness goals and want to support each other.

3.2. Data

Data was collected from DailyBurn.com. In order to test our hypotheses, we use the number of accomplished exercise goals as an indicator of a user's exercise level. On DailyBurn, awards are given to users who accomplish their exercise goals based on his reported exercise activities. The number of postings is used to measure a user's social networking activity. The number of motivators measures the size of the support network a user has in the digital health community.

Previous research has shown that the level of physical activity declines markedly with increasing age [39]. Campbell et al. [8] report that there are significant differences between younger and elder people in terms of personal goals and the perceived efficacy of exercise in achieving these goals. Caspersen et al. [9], using the U.S. data to study how age and gender determine people's physical activity patterns, find that physical activity patterns erode most among young adults; whereas middle aged people have relatively stable patterns. People at the retirement age have a stabilizing or even improving physical activity pattern.

In addition to age, gender also plays a role in one's exercise activities. Previous research shows that gender differences exist in motivational orientations in several life domains. It is suggested that females display

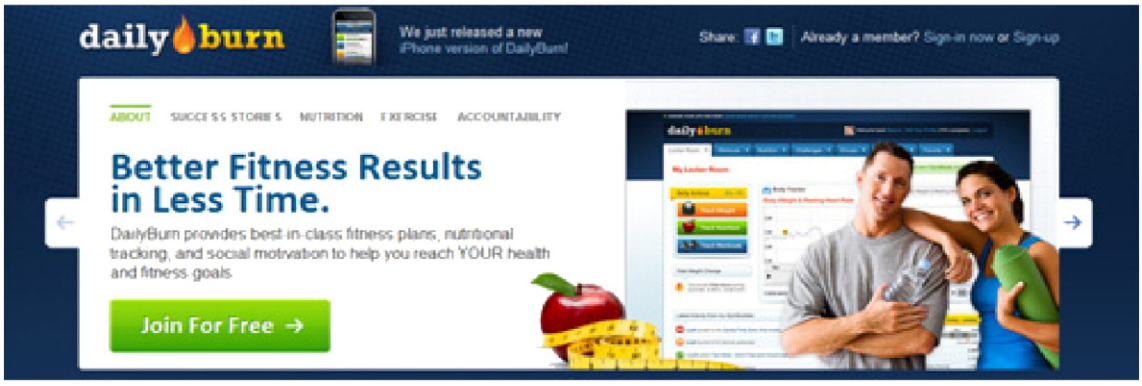

Fig. 1. Dailyburn.com home page (from November 2011).

a more self-determined motivational profile than males. Fortier et al. [20] report that female athletes were more intrinsically motivated to accomplish things and exhibited more identified regulation than male athletes. Although we do not explicitly examine the role of gender and age in our study, from the previous literature, it is obvious that age and gender are factors that need to be controlled for. Therefore, in our paper, we also collect gender and age information as our control variables.

Our sample was collected from the discussion forum on the website. We chose those users who posted on the forum in a six-month time span (May 2010 to November 2010) and also provided their age and gender information. Then, from their own personal webpage on the website, we collected the data for the number of their reported exercise activities, the number of awards they earned and the number of motivators they had. The sample size for our study is 707 users. In sum, for each user, we collected his/her age, gender, membership type (paid or free), number of posts he/she made on the forum, number of exercise activities tracked on DailyBurn, number of awards earned and how many motivators he/she had on DailyBurn, in other words, how large his/her network is. Table 1 reports the summary statistics of our major variables.

In our data, there were 200 female users and 507 male users. Out of the 707 users, 275 were paying members. Surprisingly, the average age of people who use DailyBurn is a more mature age of 32, not young adults around 20 years old who like to surf online a lot. One possible explanation is that older, more mature people pay more attention to their health and are more willing to track their exercises online than the younger ones. We use the number of motivators as a measure of a user's social network size. The large variance for the number of post variable suggests that we should use a log transformation for this variable. The correlations among these variables are low and reported in Table 2. No VIF (variance inflation factor) statistic for the variables is greater than 1.6, which indicates the absence of multicollinearity.

