Let's Workout! Exploring Social Exercise in an Online Fitness Community

Li Zeng[1], Zack W. Almquist[2], Emma S. Spiro[1]
[1]University of Washington, USA
[2]University of Minnesota, USA

Abstract
Increasing attention has been paid to promoting certain healthy habits through social interaction in online communities. At the intersection of social media and activity tracking applications, these platforms capture information on physical activities as well as peer-to-peer interactions. Importantly, they also offer researchers a novel opportunity to understand health behaviors by utilizing the large-scale behavioral trace data they archive. In this study we explore the characteristics and dynamics of social exercise (i.e. fitness activities with at least one peer physically co-present) using data collected from an online fitness community popular with cyclists and runners. In particular, we ask if factors such as temporal seasonality, activity performance and social feedback vary by the number of people participating in an activity; we do so by comparing associations for both men and women. Our results indicate that when peers are physically co-present for fitness activities (i.e. group workouts), exercise tends to be more intense and receive more feedback from other users, across both genders. Findings also suggest gender differences in the observed tendency to complete activities with others. These results have important implications for health and wellness interventions.

Keywords: social exercise; health behaviors; online fitness communities; social media; behavioral traces

Citation: Zeng, L., Amquist, Z. W. & Spiro, E. S. (2017). Let's Workout! Exploring Social Exercise in an Online Fitness Community. In iConference 2017 Proceedings, Vol. 2 (pp. 87-98). `https://doi.org/10.9776/17028`

Acknowledgements: This material is based upon work supported by, or in part by, the U.S. Army Research Laboratory and the U.S. Army Research Office under YIP awards # W911NF-14-1-0577 and # W911NF-15-1-0270 and the Office of the Vice President for Research, University of Minnesota.

Contact: Li Zeng, lizeng@uw.edu.

1 Introduction

Exercising is known to be associated with numerous physical and mental benefits such as controlling weight (Blair, 1993), decreasing the risks of cardiovascular diseases and reducing stress (Fletcher et al., 1996). Although aware that exercising is good for health, not everyone engages in physical activity on a regular basis. The Center for Disease Control in the United States estimates that only 20% of adults meet exercise guidelines (Jaslow, n.d.).[1] Indeed, the World Health Organization continues to combat the global obesity epidemic (Organization, 2000). Health, and more specifically physical activity, is a complex issue and as such has been studied in many fields. Beyond the medical community, issues of health are studied in the social sciences, where research has examined how social, racial, emotional, and socioeconomic factors influence health promotion and likewise health disparities (Walker, Sechrist, & Pender, 1987; Frankish, Milligan, & Reid, 1998; Lee, Wildeman, Wang, Matusko, & Jackson, 2014; Dishman, Sallis, & Orenstein, 1985).

A number of studies demonstrate that peer influence and social support have positive health-related effects, such as helping people lose weight and participate in more physical activities (Ahtinen et al., 2009; Chen & Pu, 2014; Wing & Jeffery, 1999; Kulik & Mahler, 1989; Dishman et al., 1985). Prior research also points out that exercising with others can improve psychological functioning (Plante, Coscarelli, & Ford, 2001). However, many of these early studies of peer effects are based on surveys or experiments involving a small number of participants. Recently, social media and online fitness communities are gaining scholarly attention as a new research environment in which to study health behaviors (Centola, 2013).

Social media have been used to explore health communication and promotion (Paul & Dredze, 2011; Morris et al., 2011; Vaterlaus, Patten, Roche, & Young, 2015; Pechmann, Pan, Delucchi, Lakon, & Prochaska,

[1]`http://www.cdc.gov/nchs/fastats/exercise.htm`

2015) and physical activity (Teodoro & Naaman, 2013; Munson, Cavusoglu, Frisch, & Fels, 2013). Studies have even used randomized experiments to establish causal peer influence effects (Zhang, Brackbill, Yang, & Centola, 2015). Online fitness communities offer even more promising directions for work in this area (Centola & van de Rijt, 2015). These new platforms are specifically designed to provide participants with a group of peers and social support in reaching their fitness or health goals. Moreover, users are able to use wearable devices to track personal activities, including exact Global Positioning System (GPS) traces of routes, and upload them to their online profiles within in the community.

For researchers, an important feature of online platforms is their ability to archive a large volume of behavioral trace data, including fitness statistics, user profile data, and potentially users' social networks, as part of their normal operation. This enables users to explore and compare their own activity efforts to others in their "fitness circles", but it also presents novel opportunities to analyze health behaviors. Researchers now have the opportunity to observe not what people *say* they do, but what they actually do.[2]

In this study, we employ behavioral trace data from one such fitness community to study social exercise. In particular, this work analyzes how factors including gender, temporal seasonality, activity performance and social feedback may vary by number of people participating in exercise. Our work aims to answer the following research questions: (1) *When do individuals choose to exercise alone and in groups, and are these dynamics gender dependent?* (2) *How do peoples' fitness behaviors differ, in terms of performance and social feedback, when exercising alone compared to activities with others physically co-present?* In answering these questions, this study has implications for health promotion and social network-based health interventions.

