Can social media assess demographic variations in physical activity attitudes?

Kivan Polimis

2017-04-07

Abstract

Researchers are evaluating social media's ability to clarify difficult-to-measure concepts such as attitudes and advance opinion-driven research. Unsolicited opinions from social media could provide insight into conflicting racial variation findings in physical activity attitudinal research. In survey research, racial minorities report more favorable attitudes towards physical activity than Whites; contrastingly, ethnographic research suggest racial minorities have more attitudinal variability. Twitter offers researchers opportunities to systematically investigate physical activity attitudinal differences by race with user-generated text data corresponding to digital trace ethnography. This paper examines demographic variation (race, gender) in attitudes towards moderate to vigorous physical activity with tweets gathered from Twitter's Streaming API. Twitter users' demographic background is estimated with the Face++ API and a last name, Census-based predictor. Sentiment analyses explore physical activity attitude differences with 147,178 tweets from 54,115 Twitter users gathered between August 2016 and January 2017. Tweet sentiment analysis revealed racial differences where Whites and Blacks were equally positive in their discussion of physical activity and more positive than Asians. Gender analysis revealed that women had more positive sentiment than men towards physical activity. Supplemental findings suggest that establishing thresholds and filters for "usable data" (e.g., confidence thresholds for demographic data, geographic filters) can improve the accuracy of claims.

Keywords
attitudes, racial disparities, physical activity, Twitter, sentiment analysis

1. Introduction

Social media create novel, user-generated forums that can mirror observing human behavior. Attitudinal researchers gravitate towards social media data because these data are unsolicited and produced at a tremendous scale. However, social media data are not without their own limitations and the efficacy of these data to explore social phenomena is continuously being evaluated. Social media research could provide insight into racial differences in chronic disease prevalence by leveraging individual expression to better understand disease risk factors.

Researchers consistently observe large and persistent racial differences in chronic disease prevalence (Smedley, Stith, and Nelson 2003). Racial minorities have higher comorbidity rates and are susceptible to increased mortality (Cossrow and Falkner 2004). Longitudinal and cross-sectional population health surveys regularly highlight racial and ethnic disparities in protective health behaviors including moderate to vigorous physical activity which may drive disease prevalence disparities (Crespo et al. 2000; Dietz 1998; Schwarz and Peterson 2010; Stephens, Jacobs Jr., and White 1985; Tucker, Welk, and Beyler 2011). Gender is also correlated with physical activity and interacts with race in important ways; for example, minority (Black and Hispanic) women are on average less physically active than the average woman and individual with their racial background (Wilcox et al. 2000).

Although physical activity is determined by individual, social and other ecological determinants, a significant body of research asserts that individual attitudes are important physical activity predictors (Ajzen 1991; Azjen 1985; Godin et al. 1987; Hagger et al. 2003). Attitudes influence physical activity independent of many social and ecological factors known to affect physical activity rates such as social networks and built environments (Brenes, Strube, and Storandt 1998; Courneya et al. 2000). As mentioned before, physical activity is lower for racial minorities, particularly minority women. The available attitudinal survey research with diverse samples includes findings that racial minorities often have similarly positive or more positive attitudes towards physical activity than their White peers which complicates the established relationship between attitudes and engagement. Moreover, female-specific studies have found that Black and Hispanic women report more positive attitudes towards physical activity than White women despite health literature showing these women engage in less physical activity than their White peers (Crespo et al. 2000; Eyler et al. 2002; Im, Chang, et al. 2012). Racial similarities in physical activity attitudes despite behavioral differences in physical activity trends challenge well established links between attitudes and behaviors. Either attitudes are less salient for physical activity or current methods have not revealed physical activity attitudinal complexity for minority groups.

Traditional survey data may not capture the multidimensionality inherent in physical activity attitudes. Ethnographic studies examining physical activity utilizing diverse racial samples implicate barriers, knowledge gaps, activity preferences and other difficult to measure factors that may be related to racial variations in physical activity attitudes (Lavizzo-Mourey et al. 2001). Through open-ended and semi-structured approaches, ethnographies have added nuance to attitudinal variation research by providing a forum for individuals to voice perceived physical activity benefits and constraints. However, ethnographic studies face challenges related to small sample size and limited geographies. A more systematic investigation of racial and gender differences that can both capture attitudinal complexity and address larger population segments is needed to better provide nuance to physical activity attitudes.