3.3. Model estimation

To test our hypotheses about the effectiveness of the motivation mechanisms, we formulate the following empirical model. In order to capture the effectiveness of the motivation mechanisms of interest, we use the number of awards as the outcome variable because this variable measures how many exercise goals have been achieved. Our dependent variable, number of awards, is a count variable instead of a continuous variable, which violates the basic requirement for the OLS method. We notice that this variable has a lot of zeros. Therefore, we use zero-inflated Poisson regression instead for our analysis.

A zero-inflated model assumes that the zero outcomes are due to two different processes, one that determines if the individual is eligible for a non-zero response, and the other that determines the count of that response for eligible individuals. The two processes involved in our study are that a user does exercise vs. not exercise. If not exercising, the only possible outcome is zero. If exercising, then it is a count process. The two parts of a zero-inflated model include: (1) a binary model, usually a logit model, used to model which of the two processes the zero outcome is associated with; (2) and a count model, in this case, a Poisson model, used to model the count process. In this research, we use variables such as the number of motivators, type of membership (paid vs. free), the number of posts and gender to model the count of awards a user gets in the Poisson part of the model. Based on the previous literature about the effect of age on exercise, the variable *Age* is used in the logit part of the model.

The basic model is model 1 where we explore how posting behavior, the size of the motivator network, and the type of membership (paid or free) influence the number of awards a user earns.

$$Award = \beta_0 + \beta_1 \log(Post) + \beta_2 Motivator + \beta_3 Paid + \beta_4 Gender + \varepsilon. \quad (1)$$

Post is how many posts a user had made online. *Paid* is a binary variable indicating whether the user had a paid membership (=1) or a free membership (=0). *Motivator* refers to the size of the motivator network a user had on the website. *Gender* is a dummy variable with 1 indicating female and 0 male.

As argued before, paying money for the membership is a personal investment an individual makes to the exercise activity. Previous research indicates that this investment indeed affects a person's exercise behavior [1]. It is possible that this investment also affects a person's participation level in the online social network in terms of the number of postings and the size of the motivator group. We

Table 1
Summary statistics.

Variable	Mean	Std. Dev.	Minimum	Maximum
FitnessAction	8.76	19.06	0	165
Post	17.27	37.54	1	411
Award	2.67	6.95	0	123
Motivator	5.22	8.98	0	87

N = 707.

Table 2
Correlation table.

Variables	FitnessAction	Log(post)	Award	Motivator	Gender	Age	Paid
FitnessAction	1.00						
Log(post)	0.19	1.00					
Award	0.37	0.35	1.00				
Motivator	0.16	0.47	0.3	1.00			
Gender	−0.01	0.01	−0.02	0.09	1.00		
Age	0.16	0.01	0.1	−0.06	−0.02	1.00	
Paid	0.17	0.39	0.14	0.25	0.01	0.09	1.00

therefore conduct two pairwise mean comparisons for the two user groups (paid user group and free user group) and the results are presented in Table 3.

Table 3 suggests that paid users and free users are indeed different in terms of the number of postings they made, and the number of motivators they had on DailyBurn. In order to see how different they are and account for the possible moderating effects of membership type, we add two interactions terms, $Paid*\log(Post)$ and $Paid*Motivator$, into model 1 and formulate model 2.

$$Award = \beta_0 + \beta_1 \log(Post) + \beta_2 Motivator + \beta_3 Paid + \beta_4 Gender + \beta_5 Paid * \log(Post) + \beta_6 Paid * Motivator + \varepsilon. \quad (2)$$

The regression results for the two models are shown in Table 4. A comparison of the two models indicates model 2 has a better overall fit, which has a higher log likelihood. Therefore, our analysis of the results will focus on model 2. The Vuong test provides a comparison of the zero-inflated Poisson model with the standard Poisson model. The significant p-value for this test suggests that the zero-inflated Poisson model is indeed a better model.