2 Related Work

2.1 Social Support and Physical Activity

Previous work suggests that factors such as pleasant surroundings, an enthusiastic exercise leader, and sympathetic co-exercisers during leisure-time activities are all likely to relieve negative emotions associated with exercise (Haskell, Montoye, & Orenstein, 1985; Pelphrey et al., 2003; Flaherty, 2005). A laboratory-based study found that exercising with others helped to reduce stress and produce overall positive effects on energy, calmness and tiredness, compared with a control group exercising alone (Plante et al., 2001). However, this experiment was conducted in a laboratory setting and participants (recruited from a college student population) were fairly homogeneous in terms of age and fitness levels, making its applicability in real-world settings a open question. Despite limitations of prior studies, it is well-established that social support and physical activity are linked (Dishman et al., 1985; McAuley et al., 2000; Berkman & Glass, 2000).

More recently, the relationship between social support and physical activity has been studied using mobile fitness applications (Munson & Consolvo, 2012). Some new platforms explicitly include the element of social support, allowing users to exercise in a virtual group environment so as to motivate them to perform physical activities (Campbell, Ngo, & Fogarty, 2008; Consolvo, Everitt, Smith, & Landay, 2006; Chen & Pu, 2014). For example, (Chen & Pu, 2014) designed a mobile application with gamification settings of competition (i.e. two users compete to gain more virtual rewards by exercising), cooperation (i.e. two users contribute equally to win virtual rewards) and hybrid (i.e. weighting the cooperation and competition settings). Even though users are not required to exercise side by side in the physical environment, all three conditions of virtual group activities were found to increase users' activity frequency and intensity.

2.2 Online Fitness Communities

The past few years have seen in explosion of new online fitness communities (e.g. RunKeeper, MapMyRun, Strava, etc.) where users' natural, everyday activity can be tracked and explored with a rapidly expanding collection of tools and technologies (Centola, 2013). These fitness communities sit at the intersection of social media and activity tracking applications; users can not only track/log their activities, but also interact with a group of peers and posted activities. One example of such a platform is Strava. Promotional content on

[2]This is not to say behavior trace data from online fitness communities is not without limitations (as we discuss at the end of this paper).

the site's home page[3] says: " The social network for athletes. Connect with friends and make the most of every run and ride." The proliferation of similar platforms, coupled with recent research indicating that just over 20% of adults use some form of technology to track their health data (Fox, 2011), signals new opportunities for understanding the social dimensions of health-oriented behaviors. In particular, behavioral traces of human behavior and interaction collected from these online sources offer novel data and strategies for understanding social dynamics and peer influence.

Online fitness communities have attracted researchers from many disciplines. Some scholars are interested in the technical potential of sensors and human-computer interaction aspects of these technologies (Consolvo et al., 2008), others have focused on play, incentives, and user engagement (Chen & Pu, 2014). A growing body of work concerns social media as a potential tool in medicine (Centola, 2013). All of these approaches promise insight into the social aspects of health, however, limited work has specifically explored the effects of peer co-presence, leaving a gap in our current understanding of the social dynamics in these settings.

3 Data

Data were collected for the online fitness community Strava. Strava continues to grow in popularity among cyclists and runners in recent years. Strava provides two main competitive, gamifying features to motivate users to reach their fitness goals. The one is the ability to compare users' activity efforts against their history efforts or compete with other athletes. Another important feature is to accomplish challenges and earn achievement badges. As such, millions of people upload their rides and runs to Strava every week via their smartphones or GPS devices.

Strava was also chosen as the research environment because it has a number of desirable characteristics: (1) it attracts an increasing number of users around the world who upload millions of activities to the platform every week; (2) the Strava Application Programming Interface (API)[4] provides access to public Strava behavioral trace data; and (3) data include activity characteristics, user characteristics and user social network characteristics, providing rich data for research that seeks to understand health behaviors.

To retrieve data about an activity posted to a user's profile on Strava, a valid `activityID` is required. We randomly generate a list of `activityIDs` from a previously-built (and ideally exhaustive) ID space. We then query each `activityID` so as to check if this ID exists. If that `activityID` does not exist on the platform, we discard this one. If it exists, we retrieve the data associated with that `activityID` (i.e. information and metadata about a particular activity). As each activity is associated with a particular user, this data includes a summary representation of the posting athlete which allows us to query for a detailed representation of that user. Study procedures were reviewed by the Institutional Review Board at the authors' university.

As stated previously that Strava API provides access to its rich metadata, our data include but not limit to the following main components: (1) activity characteristics such as activity type (e.g. cycling, running, swimming, etc.), activity location, activity names, activity-related stats (e.g. distance, moving time, elevation, etc.); (2) user characteristics such as user demographics, user location, physiological measurements (e.g. height, weight, etc.), equipment; (3) social interaction characteristics such as following and followed relationship, comments, kudos (or "likes").

We collected 888,093 sampled activities posted during 2011-2016 from 514,362 unique users. 81.33% of users report their gender as male. 14.64% of users report their gender as female and 4.03% of users' self-reported gender are unknown. 93.98% of data represent rides (cycling) and runs, but data also represents workout types such as swimming, walking, hiking, skiing, etc. It is important to note that this data does not represent a random sample of platform users, but is instead more likely to capture the behaviors of highly active users. While this limits the generalizability of any user-specific findings, it also means our analysis is conducted on regular users who are more likely to fully utilize platform features. This is important for this case, because many of our research questions focus on group activities - fitness events where users specify in the application that they are physically co-present with others. Moreover, we do obtain a random sample of activities, and much of the following analysis uses the activity itself as the unit of analysis.

[3]Strava homepage is at `https://www.strava.com/`

[4]Strava V3 API Documentation is at `https://strava.github.io/api/`

4 Methods

To explore the characteristics and dynamics of solo and group exercise, we begin by classifying observed data based on the number of peers co-present for the activity. Each activity record has an attribute that represents the number of athletes/users taking part in that activity. We identify activities involving only one athlete as *solo activities* and activities having more than one athletes as *group activities*. Our data have 696,856 (78.47%) solo activities and 191,237 (21.53%) group activities. In the analysis that follows, we evaluate the characteristics and dynamics of each type of activity, comparing solo exercise against group exercise. We do so for men and women separately, in order to tease apart any gender differences in these results. Comparing between genders is also important because the Strava platform is heavily male dominated and prior work has noted that individuals within this environment may have different experiences and social networks (Spiro & Almquist, 2016).

When exploring the temporal dynamics of exercise, we consider: (1) the day of the week (i.e. Monday to Sunday) and (2) the hour of the day (i.e. 0:00 to 23:00) during which activities are observed. Each activity has a local timestamp indicating the start time of the event. An analysis of temporal features could help understand the seasonal patterns of solo and group activities. We hypothesize that people prefer to do more solo activities on weekdays because it is possibly harder to coordinate time among multiple people for group activities during these days. Hence, we also hypothesize that group activities take place more frequently on weekends. We also want to find out the "busy" time periods for solo activities and group activities.

Next, we want to understand how performance, that is physical exertion, is related to peer co-presence. Prior work on peer influence and social support suggests that peer co-presence motivates individuals to engage in physical activity more regularly and more often, but it might also motivate them to work harder, exerting themselves more throughout their physical activity. Measuring performance is challenging and likely involves a multifaceted approach. Strava also applies a diversity of measurements for physical activities. Therefore we consider five distinct measures to operationalize activity performance. These include:

a. Distance: total distance of an activity (available on all data)

b. Elevation: total elevation gain of an activity (available on all data)

c. Duration: total moving time of an activity (available on all data)

d. Activity effort: average watts (available on cycling activities - around 60% data) and average speed (available on all data)[5]

e. Physical challenge level: Strava provides its users with a computed "suffer score" which it calculates based on estimated heart rate intensity (available on premium users' activities - around 10.5% of data)[6]

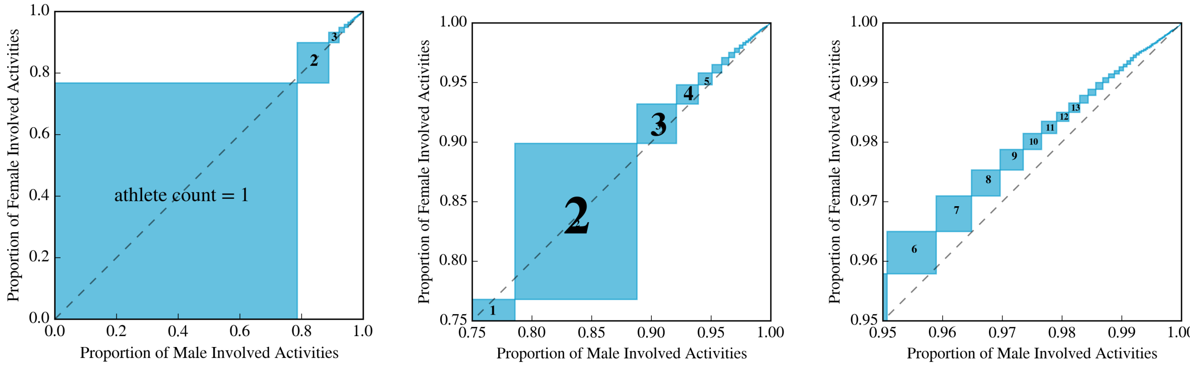
Finally, our work aims to compare social feedback for activities that are complete solo versus in groups. Strava users can post comments and kudos (i.e. "likes" or +1s) on an activity. Related work suggests that these social interaction functions have motivating effects on physical activities (Chen & Pu, 2014). Hence, we are interested in analyzing whether workouts as a group receive more comments and/or kudos from activity participants or other Strava users.

5 Results

In this section, we present findings to address the research questions outlined previously. First, we discuss overall gender differences in posting behavior and exercising alone or with a group. We then continue, considering the temporal dynamics of when individuals choose to exercise alone and in groups, and how these dynamics are gender dependent. Next we evaluate how fitness behaviors differ, in terms of performance

[5] Average watts measures the rate of energy conversion with respect to time. Since it is available on partial data, we use the measure of average speed that is available on activities of other types including running, hiking so as to avoid possible biased sampling merely from rides.

[6] Solo activities and group activities account for 76.25% and 23.75% of premium users' activities, respectively, roughly matching the proportions in the entire data sample. Therefore, we believe that the measure of `suffer score` is still representative and not likely to introduce large bias to the analysis.



(a) 1-3 activity participants (b) 2-5 activity participants (c) 5-N activity participants

Figure 1: Proportion of different athlete counts by gender. Each rectangle visualizes the proportion of activities with a specified athlete count. The width and height of a rectangle indicate the proportion of men's activities and the proportion of women's activities respectively with that count. If the upper right vertex of a rectangle falls on the dashed line (y = x), this indicates the cumulative women's proportion is equal to cumulative men's proportion at that point.

and social feedback, when individuals exercise alone compared to when they exercise with others physically co-present. Again, we consider the differential effect of these activity features by gender.

5.1 Gender Differences in Activity

	Activity counts	Percentage
Female Alone	91,248	0.768
Female with Others	27,576	0.232
Male Alone	580,832	0.786
Male with Others	158,448	0.214

Table 1: Counts and Percentages of Solo/Group Activities by Gender

Strava is a male-dominated platform, where the large majority of platform users are males, and this is reflected in our dataset. To begin our analysis, we count the number of activities of both types for each gender, and calculate the corresponding percentages. Table 1 shows a greater percentage of activities posted by females are group activities than among males, indicating that there are proportionally more women who are involved in group activities.[7]

Figure 1 shows how each gender is observed to participate in activities that involve a specified number of participants. For example, in the Figure 1(a), the largest rectangle represents the proportion of activities posted that include only one user across gender. The width (0.7857) and height (0.7679) of the rectangle correspond to the proportion for men and women, respectively. Since, in this case, the width is greater than the height, we know that solo activities enjoy a larger proportion among men than among women. However, for activities having two participants, we find a much larger proportion among women, indicating exercising with a single peer is observed more frequently among women. As the number of activity participants increases, rectangles gradually deviate from the dashed line, indicating that female users tend to engage in more activities in smaller groups (mostly in a group of size two); as participants continue to increase, we find that the trajectory of the rectangle position goes back, closer to the dashed line, indicating that men (in proportion) are involved in larger group activities.

[7] A chi-squared test was performed to determine if significant difference exists in these counts. Unsurprisingly, given the dataset size, we find a highly significant ($p < 0.001$) relationship between gender and exercising alone versus with others.

5.2 Temporal Dynamics of Activity

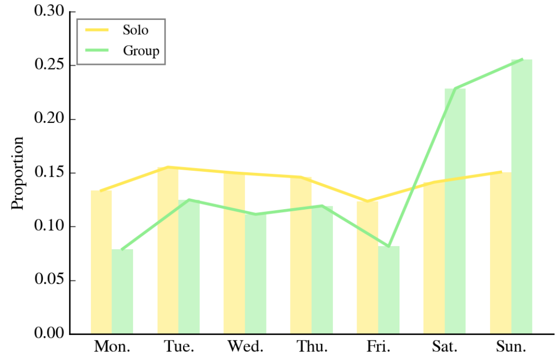


Figure 2: Distribution of solo (yellow) and group (green) activities across the seven weekdays. Corresponding lines map trends over the week.

One of our primary research questions aims to identify seasonality patterns for solo and group exercise. Figure 2 shows the proportion of solo and group activities posted to Strava across the week. We observe that proportions of group activities are smaller on weekdays compared to that of solo activities. Moreover, about 50% group activities occur over weekends, greatly exceeding the proportion of solo activities. For solo activities, we see a relatively stable and consistent pattern throughout the week. Exercising on Mondays and Fridays appears to be less attractive to athletes, as fewer activities - both solo and group activities - are posted on these days.

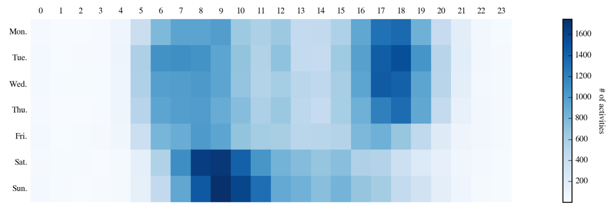
We further examine the seasonality patterns of solo and group activities in terms of the hour of the day and the day of the week. Figure 3 visualizes solo/group activities occurring during a specific hour on a specific day of the week. Greater numbers of activities are represented by darker blue squares; lighter squares indicate smaller numbers of activities.

We observe that group activities, in general, are not frequent during regular work hours as we see clusters of dark blue squares positioned at the hours after work (nearly 5pm - 7pm) on weekdays or in the mornings (nearly 6am - 11am) on weekends. This pattern is consistent across gender, however males exercising with others tend to do so slightly early on weekends. We find that solo activities occur most often early in the morning or after work on weekdays, and in the mornings on weekends. Again, this pattern is consistent across gender with males exercising slightly earlier in the morning on weekdays and weekends.

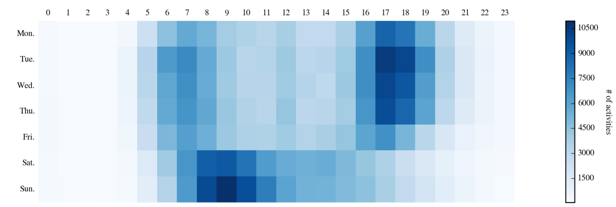
5.3 Co-Present Peers and Activity Performance

Our second research question considers the relationship between the number of activity participants (i.e. peer co-presence) and activity performance. We measure performance in terms of multiple dimensions, including, *distance*, *elevation*, *duration*, *activity effort*, and *physical challenge level*. These measures were discussed in detail in Section 4. For each measure, we take the average of its value across all activities given a specific `athlete count`. Then, we examine trends as the number of activity participants increases. We find a consistent pattern across all measures: performance increases sharply as the number of participants increases up to five, when performance shows diminishing returns – increasing but at a much smaller rate.

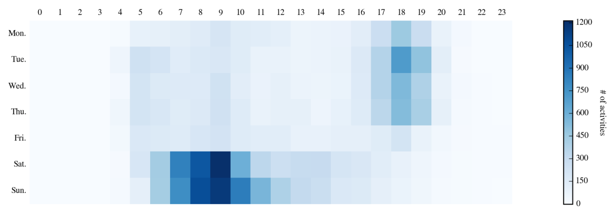
Figure 4 shows this result for average watts, as well as moving time, as a function of athlete count. Other performance metrics show similar results, and are available in the appendix. It should be noted that we have few activities with very large group size, so we expect greater noise (e.g. greater uncertainty about estimates and larger confidence intervals) as group size goes up. In order to present readable visualizations, we truncate athlete count at 20. Our preliminary analysis shows some gender differences in baseline activity effort, such as average watts for solo activities, so visualizations show results by gender. However, the observed relationships between performance and group size are consistent across both gender groups, as seen. Moving



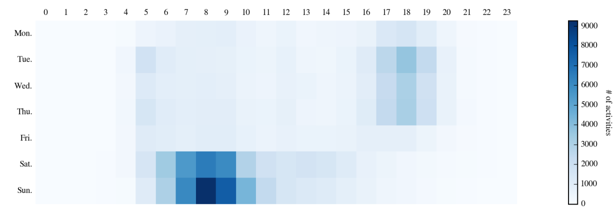
(a) Female - Solo Activities



(b) Male - Solo Activities



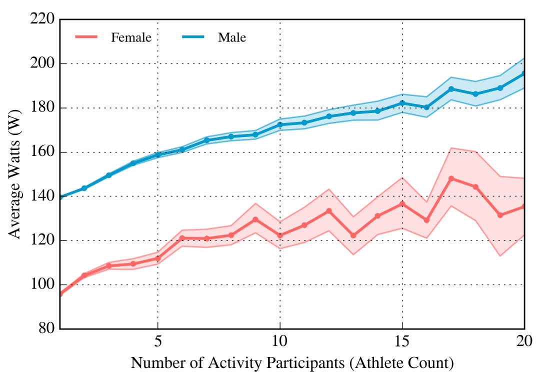
(c) Female - Group Activities



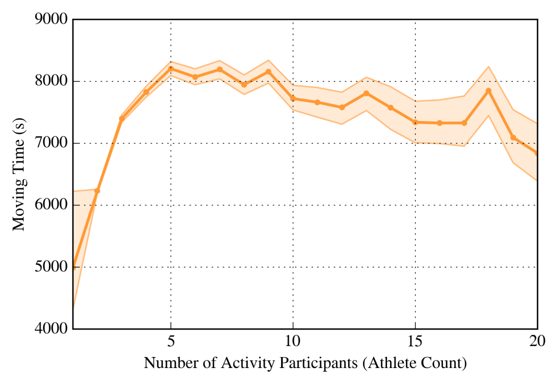
(d) Male - Group Activities

Figure 3: Heat maps visualizing the distribution of activities across local start time and day of the week for solo and group activities by gender.

time is one of the few performance metrics that shows a negative relationship with group size, and only for groups larger than 5-10 athletes.



(a) Average watts of activities posted by female users (red) and male users (blue) as a function of number of activity participants.



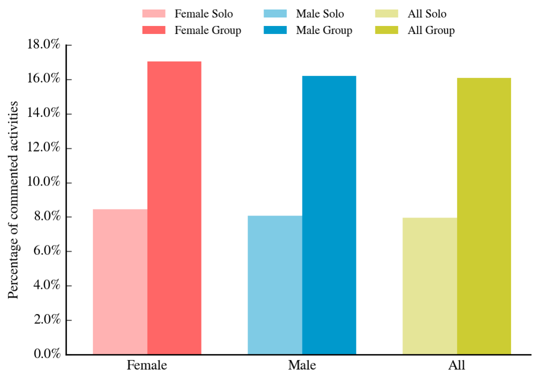
(b) Average moving time of activities as a function of number of activity participants.

Figure 4: Activity performance metrics as a function of increasing number of participants. Colored bands around mean line represent bootstrapped 95% confidence intervals.

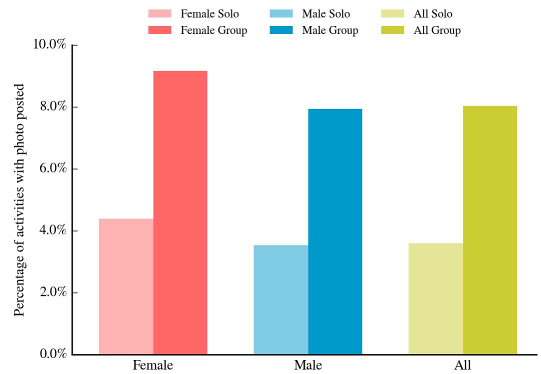
5.4 Social Feedback for Activities

Finally, we analyze how the number of athletes involved in a particular activity is associated with subsequent feedback received by the posting athlete by examining three main interaction types. Each of these types of social interaction enables Strava users to provide peers with social feedback about their posted activities. Users can make comments and give kudos (or “likes”). In addition, the original author of the activity can post associated photos.

Figure 5(a) shows what percentage of activities that were ever commented on by other platform



(a) Percentage of activities earning at least one comment by another Strava user



(b) Percentage of activities with photos available on Strava or Instagram

Figure 5: Measure of social feedback by gender and activity (solo versus group).

users for type of activity, across genders and then combined. We find that group activities are much more likely to be commented on; percentages of activities commented involving groups are twice as high as those of solo activities in across all cases. Additionally, we do not see significant gender differences here. We do not show results for kudoed activities because it has roughly the same pattern as commented activities.

Figure 5(b) shows the percentage of activities with accompanying photos posted in Strava or Instagram. We see that users are more likely to post photos to group activities. Moreover, we observe that female users tend to post more photos to both solo and group activities than male users.

Overall, group activities and solo activities differ in terms of the proportion of received social feedback. We find that group activities are much more likely to attract social feedback including comments and likes from peers. Moreover, group activities tend to motivate users' behavior of content sharing by posting activity-related photos, which in turn is likely to gain more attention among users' online social circle.

6 Discussion

This study compares activities posted by users in an online fitness community. In particular, we focus analysis on how the characteristics of these activities – when they occur, how intense they seem to be, and how much social feedback they receive – may be associated with the number of co-participants. To do so we make use of a unique dataset collected from the online community Strava, utilizing application features that allow users to specify who they are exercising with; data comprise not only the behavior of individual athletes (users), but also detailed records of who is physically co-present with these users. Our analysis demonstrates a number of significant findings.

First, we observe that female users tend to post activities that involve a single peer – exercise events where the number of total participants is two. Males, on the other hand, tend to post solo activities or activities that involve larger groups. These results hint at specific gender preferences in group exercise and have numerous implications for peer effects on motivation and health promotion. Importantly, for any network-based intervention or behavior change, the social networks (and as a consequence influential peers) for men and women look very different (Granovetter, 1973; Centola & Macy, 2007; Bakshy, Rosenn, Marlow, & Adamic, 2012; Lewis, Gonzalez, & Kaufman, 2012). Results suggest that females might have a single or small set of influential strong ties (i.e. exercise partners), while men may have a large, diverse set of peers who could be influential.

This study finds evidence for strong seasonal effects on group exercise. Group activities usually take place after work during the week or early in the day on weekends, whereas many solo activities also take place in the early mornings on weekdays. Building from the previous discussion, while strong diurnal patterns are unsurprising in human behavior (Golder & Macy, 2011), results demonstrate that opportunities for peer influence on health behaviors are likely to be restricted or constrained in systematic ways. For example, designers of application features might suggest that exercise partners should take into account optimal times for group exercise and individuals preferences for when to work out. While outside the scope of this study, there are many interesting directions for future work that considers mechanisms to affect behavior change.

Group activities differ from solo activities, in terms of effort, exertion and performance, our analysis indicates. When exercising with others, even just a single peer, athletes see notable gains in workout intensity and energy expended – increases in average power output (measured in average watts for cycling events), moving time and distance. Interestingly, these gains continue to increase for every additional activity participant (though primary gains are seen for the first 5 additional co-present peers). Activities with co-present peers might be informal (organized by the participants themselves) or formal (group rides perhaps organized by a local club or other organizational entity). Further work might tease apart these different conditions to offer insight into peer effects and impact of institutional structure on exercise (Vilhjalmsson & Kristjansdottir, 2003).

Co-presence and social interaction are distinct but related concepts. In the final component of the analysis presented here, we consider observations of social exchange among athletes. In particular, we consider social feedback behaviors - platform users commenting and liking each others' activities. Findings demonstrate that group activities are associated with higher levels of social feedback than solo activities. Moreover, group activities are significantly more likely to include multimedia (photos). In the latter case, data also reveals gender differences, where females are more likely to post group activities with photos than males. Increased engagement and social feedback may also be related to motivation and future activity, suggesting more promising directions for further work.

7 Limitations

While the study presented here offers novel insight into the characteristics of physical activities where peers are co-present, it is not without limitations. One notable concern is the ability of Strava application users to restrict their activities to be private, shared only with pre-screened peers. Private accounts, and likewise private activities, cannot be accessed from the Strava API, and therefore are excluded from the data used in this study. Athletes who choose to restrict access to their data may systematically differ from users who make their data public. Unfortunately, we are unable to assess the impact of this bias because of lack of data. Instead, one should be careful about generalizing these results beyond the population of study.

8 Conclusion

As social fitness mobile applications become widely used for personal activity tracking, social support and health promotion, opportunities for understanding the effects of social networks and peer influence on behavior change and health expand. Drawing on features of social media and activity tracking applications, many of these new platforms capture rich data about physical activities as well as peer-to-peer interactions. The behavioral trace data they archive have the potential to significantly alter understanding of health and well-being. In this study, we explore the characteristics and dynamics of social exercise, that is fitness activities with at least one peer physically co-present. Our research focuses on quantifying diurnal patterns, activity performance and social feedback as they vary by the number of people participating in an activity; we also compare associations by gender. Our results indicate that when peers are physically co-present exercise tends to be more intense and receive more feedback from other users. Findings also suggest gender differences in the observed tendency to engage in physical activity with others. The implications of these results for network-based health and wellness interventions are also discussed.

References

Ahtinen, A., Isomursu, M., Mukhtar, M., Mäntyjärvi, J., Häkkilä, J., & Blom, J. (2009). Designing social features for mobile and ubiquitous wellness applications. In *Proceedings of the 8th international conference on mobile and ubiquitous multimedia* (p. 12).

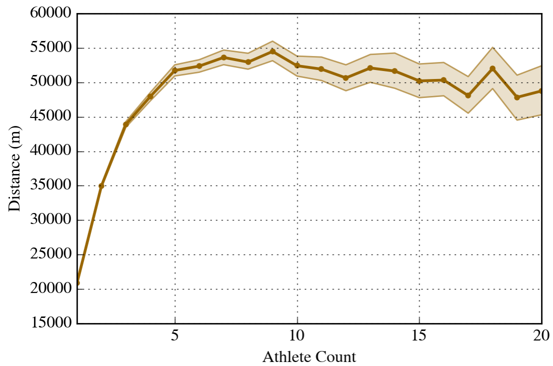
Bakshy, E., Rosenn, I., Marlow, C., & Adamic, L. (2012). The role of social networks in information diffusion. In *Proceedings of the 21st international conference on world wide web* (pp. 519–528).

Berkman, L. F., & Glass, T. (2000). Social integration, social networks, social support, and health. *Social epidemiology*, *1*, 137–173.
Blair, S. N. (1993). Evidence for success of exercise in weight loss and control. *Annals of Internal Medicine*, *119*(7_Part_2), 702–706.
Campbell, T., Ngo, B., & Fogarty, J. (2008). Game design principles in everyday fitness applications. In *Proceedings of the 2008 acm conference on computer supported cooperative work* (pp. 249–252).
Centola, D. (2013). Social media and the science of health behavior. *Circulation*, *127*(21), 2135–2144.
Centola, D., & Macy, M. (2007). Complex contagions and the weakness of long ties1. *American journal of Sociology*, *113*(3), 702–734.
Centola, D., & van de Rijt, A. (2015). Choosing your network: Social preferences in an online health community. *Social Science & Medicine*, *125*, 19–31.
Chen, Y., & Pu, P. (2014). Healthytogether: exploring social incentives for mobile fitness applications. In *Proceedings of the second international symposium of chinese chi* (pp. 25–34).
Consolvo, S., Everitt, K., Smith, I., & Landay, J. A. (2006). Design requirements for technologies that encourage physical activity. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 457–466).
Consolvo, S., McDonald, D. W., Toscos, T., Chen, M. Y., Froehlich, J., Harrison, B., … others (2008). Activity sensing in the wild: a field trial of ubifit garden. In *Proceedings of the sigchi conference on human factors in computing systems* (pp. 1797–1806).
Dishman, R. K., Sallis, J. F., & Orenstein, D. R. (1985). The determinants of physical activity and exercise. *Public health reports*, *100*(2), 158.
Flaherty, A. W. (2005). Frontotemporal and dopaminergic control of idea generation and creative drive. *Journal of Comparative Neurology*, *493*(1), 147–153.
Fletcher, G. F., Balady, G., Blair, S. N., Blumenthal, J., Caspersen, C., Chaitman, B., … others (1996). Statement on exercise: Benefits and recommendations for physical activity programs for all americans a statement for health professionals by the committee on exercise and cardiac rehabilitation of the council on clinical cardiology, american heart association. *Circulation*, *94*(4), 857–862.
Fox, S. (2011). *The social life of health information, 2011.* Pew Internet & American Life Project Washington, DC.
Frankish, C. J., Milligan, C. D., & Reid, C. (1998). A review of relationships between active living and determinants of health. *Social Science & Medicine*, *47*(3), 287–301.
Golder, S. A., & Macy, M. W. (2011). Diurnal and seasonal mood vary with work, sleep, and daylength across diverse cultures. *Science*, *333*(6051), 1878–1881.
Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 1360–1380.
Haskell, W. L., Montoye, H. J., & Orenstein, D. (1985). Physical activity and exercise to achieve health-related physical fitness components. *Public Health Reports*, *100*(2), 202.
Jaslow, R. (n.d.). *Cdc: 80 percent of american adults don't get recommended exercise. cbc news may 3, 2013.*
Kulik, J. A., & Mahler, H. I. (1989). Social support and recovery from surgery. *Health Psychology*, *8*(2), 221.
Lee, H., Wildeman, C., Wang, E. A., Matusko, N., & Jackson, J. S. (2014). A heavy burden: the cardiovascular health consequences of having a family member incarcerated. *American journal of public health*, *104*(3), 421–427.
Lewis, K., Gonzalez, M., & Kaufman, J. (2012). Social selection and peer influence in an online social network. *Proceedings of the National Academy of Sciences*, *109*(1), 68–72.
McAuley, E., Blissmer, B., Marquez, D. X., Jerome, G. J., Kramer, A. F., & Katula, J. (2000). Social relations, physical activity, and well-being in older adults. *Preventive medicine*, *31*(5), 608–617.
Morris, M. E., Consolvo, S., Munson, S., Patrick, K., Tsai, J., & Kramer, A. D. (2011). Facebook for health: opportunities and challenges for driving behavior change. In *Chi'11 extended abstracts on human factors in computing systems* (pp. 443–446).
Munson, S. A., Cavusoglu, H., Frisch, L., & Fels, S. (2013). Sociotechnical challenges and progress in using social media for health. *Journal of Medical Internet Research*, *15*, e226.
Munson, S. A., & Consolvo, S. (2012). Exploring goal-setting, rewards, self-monitoring, and sharing to motivate physical activity. In *2012 6th international conference on pervasive computing technologies for healthcare (pervasivehealth) and workshops* (pp. 25–32).
Organization, W. H. (2000). *Obesity: preventing and managing the global epidemic* (No. 894). Author.
Paul, M. J., & Dredze, M. (2011). You are what you tweet: Analyzing twitter for public health. *ICWSM*, *20*, 265–272.
Pechmann, C., Pan, L., Delucchi, K., Lakon, C. M., & Prochaska, J. J. (2015). Development of a twitter-based intervention for smoking cessation that encourages high-quality social media interactions via automessages. *Journal of medical Internet research*, *17*(2), e50.
Pelphrey, K. A., Mitchell, T. V., McKeown, M. J., Goldstein, J., Allison, T., & McCarthy, G. (2003). Brain activity evoked by the perception of human walking: controlling for meaningful coherent motion. *The Journal of Neuroscience*, *23*(17), 6819–6825.
Plante, T. G., Coscarelli, L., & Ford, M. (2001). Does exercising with another enhance the stress-reducing benefits of exercise? *International Journal of Stress Management*, *8*(3), 201–213.

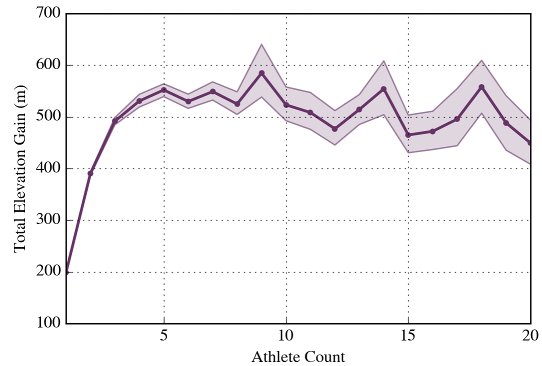
Spiro, E. S., & Almquist, Z. W. (2016). *Mechanisms of tie formation in activity-based online social networks, 2016.* 36th Sunbelt Network Conference (INSNA). Newport Beach, California.
Teodoro, R., & Naaman, M. (2013). Fitter with twitter: Understanding personal health and fitness activity in social media. In *Icwsm.*
Vaterlaus, J. M., Patten, E. V., Roche, C., & Young, J. A. (2015). # gettinghealthy: The perceived influence of social media on young adult health behaviors. *Computers in Human Behavior*, *45*, 151–157.
Vilhjalmsson, R., & Kristjansdottir, G. (2003). Gender differences in physical activity in older children and adolescents: the central role of organized sport. *Social science & medicine*, *56*(2), 363–374.
Walker, S. N., Sechrist, K. R., & Pender, N. J. (1987). The health-promoting lifestyle profile: development and psychometric characteristics. *Nursing research*, *36*(2), 76–81.
Wing, R. R., & Jeffery, R. W. (1999). Benefits of recruiting participants with friends and increasing social support for weight loss and maintenance. *Journal of consulting and clinical psychology*, *67*(1), 132.
Zhang, J., Brackbill, D., Yang, S., & Centola, D. (2015). Efficacy and causal mechanism of an online social media intervention to increase physical activity: results of a randomized controlled trial. *Preventive medicine reports*, *2*, 651–657.

9 Appendix: Peer Co-presence versus Activity Performance

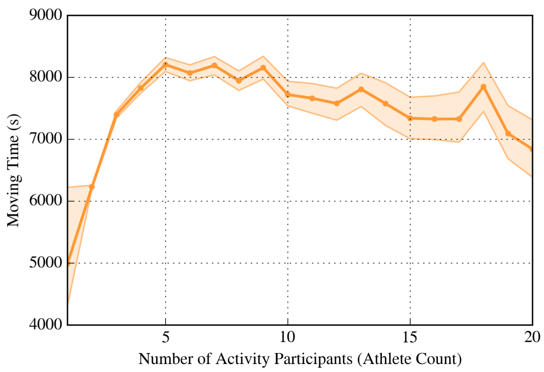
This appendix contains results demonstrating how all measurements of activity performance change as the number of participants increases.



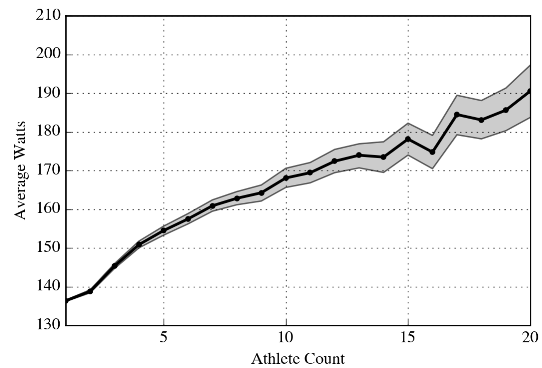
(a) Average distance of activities as a function of number of activity participants.



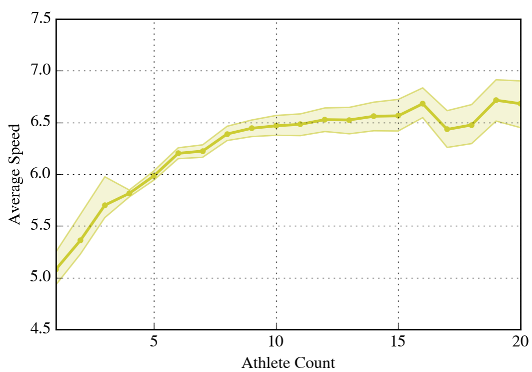
(b) Average total elevation of activities as a function of number of activity participants.



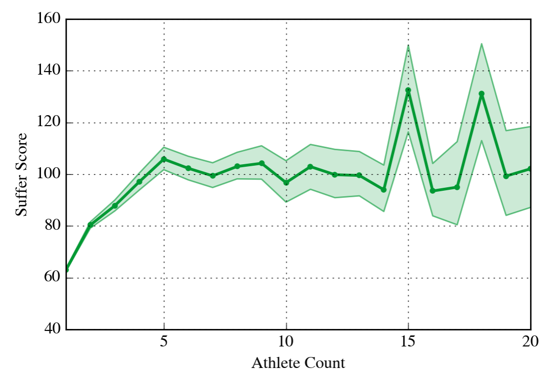
(c) Average moving time of activities as a function of number of activity participants.



(d) Average watts of activities as a function of number of activity participants.



(e) Average speed of activities as a function of number of activity participants.



(f) Average Strava suffer score of activities as a function of number of activity participants.

Figure 6: Activity performance metrics as a function of number of participants. Colored bands around mean line represent bootstrapped 95% confidence intervals.