

# Tweeting about physical activity: can tweeting the walk help keeping the walk?

Janice Y. Tsoh

Department of Psychiatry, University of California, San Francisco, CA, USA

Correspondence to: Janice Y. Tsoh, PhD. 401 Parnassus Ave (0984-TRC), Department of Psychiatry, University of California San Francisco, San Francisco, CA 94143, USA. Email: Janice.Tsoh@ucsf.edu.

**Abstract:** Vickey and Breslin's research (published on *mHealth*, November 2015 issue) that involved analyzing nearly 2 million fitness tweets revealed a low percentage of mobile fitness app users meeting the recommended physical activity level. This commentary explores contextual and psychological factors that may underlie the observed low physical activity levels among these mobile fitness app users. Much remains unknown about how best to leverage technologies and social media support to promote adherence to physical activity recommendations. With the use of innovative and validated content mining strategies and taking consideration of relevant contextual and psychological factors associated with tweeting, tweets on physical activity offer a valuable data source to help us better understand: How can we mobilize people to 'tweet the walk' and 'keep the walk'?

**Keywords:** Twitter; social media; physical activity; mobile fitness apps

Received: 26 January 2016; Accepted: 25 February 2016; Published: 02 March 2016.

doi: 10.3978/j.issn.2306-9740.2016.02.03

**View this article at:** <http://dx.doi.org/10.3978/j.issn.2306-9740.2016.02.03>

Twitter, a microblogging social media site, has 320 million monthly active users globally (1). In 2015, 20% of all U.S. adults report using Twitter (2). Twitter provides real-time user-generated contents in tweets, which enable big data and in-depth qualitative data analyses across a number of health-related areas. Vickey and Breslin's research illustrated an innovative approach using a fitness tweet classification dataset to describe the levels of physical activity of mobile fitness app users in comparison to national self-reported survey data (3). The purpose of this commentary is to discuss additional insights and considerations of using data from fitness tweets to advance physical activity surveillance and intervention research.

In analyzing nearly 2 million tweets with workout durations from 102,544 users of 5 mobile fitness apps, Vickey and Breslin (3) found only 13% to 37% of the users met the recommended physical activity level (at least moderate intensity for 150 min/week). These percentages were lower than the national average (44%) obtained from the 2008 National Health Interview Survey based on self-reported data (3). As suggested by Vickey and Breslin, the

lower physical activity levels obtained from the fitness tweets could imply that the real-time tweets sent from the users' mobile fitness apps were more accurate and could provide a reliable data source that would not be subjected to recall-bias as in self-reported data (3). Given the data were obtained from users who were motivated to increase their physical activity level with the use of wearable devices and/or mobile fitness apps, the finding that a low percentage of these users meeting the recommended levels of physical activity is indeed concerning. Thus, another important research question is: which factors underlie the lower than the national average levels of physical activity among mobile fitness app users? We can approach this question with two scenarios as postulated below. The exploration of potential factors underlying each scenario can result in important implications for using fitness tweets to advance physical activity research and highlighting gaps in knowledge of leveraging mHealth technologies to promote physical activity.

Scenario 1: The fitness tweets data under-reported physical activity levels, specifically, the duration of physical

activity was under-reported. Common technical issues leading to under-reporting include malfunctions of wearable or mobile devices, and end-users' incorrect or inconsistent use of either the wearables or the mobile fitness apps. There is also a psychological aspect, however, which is: what drives a user's decision to select which physical activity to tweet? In Vickey's study (3), the users of Nike+ and Runkeeper, who were assumed to be among the most physically active user groups, reported the lowest average weekly minutes of physical activity. One plausible reason for this finding is that users did not tweet all of their physical activities. Some users might tweet a physical activity event to communicate special achievements (e.g., a record-breaking distance). Others might tweet the event to share memorable experience (e.g., running in an exceptionally scenic trail). Given the social media nature of Twitter, one's basic social needs such as social acceptance, self-esteem, and self-validation could drive what gets tweeted (4,5). For example, content analyses of 1,500 selected tweets mentioning users' participation in or intention to do physical activity showed that sentiments used with describing physical activity were associated with the number of users' followers and followings (6). Those who had fewer followers and followings were more likely to talk about physical activity positively, while those with more followers tended to post neutral tweets about physical activity (6). These findings suggest that a good understanding of "the psychology of tweeting" with consideration of relevant contextual and psychological factors is important in interpreting the data from fitness tweets. Thus, fitness data extracted from real-time tweets can not be blindly assumed to be more accurate than self-reported data obtained from other sources.

Scenario 2: The fitness tweets data were accurate and only a small percentage of mobile fitness app users actually met the recommended physical activity level. This points to a significant but missed opportunity to effectively promote physical activity among mobile fitness app users. In a review of 379 physical activity English apps with 55% included social networking features, Knight and colleagues found that only one app referenced physical activity national guidelines and very few incorporated evidence-based behavior change techniques (7). Thus, it is not surprising to see consumer statistics showing one in three owners of a wearable physical activity tracking device stopped using the device within 6 months (8). Similar observation was reported from a randomized controlled trial testing a mobile fitness app with >300 participants who were motivated to be physically active, 34% dropped out during

the first 2 weeks of a run-in period due to non-adherence of using the mobile app or a pedometer (9). Little is known about how best to leverage technologies and social support to promote and sustain individuals' physical activity at the recommended level. The Vickey's fitness tweet classification dataset (3) offers a unique platform to investigate how to utilize social media support to promote long-term physical activity. Future research should conduct in-depth qualitative analyses by following conversations of selected fitness tweets to understand how the types or nature of the conversations or feedback may facilitate or hinder adherence to physical activity recommendations. Depending on the research question, in addition to the Vickey's fitness tweet classification strategy (3), researchers should consider other content-mining strategies specifically developed for analyzing physical activity tweets data. Two such examples are Yoon and colleagues' use of a word frequency approach to describe various phenomenon including perceived social norms on various physical activity types and situational contexts (e.g., weather conditions, time of the day) (10); and the tweet classification strategies developed by Zhang and colleagues (6) that include coding sentiments and users' social media networking characteristics (e.g., the number of followers and followings) in the analyses.

Addressing physical inactivity is an important public health mission globally. The increased use of mobile health and social media technologies offers important vehicles for both physical activity surveillance and intervention research to promote physical activity. The use of Twitter data such as the fitness tweet classification dataset with innovative and validated content mining strategies offers a promising opportunity to further our understanding of "How can we mobilize people to 'tweet the walk' and 'keep the walk?'"

### Acknowledgements

Barbara Gerbert, PhD, provided thoughtful comments to the manuscript.

### Footnote

*Conflicts of Interest:* The author has no conflicts of interest to declare.

*Comment on:* Vickey T, Breslin JG. Do as I tweet, not as I do: comparing physical activity data between fitness tweets and Healthy People 2020. *mHealth* 2015;1:19.

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doi: 10.3978/j.issn.2306-9740.2016.02.03

**Cite this article as:** Tsoh JY. Tweeting about physical activity: can tweeting the walk help keeping the walk? *mHealth* 2016;2:6