The coefficient for log(*Post*) is 0.58 with a significant p-value. It means that people's exercise levels are indeed correlated with their online social networking activities. To be more specific, users who make lots of postings in the online community tend to exercise more. Therefore, H1 is supported. The significant p-value for *Motivator* suggests that the support network is important to a person's exercise accomplishments for both paid members and free members. The larger a member's support network is, the more exercise goals he/she will achieve. Therefore, H2 is supported. H3 is also supported—compared to members who only use the free services provided by the website, those members who have a paid membership are more likely to exercise and achieve more goals: a paid member will get more ($e^{0.49} = 1.63$) awards than a free member.

The two interaction terms are also significant (although *Paid* Motivator* is only significant at the 0.1 significance level), indicating that membership type does play a moderating role on a user's social networking behavior. Interestingly, both coefficients are negative. The effect of post is smaller for paid members (0.58–0.25 = 0.33) compared to users who pay nothing (0.58). For a free member, if he has one more motivator in his support network, his awards will increase by 1% (i.e., multiplied by $e^{0.01}$). For a paid member, his number of awards will increase by only 0.9% (multiplied by $e^{0.009}$) for each additional motivator in his network, less than for free members. Similar as before, the support network size has a smaller impact on paid members than free members. These two findings are contrary to our initial expectations that paid members would be more active in not only fitness activities but also social networking activities. One possible explanation is that paid members are more geared towards utilizing the exercise training services provided by DailyBurn and less interested in participating in the social networking activities. Finally, our result for the impact of *Gender* shows that compared to females, males are more likely to exercise. The significant p-value for *Age* (0.03) suggests that *Age* is a significant variable to predict excess zeros.

3.4. Robustness check

In order to check the robustness of our results, we use the number of reported fitness activities as our dependent variable and run the two models again. *FitnessAction* is the indicator of how many times a user reported his/her fitness activities in the data collection period. We still use zero-inflated Poisson model to estimate the model. The results are presented in Table 5.

The results are consistent with the previous model using the number of awards as the dependent variable. The motivator network size and the number of postings still have a significant positive effect on the reported fitness activity, and these two effects are higher for free members compared to paid members. In terms of the impact of user type, paid members report more exercises compared to free members. The Vuong test result again shows that this zero-inflated Poisson model is preferred to a standard Poisson model and *Age* is a significant variable to predict excess zeros.

Table 3
Pairwise mean comparison.

Paid vs Free	Contrast	Std. Err.	[95% Conf.	Interval]
Log(post)	1.13	0.1	0.934	1.326
Motivator	4.544	0.672	3.224	5.863

Table 4
Regression analysis results.

Award	Model 1		Model 2	
	Coefficient	P-value	Coefficient	P-value
Intercept	0.55	0.00	0.12	0.21
Gender	−0.17	0.00	−0.17	0.00
Motivator	0.01	0.00	0.01	0.03
Paid	0.24	0.00	0.49	0.00
Log(post)	0.42	0.00	0.58	0.00
Paid*motivator			−0.001	0.09
Paid*log(post)			−0.25	0.00
Inflate				
Age	−0.02	0.02	−0.03	0.03
_cons	0.43	0.20	0.34	0.33
Vuong test		0.00		0.00
Log likelihood	−1881.38		−1861.09	

4. Conclusions

In this paper, we investigate the effectiveness of the motivation mechanisms used in an online fitness community. We hypothesize that online social networking activities and one's support network motivate people to exercise more, and people who pay for services are more likely to exercise compared to the ones with only a free membership. We build our theory based on the sports motivation literature and the social network literature. Our empirical results support all of our hypotheses.

There is a clear trend that young people's participation in physical activity declines as they get older. Previous studies also show the importance of early interventions in order to assist young adolescents and adults to keep physical activity at a healthful level. Our preliminary results are encouraging in the sense that digital health communities do seem to play a role in motivating people to exercise. More health and fitness oriented websites and mobile apps are emerging every day. They not only provide tools that enable people to track their own activity levels, but also connect users to a community of like-minded people. Our results show that the social networking

Table 5
Robustness check results.

FitnessAction	Model 1		Model 2	
	Coefficient	P-value	Coefficient	P-value
Intercept	2.45	0.00	2.32	0.00
Gender	−0.05	0.06	−0.05	0.07
Motivator	0.01	0.00	0.02	0.00
Paid	0.19	0.00	0.41	0.00
Log(post)	0.08	0.00	0.13	0.00
Paid*motivator			−0.01	0.00
Paid*log(post)			−0.08	0.00
Inflate				
Age	−0.02	0.05	−0.02	0.01
_cons	0.35	0.21	0.35	0.21
Vuong test		0.00		0.00
LogLik	−5742.62		−5725.76	

functions provided by these websites are indeed linked to people's exercise level. This conclusion is consistent with the traditional sports motivation literature that social support is an important motivator of one's physical exercise activities, although the social networking function comes in the form of digital networking. These findings encourage the research community as well as the digital health community providers to further investigate the effectiveness of online social networking tools on their users' health and fitness.

Our research also provides insights into the design of motivation mechanisms. The significant positive correlation between the number of motivators and the number of achieved goals indicates that motivators play an important role in encouraging people to exercise more. Therefore, when health providers decide to go digital and use some mechanisms to motivate people to exercise, setting up motivator groups is a good choice. Some other possible motivation mechanisms include giving points or badges once a user achieves his/her exercise goals, creating competition among motivation groups, etc. Different mechanisms vary in their effectiveness of motivating users to exercise. In order to keep their users exercising and maintain the growth of their websites, incorporating the most effective mechanisms into the service should be an important consideration in the design process. Our research is a first step that sheds light on this important process.

This is preliminary work. We used data from one health-related social networking website only and tested three hypotheses. We have found that there is a relationship between a user's fitness achievements and his social activity online. However, we do not infer any causal relationship here. In the future, we will collect more data from other similar websites which might have different motivation mechanisms to validate our results. Some of the interesting questions we may consider in the future are: what other motivation mechanisms can be effective besides the online motivator group? How can people use these health websites to improve their health status? How shall we design the digital health communities to induce adherence to fitness activities?

There have been much recent discussions about using information technology to improve the quality of healthcare in the U.S. Given the prevalence of social networking technologies such as Facebook and Twitter, understanding whether IT-enabled social networking activities would and how to motivate people to exercise and stay fit is extremely important. In today's environment where our national obesity rate is over 20%, and 9 out of every 10 U.S. Internet users now visit a social networking site in a month, this research activity could potentially discover an important tool that benefits the nation as a whole to stay healthy and fit.

Appendix A

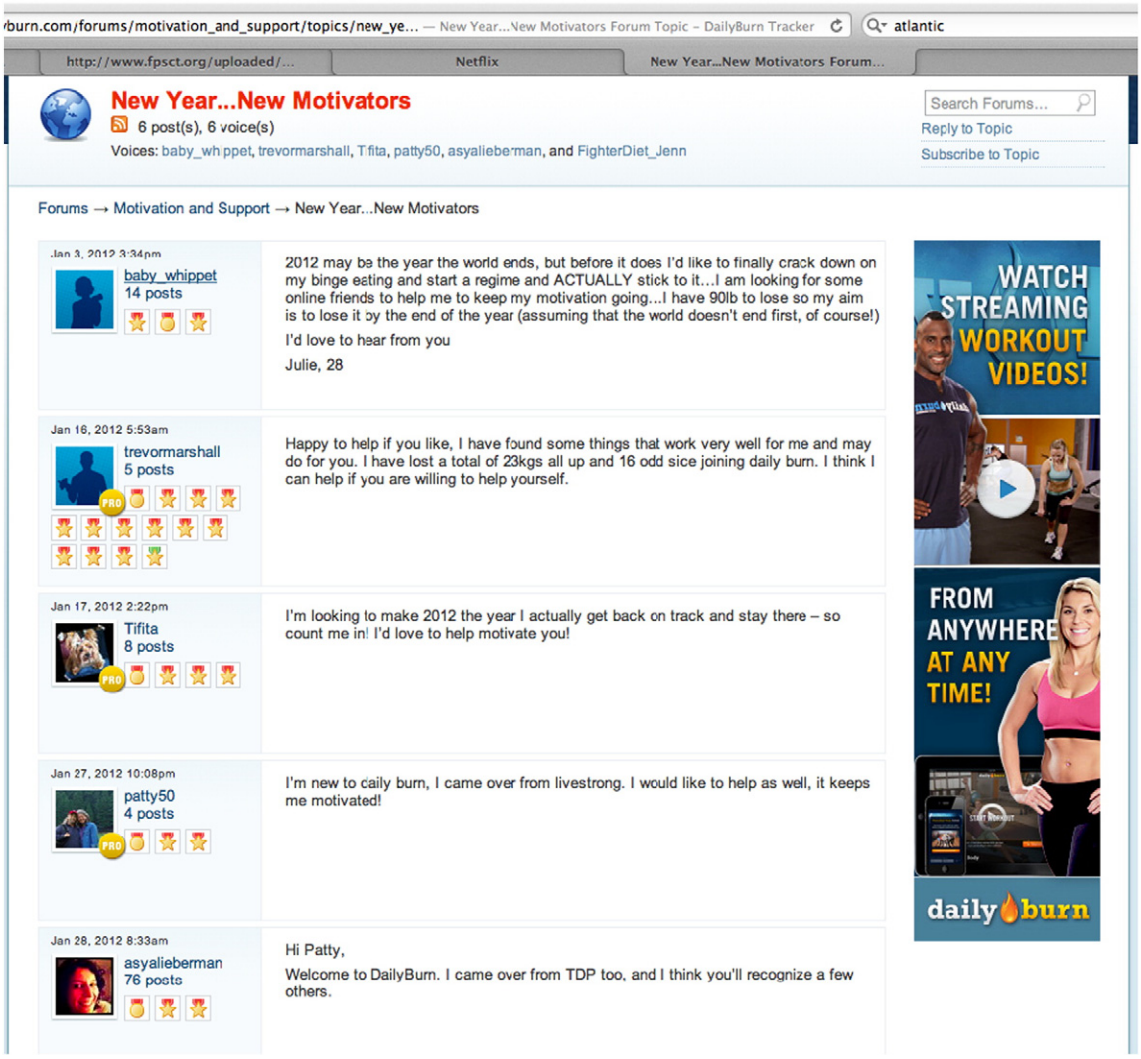

Fig. A. Social networking on Dailyburn.com: a screenshot of a conversation thread.

References

[1] K. Alexandris, P. Zahariadis, C. Tsorbatzoudis, G. Grouios, Testing the sport commitment model in the context of exercise and fitness participation, Journal of Sport Behavior 25 (2002) 217–230.
[2] J.B. Allen, Social motivation in youth sport, Journal of Sport & Exercise Psychology 25 (2003) 551–567.
[3] American Psychological Association, Sedentary Lives Can Be Deadly: Physical Inactivity Poses Greatest Health Risk To Americans, Expert Says, ScienceDaily. Retrieved February 17, 2011, from http://www.sciencedaily.com/releases/2009/08/090810024825.htm.
[4] G. Bansal, F. Zahedi, D. Gefen, The impact of personal dispositions on information sensitivity, privacy concern and trust in disclosing health information online, Decision Support Systems 49 (2010) 138–150.
[5] L.F. Berkman, Assessing the physical health effects of social networks and social support, Annual Review of Public Health 5 (1984) 413–432.
[6] L.F. Berkman, L. Breslow, Health and Ways of Living: The Alameda County Study, Oxford University Press, New York, 1983.
[7] D. Boyd, N. Ellison, Social network sites: definition, history, and scholarship, Journal of Computer-Mediated Communication 13 (2008) 210–230.
[8] P.G. Campbell, D. MacAuley, E. McCrum, A. Evans, Age difference in the motivating factors for exercise, Journal of Sport & Exercise Psychology 23 (2001) 191–199.
[9] C.J. Casperson, M.A. Pereira, K.M. Curran, Changes in physical activity patterns in the United States, by sex and cross-sectional age, Medicine & Science in Sports & Exercise 32 (2000) 1601–1609.
[10] DailyBurn Review, TopTenReviews.com. Available at: http://online-fitness-services-review.toptenreviews.com/dailyburn-review.html 2012.
[11] E.L. Deci, R.M. Ryan, Intrinsic Motivation and Self-determination in Human Behavior, Plenum, New York, 1985.
[12] E.L. Deci, R.M. Ryan, A motivational approach to self: integration in personality, in: R. Dientsbier (Ed.), Nebraska Symposium on Motivation, Perspectives on Motivation, vol. 38, University of Nebraska press, Lincoln, 1991.
[13] E.L. Deci, R.M. Ryan, The "What" and "Why" of goal pursuits: human needs and the self-determination of behavior, Psychological Inquiry 11 (2000) 227–268.
[14] R.K. Dishman, Motivation and exercise adherence, in: J.M. Silva, R.S. Weinberg (Eds.), Psychological Foundations of Sports, Human Kinetics, Champaign, 1984.
[15] P.M. Dubbert, G.T. Wilson, Goal-setting and spouse involvement in the treatment of obesity, Behaviour Research and Therapy 22 (1984) 227–242.
[16] L. Eisenberg, A friend, not an apple, a day will help keep the doctor away, Journal of the American Medical Association 66 (1979) 551–553.
[17] N.B. Ellison, C. Steinfield, C. Lampe, The benefits of Facebook "friends:" social capital and college students' use of online social network sites, Journal of Computer-Mediated Communication 12 (2007), (Published in digital form at http://jcmc.indiana.edu/vol12/issue4/ellison.html).
[18] A.A. Eyler, R.C. Brownson, R.J. Donatelle, A.C. King, D. Brown, J.F. Sallis, Physical activity social support and middle- and older-aged minority women: results from a US survey, Social Science & Medicine 49 (1999) 781–789.
[19] G. Felton, M. Parsons, Factors influencing physical activity in average-weight and overweight young women, Journal of Community Health Nursing 11 (1994) 109–119.
[20] M.S. Fortier, R.J. Vallerand, N.M. Briere, P.J. Provencher, Competitive and recreational sport structures and gender: a test of their relationship with sport motivation, International Journal of Sport Psychology 26 (1995) 24–39.
[21] J.W. Hill, E. Mannweiler, Insights on the Future of Health Information Technology: An Interview with Pamela Pure, Formerly President of McKesson Technology Solutions, Business Horizons (March–April), 2010.
[22] G.C. Kane, S. Ransbotham, It's a network, not an encyclopedia: the quality of peer produced medical information on Wikipedia, Workshop on Health IT and Economics, Maryland, October 8–9, 2010.
[23] J. Lee, D. Macdonald, J. Wright, Young men's physical activity choices: the impact of capital, masculinities, and location, Journal of Sport & Social Issues 33 (2009) 59–77.
[24] A.S. Leon, J. Connett, D.R. Jacobs, Leisure-time physical activity levels and risk of coronary heart disease and death the multiple risk factor intervention trial, Journal of the American Medical Association 258 (1987) 2388–2395.
[25] K. Lewis, J. Kaufman, M. Gonzalez, A. Wimmer, N. Christakis, Tastes, ties, and time: a new social network dataset using Facebook.com, Social Networks 30 (2008) 330–342.
[26] F. Li, The exercise motivation scale: its multifaceted structure and construct validity, Journal of Applied Sport Psychology 11 (1999) 97–115.
[27] A. Mayer, S.L. Puller, The old boy (and girl) network: social network formation on university campuses, Journal of Public Economics 92 (2008) 329–347.
[28] P. McCullagh, K. Matzkanin, S. Shaw, M. Maldonado, Motivation for participation in physical activity, Pediatric Exercise Science 5 (1993) 224–233.
[29] I. Mehus, Distinction through sport consumption: spectators of soccer, basketball, and ski-jumping, International Review for the Sociology of Sport 40 (2005) 321–333.
[30] J. Ni, B. Sun, A dynamic game of doctors' participation in online health information platform, Workshop on Health IT and Economics, Maryland, October 8–9, 2010.
[31] R.S. Paffenbarger, R.T. Hyde, A.L. Wing, C.C. Hsieh, Physical activity, all-cause mortality, and longevity of college alumni, The New England Journal of Medicine 314 (1986) 605–613.
[32] M.W. Passer, Children in sport: participation motives and psychological stress, Quest 33 (1982) 231–244.
[33] R.R. Pate, M. Pratt, S.N. Blair, W.L. Haskell, et al., Physical activity and public health, Journal of the American Medical Association 273 (1995) 402–407.
[34] B.S. Rosenthal, G.J. Allen, C. Winter, Husband involvement in the behavioral treatment of overweight women: initial effects and long-term follow up, International Journal of Obesity 4 (1980) 165–172.
[35] R.M. Ryan, C. Frederick, D. Lepes, N. Rubio, K. Sheldon, Intrinsic motivation and exercise adherence, International Journal of Sport Psychology 28 (1997) 335–354.
[36] J.F. Sallis, R.M. Grossman, R.B. Pinski, T.L. Patterson, P.R. Nader, The development of scales to measure social support for diet and exercise behaviors, Preventive Medicine 16 (1987) 825–836.
[37] T.K. Scanlan, R. Lewthwaite, Social psychological aspects of competition for male youth sport participants: I. Predictors of competitive stress, Journal of Sport Psychology 6 (1984) 208–226.
[38] T.K. Scanlan, P.J. Carpenter, M. Lobel, J.P. Simons, Sources of enjoyment for youth sport athletes, Pediatric Exercise Science 5 (1993) 275–285.
[39] T. Stephens, C.J. Caspersen, The Demography of Physical Activity, Physical Activity, Fitness and Health, Human Kinetics, Champaign, 1994.
[40] A. Traud, E. Kelsic, P. Mucha, M. Porter, Community Structure in Online Collegiate Social Networks, Working Paper, 2008.
[41] F. Treiber, T. Baranowski, D. Braden, W. Strong, Social support for exercise: relationship to physical activity in young adults, Preventive Medicine 20 (1991) 737–750.
[42] United States Department of Health and Human Services, Healthy People 2010, Government Printing Office, Washington, DC, 2001.
[43] R.J. Vallerand, G.F. Losier, An integrative analysis of intrinsic and extrinsic motivation in sport, Journal of Applied Sport Psychology 11 (1999) 142–169.
[44] L.M. Wankel, Decision-making and social-support strategies for increasing exercise involvement, Journal of Cardiac Rehabilitation 4 (1984) 124–135.
[45] L.M. Wankel, The importance of enjoyment to adherence and psychological benefits from physical activity, International Journal of Sport Psychology 24 (1993) 151–169.
[46] R.S. Weinberg, The relationship between extrinsic rewards and intrinsic motivation, in: J.M. Silva, R.S. Weinberg (Eds.), Psychological Foundations of Sports, Human Kinetics, Champaign, 1984.
[47] R. Weiss, The fund of sociability, Transaction 1 (1969) 36–43.
[48] B. Wellman, Structural analysis: from method and metaphor to theory and substance, in: B. Wellman, S.D. Berkowitz (Eds.), Social Structures: A Network Approach, Cambridge University Press, Cambridge, 1988.
[49] T.C. Wilson, The paradox of social class and sports involvement: the roles of culture and economic capital, International Review for the Sociology of Sport 37 (2002) 5–16.
[50] N. Xiao, R. Sharman, H.R. Rao, S. Upadhyaya, Factors influencing online health information search: an empirical analysis of a national cancer-related survey, Decision Support Systems Available online November 5th, 2012.
[51] L. Yan, Y. Tan, Feeling blue so going online: an empirical study on effectiveness of virtual social networking, Workshop on Health IT and Economics, Maryland, October 8–9, 2010.

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