This paper's purpose is twofold: this study substantively assesses demographic variation in physical activity attitudes and methodologically explores social media data challenges and limitations. First, this paper examines physical activity attitude variation by race and gender with Twitter as a large scale ethnography with respondents' unsolicited views toward various physical activities. Analyses also investigate variations at the intersections of demographic characteristics. Textual data on moderate to vigorous leisure time physical activity from Twitter is analyzed with sentiment analysis to understand demographic variations in physical activity attitudes. These analyses reveal attitudes towards physical activity vary by activity and across racial groups with minimal gender variation within racial groups. Lastly, this study contributes to growing literature on social media and demographic research by highlighting methodological challenges facing Twitter-based demographic studies and providing suggestions to address potential social media data biases.

2. Background

This review examines key relationships between physical activity and attitudes, demographic variation in physical activity attitudes, and the viability of social media data to understand physical activity.

2.1. Physical Activity and Attitudes

Physical activity is broadly defined as "any bodily movement produced by skeletal muscles that results in energy expenditure" (Pate et al. 1995). Health professionals recommend moderate and vigorous physical activity, measured by metabolic equivalent (MET), because these activities provide substantive contributions to individuals' total caloric expenditure and overall health status (Haskell et al. 2007; Hendelman et al. 2000; Westerterp and Plasqui 2004). Typically, vigorous activities like running exert greater than 6 METs while moderate activities including walking are equivalent to 4-6 METs (Lee and Paffenbarger 2000).

Numerous models exist for describing the relationship between health behaviors, specifically physical activity, and attitudes. Previous health research has focused on latent measures and adapted psychological constructs to understand factors that affect the attitude-behavior relationship (Ajzen 1991; Ajzen and Timko 1986; Azjen 1985; Giles-Corti and Donovan 2002; Godin et al. 1987; Hagger et al. 2003; Voas 2014). Attitudinal health studies find that attitudes influence key physical activity predictors, including persistently engaging in physical activity and behavioral intention[1]. Individuals with positive attitudes towards physical activity intend to (and measurements confirm) engage in physical activity more regularly and across the lifespan than individuals without these attitudes (Affuso et al. 2011; Hagger, Chatzisarantis, and Biddle 2002; Tammelin et al. 2003). Some researchers have critiqued attitudes' importance to physical activity; however, psychological constructs appear important predictors for health behaviors (see: (Trost et al. 2002)) .

2.2. Physical Activity Attitudes and Demographic Variation

Health attitudes (e.g, orientation to physical activity) vary by race and gender as well as the intersection of these demographic backgrounds (Clark and Nothwehr 1999; Courtenay, McCreary, and Merighi 2002; Mcguire et al. 2002). While we have a broad understanding of demographic differences in physical activity trends, we have a limited understanding of attitudinal variation along demographic background intersections (Harden 2004). Exploring demographic characteristics individually and in combination can clarify physical activity attitudinal variation.

2.3 Racial Variation

Attitudinal research with multiple racial groups produces conflicting comparisons that highlight differences between survey and ethnographic methods. For instance, Affuso et al. (2011) use a telephone survey with general questions about exercise (Appendix A) and find majority agreement amongst African-American men and women agree that physical activity is important. Contrastingly, ethnographic research observes a broader range of minority attitudes towards physical activity influenced by cultural ideals towards self-rated health, body-size, and fatalism (Baptiste-Roberts et al. 2007; Egede and Bonadonna 2003; Krause and Jay 1994). Ethnographic studies suggest that less positive attitudes toward physical activity may reflect cultural norms interacting with ecological constraints instead of generic views toward exercise. Additionally, attitudinal studies often focus on Black-White differences, limiting information about other minority attitudes towards physical activity, such as Hispanic and Asian-American attitudes. Studies that do investigate Hispanic or Asian physical activity attitudes favor examining acculturation and immigration processes instead of broadly studying these communities (Johnson 2000; Kandula and Lauderdale 2005; Unger et al. 2004)[2]. Acculturation- or immigration-based studies find that the migration experience adversely impacted immigrant health by increasing obesity-related behaviors.

2.4 Gender Variation

Gendered social and cultural norms could produce variation in physical activity attitudes. For instance, Eyler et al. (1998) and Dwyer et al. (2006) find that women and girls attitudes towards physical activity

[1] "Intentions are assumed to capture the motivational factors that influence a behavior; they are indications of how hard people are willing to try, of how much of an effort they are planning to exert, in order to perform the behavior" (Ajzen (1991), pg.181)

[2] see (Eyler et al. 1998; Im, Chang, et al. 2012; Im et al. 2008, 2015 for exceptions, 2013, 2010; Im, Y. Ko, et al. 2012).

are influenced by gender norms that deter physical activity. The effect of gendered norms are illustrated by studies such as Hayes, Crocker, and Kowalski (1999) survey finding that women subjectively rated their physical activity engagement self-perceptions lower than men. Intersectional studies provide opportunities to assess cultural norm influences on gendered attitudes towards physical activity. These studies demonstrate how overlapping social identities (e.g., race, gender, age, class, religion, etc.) interact to produce and exacerbate social inequalities (Crenshaw 1991).

Intersectional race and gender studies provide opportunities to understand how cultural norms and ecological dynamics are operationalized into physical activity levels but conflicting findings have emerged. For instance, Wilcox et al. (2000) and Grieser et al. (2006) rely on survey scales to conclude that Blacks and Whites have more attitudinal commonalities than differences and caution against race-specific health interventions by gender. Wilcox et al. (2000) finds that Black and White women endorse exercise for health and a desire to increase current physical activity at similar rates while Grieser et al. (2006) states that "girls from all groups have similar perceptions of the benefits of physical activity, with staying in shape as the most important" (pg. 40). Contrastingly, an internet based midlife women's physical activity attitude study find racial differences in physical activity attitudes with scaled instruments. Im, Chang, et al. (2012) shows that midlife racial/ethnic minority women (Hispanic and Non-Hispanic African American women) report significantly *greater* positive attitudes towards physical activity than Non-Hispanic White women.

Studies using focus groups, semi-structured interviews, and other interactive forums indicate layered complexity behind African-American women's physical activity attitudes (Airhihenbuwa et al. 1995; Henderson and Ainsworth 2003; Im, Y. Ko, et al. 2012; Versey 2014). These authors suggest that African-American women less positive attitudes are influenced by marginalized experiences and cultural beauty norms (e.g. hair maintenance) instead of outright dislike for physical activity. However, because few large-scale studies offer detailed attitudinal questions there is less certainty in generalizing race-specific attitudes. Physical activity attitudinal variation by racial, gender and intersectional identities reveal methodology and item-specificity may influence results. For instance, studies with survey methods tend to focus on how much attitudes differ by race, while ethnographies on why attitudinal differences may exist. To these ends, surveys often measure attitudes with scaled responses from generic survey items about exercise. The emerging attitudinal differences (or lack thereof) from surveys may be artifacts of how individuals self-referentially interpret questions about physical activity[3]. Thus, probing attitudes with user-driven responses related to specific physical activities could enhance our understanding gender variations across physical activity.

2.5 Understanding Health Behaviors with Unstructured Data

User-generated, unstructured data provide opportunities to address the subjectivity inherent in asking individuals to declare attitudes towards physical activity via survey or in the presence of a researcher and or peers. Examples of unstructured data include textual, visual and auditory data sources, dimensionally rich information not typically available in administrative data or traditional survey methodology. The similarity across these data types is the lack of predefined model such that data are not "table-orientated as in a relation model or sorted-graph as in an object database" making it difficult to process with traditional programs (Abiteboul 1997). This paper utilizes one form of unstructured data–those derived from digital traces or records of online interactions. More specifically, this study leverages Twitter data, typically text-laden descriptions by individuals describing daily activities or social events.

The discrepancy in attitudinal findings from ethnographic and survey research discussed earlier could be related to the subjectivity inherent in attitudes. Popay, Rogers, and Williams (1998) suggest standards for using qualitative research for understanding health attitudes that include data reflecting "interpretation of subjective meaning, description of social context and attention to lay knowledge". Ethnographers rely on forums that produce user-generated, unstructured data and allow respondents bottom-up attitude descriptions instead of top-down criteria limiting response types. Ethnographic studies provide observational richness on attitudes that surpasses survey data, but ethnographers are limited by survey size and methods to manage

[3]Krause and Jay (1994) use in-depth one-on-one interviews that blended survey items with follow-up opportunities to elaborate on how individual reference points (e.g. focusing on health problems vs physical function) influence racial attitudinal variation in self-rated health responses. Their data from open-ended responses suggested that global self-rated health questions are being interpreted differentially by race further demonstrating the utility of ethnographic approaches. Similarly, Boyington, Howard, and Holmes (2008) also finds physical activity reference points vary by race

potential data biases. Multiple ethnographic studies have generated insight into attitudes from focus groups and semi-structured interviews (French et al. 2005; Mabry et al. 2003; Siddiqi, Tiro, and Shuval 2011) by allowing respondents to drive their response narrative. Ethnography can leverage individual subjectivity to improve survey scale measurement reliability (Krause and Jay 1994). However, these studies have focused on small communities and lack the respondent diversity (survey size and demographic variation).

Unstructured data from digital traces presents unique advantages and disadvantages when compared with traditional survey instruments and ethnographic studies. Traditional health survey instruments leave individuals with a limited response ranges (e.g. Likert scales) and can be uncertain in their core attitude measurement (Streiner, Norman, and Cairney 2015). Alternatively, digital data can be gathered inexpensively, rely on user-driven responses and are generated more frequently. New findings comparing social media data to traditional data sources reveals that social media can reflect the ground-truth reality of economic disadvantage and demographic distribution for studies analyzing physical activity, nutrition, and well-being (Nguyen et al. 2016). For instance, research has shown that census-level indicators including economic disadvantage are predict less frequent physical activity references for Twitter users residing in those areas. Twitter resembles traditional ethnographic approaches by providing a forum for individuals to freely discuss personal opinions eliciting more respondent control in describing attitudes that is common to ethnographic research. Despite these relative strengths compared to traditional research methodology, social media data projects have unique reliability and generalization concerns.

Profile and audience curation typify reliability concerns with social media data. Studies using social media data grapple with classical sociological concepts such as presentation of self, impression management, and self disclosure that may contextualize social interactions and individual behavior (Hogan 2010; Krämer and Winter 2008). Social media users can digitally "curate" an online persona through word choice, picture selection, and network self-selection that can distort online interactions (Arseniev-Koehler et al. 2016; Kaplan and Haenlein 2010; Papacharissi 2012). The potential to turn online interactions into a self-evaluation prism has lead social media researchers to consider audiences and visible within-person changes[4] to contextualize digital traces. Researchers have recognized demographic differences across social media sites that drive generalizability concerns. Among all adult internet users, Twitter is over-represented by young adults and racial minorities. Additionally, Twitter is used by a smaller share of adult internet users than other social media sites (e.g. Facebook)(Smith and Brenner 2012). For an in-depth review of the advantages and disadvantages of using digital traces and big data analytics for demographic research see Cesare et al. (2016) and Müller et al. (2016).

2.7 Twitter and Health/Physical Activity Studies

Emerging literature has used social media and digital traces to examine physical activity differences (Cavallo et al. 2012). This literature relies on numerous studies documenting the ability of social media in general, and Twitter in particular, to provide individual and population-health insights through observational study of human behavior (Hawn 2009; McCormick et al. 2015; Nguyen et al. 2016; Paul and Dredze 2011; Scanfeld, Scanfeld, and Larson 2010). Studies examining physical activity using social media have revealed that these data sources provide opportunities to study distinct communities, understand the relationship between offline behaviors and online discussion, and clarify social network dynamics that affect physical activity (De Choudhury 2014; De Choudhury, Counts, and Horvitz 2013; De Choudhury et al. 2013; De Choudhury, Sharma, and Kiciman 2016; Dos Reis and Culotta 2015; Eichstaedt et al. 2015; He et al. 2013; Park et al. 2016; Turner-McGrievy et al. 2013).

Social media studies show that language selection appears related to health outcomes. Eichstaedt et al. (2015) and Dos Reis and Culotta (2015) find that using positive language in tweets was a protective factor for health outcomes including heart disease and depression. Also, Gore, Diallo, and Padilla (2015) discovered geographic differences in obesity rates based on the overall discussion and physical activity tweet intensity. In sum, these social media studies assessing physical activity differences reveal that language is an important behavioral predictor and online behavior is related to offline behavior. Twitter is a powerful medium with the requisite diversity and scale to clarify associations between demographic background and physical activity

[4]social media users can always delete accounts, create new profiles, or maintain multiple profiles in ways that make tracking within-person changes difficult

attitudes.

2.8 Hypotheses

Multiple hypotheses emerge from the literature on physical activity attitudes and social media data in demographic research. First, literature reviewed on racial, gender and intersectional variation in physical activity attitudes suggests the following attitudinal differences:

1. Men will show more positive attitudes than women

- Hayes et al. (1999); Eyler et al. (1998)

2. Blacks and Asians will report less positive attitudes towards physical activity than Whites

- Baptiste-Roberts et al. (2007); Egede and Bonadonna (2003)

3. Black and Asian women will have the least positive attitudes of demographic subgroups

- Airhihenbuwa et al. (1995)

3. