

Comparing Social Support Differences in Activity Data Sharing on Dedicated and Broad Online Communities

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Additional Key Words and Phrases: Data sharing, personal informatics, health informatics, online health community, broad purpose online community, dedicated health data tracking platforms, social support

1 INTRODUCTION

People frequently share health-related data related to their activities with others online, such as when and how much they exercise, what they eat, and how they are feeling. This sharing can benefit people in various ways, such as helping them get or stay motivated, be held accountable [2, 11], request information from others [6, 10], or receive emotional or tangible support [3, 7, 10, 12]. Data could be shared through different types of online communities which vary in size or purpose. For example, broad-purpose online communities like Facebook, Twitter, and Instagram can be used to reach a diverse and existing social circle. Dedicated health data tracking platforms and health services, such as Fitbit, MyFitnessPal, Strava, and Peloton, also provide embedded social features such as social awareness streams or direct messaging systems that provide a community within their app. The differences between these platforms may be important for helping people fulfill different sharing goals. For instance, an individual might have a larger audience base on broader online communities, enabling them to get feedback and support from people who are not using the health tracking platform. However, these audiences might have less interest in seeing the shared data and provide the kind of support the sharer desires [5]. The norms of the community also impact the type and amount of social support people receive, even when sharing similar content [1]. Understanding how the breadth of the online community impacts the amount and type of social support people are able to obtain around their health data can both inform the design of communities within health-focused apps, and suggest how to present or frame health data for broader online communities.

To investigate the different types of social support people obtain from broad and narrow online health communities, we aim to first identify and analyze the quantity and quality of social support people provide in existing online communities. We focus on communities that exist in platforms which provide social feedback features such as likes and comments, as these means of communication often play an important role in signifying support and engagement [9]. To enable comparison, our goal is to identify communities within dedicated health apps that allow the sharer to cross-post to a broad purpose community. In particular, we plan to focus on broader communities where data is presented similarly (e.g., through similar written description, numeric description, or visualization) to how it is shared within dedicated health apps, and have a similar feedback systems across both communities.

To compare the support across communities, we plan to identify instances where individuals cross-posted the same health data on the two types of communities, using similar methods to prior work [4, 8]. We plan to collect and compare the likes and comments people receive through counts and lexical analysis. To account for audience size differences between the two types of communities, we plan to analyze the ratio of responses per audience members alongside the actual count. In addition, we also plan to analyze the text in comments, as well as text

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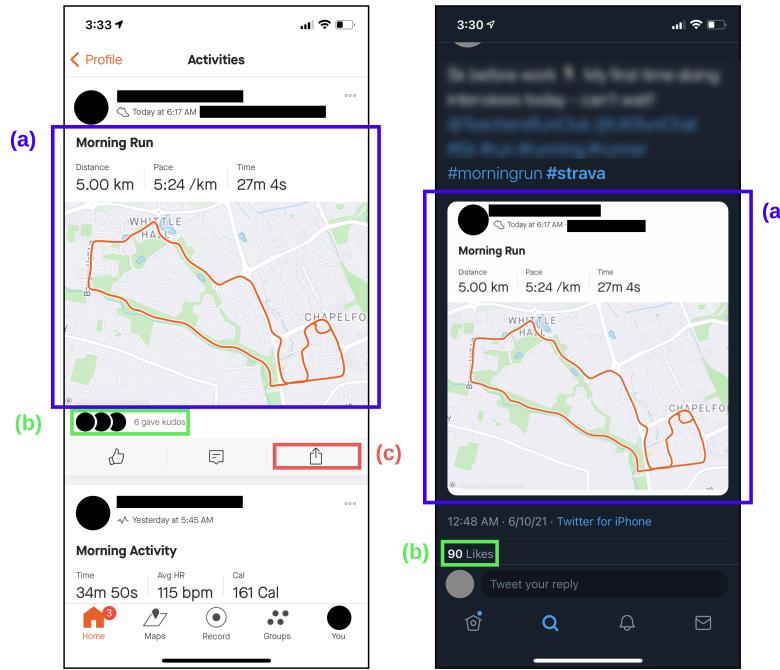


Fig. 1. Sharing the same health data on both Strava (Left, a dedicated health data tracking platform with an embedded community) and Twitter (Right, a broad-purpose online community). When sharing the data, both platforms include (a) shared physical activity tracking data and (b) the ability to respond through likes and comments. (c) Strava supports exporting tracked data to broad-purpose online communities like Twitter, Instagram, and Facebook.

people write in their posts when they share their shared health data, using lexical analysis approaches. From these analyses, we expect to understand both the quantity and the kinds of support people receive from each audience, and how they differ.

2 INITIAL EXPLORATION: COMPARING SOCIAL SUPPORT ON TWITTER AND STRAVA

As a first step towards understanding the social support differences between online health communities, we have conducted a preliminary comparison of the responses from sharing tracking data around physical activity on the Strava community, which people cross-posted to their broader Twitter community (Fig. 1). The two platforms have similar feedback-providing mechanisms through one-click responses (a Like on Twitter, a Kudo on Strava) and open-ended text comments. Strava also supports the direct export of tracked activity on Twitter by clicking the "Share to Twitter" button.

For our preliminary analysis, we collected 1000 Tweets with the Strava hashtag and a link to a corresponding Strava post. After removing Tweets that included inaccessible Strava posts and Tweets not in English, we compared the response to the remaining 165 Tweets and related Strava posts. We found that the Tweets, in general, received fewer likes ($\text{mean}=0.364$, $\text{STD}=0.856$) than their corresponding Strava posts ($\text{mean}=12.66$, $\text{STD}=17.05$) (Fig. 2). In addition, the Tweets also received fewer comments ($\text{mean}=0.079$, $\text{STD}=0.312$) than their corresponding Strava posts ($\text{mean}=0.436$, $\text{STD}=1.42$). Our preliminary results suggest that there is a potential difference in the quantity

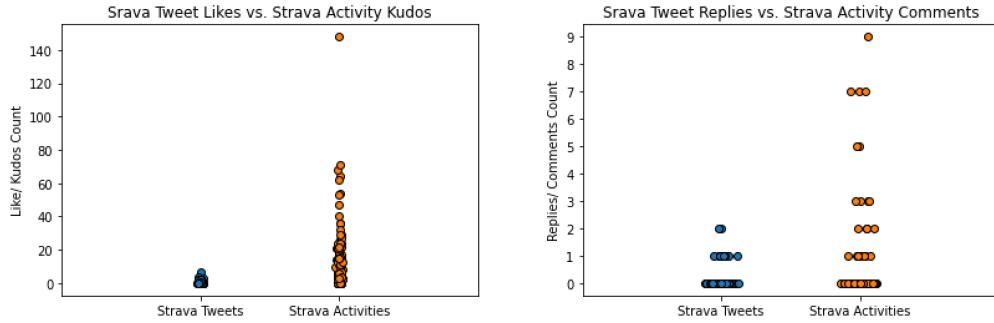


Fig. 2. In general, Tweets received fewer likes (scatter plot on the left) and also fewer comments (scatter plot on the right) than their corresponding Strava posts.

of social support received in different online health communities, with broader communities generally providing less support despite the increased audience size. We are in the process of scaling up our data collection, with the goal of analyzing millions of Tweets and Strava posts and are expecting to further identify differences between the two types of online health communities. We also plan to analyze the linguistic features of the comments to understand whether the kind of support people provide typically differs by platform.

In addition to analyzing a larger set of responses on Twitter and Strava, we aim to generalize our contribution to understanding support differences around data sharing in other dedicated and broad online health communities. We are working to identify and extend our methods to collect posts to health-data platforms supporting multiple health and well-being purposes such as food, sleep, or mood tracking. A challenge is identifying specific health platforms which include communities that fit our inclusion criteria. While many apps include internal social feeds, exported data is often presented differently or the social mechanisms diverge enough from broader social platforms to make direct comparison challenging. However, doing so will expand our understanding of how online communities around different health behaviors and goals vary in how they provide social support.

3 DISCUSSION

Through comparing the social support people obtain from sharing health data on broad-purpose communities and dedicated health data tracking platforms, our goal is to explore how the breadth of the community impacts the amount and type of social support people are able to obtain through sharing their health data. Understanding the impact of breadth will help answer whether designers and developers should heavily invest in integrating social mechanisms within their health data applications, or instead provide effective mechanisms for sharing on broader social platforms. Identifying the type of comments and discussions people have around shared health data in these different communities will also help us better understand how the kinds of support and engagement people receive differ between different kinds of social connections (e.g., close ties, people with similar interests).

At the workshop, we are excited to learn from other researchers who have examined how the structure and design of online health communities has influenced the types of conversations that exist on those platforms. Although our example is not one where medical knowledge is being disseminated or produced, we see overlap around the influence of platform's structure and design in our interest in understanding and supporting people in receiving emotional and tangible support.

ACKNOWLEDGMENTS

This work was funded in part by the National Science Foundation under award IIS-1850389 and the UCI Council on Research, Computing, and Libraries (CORCL).

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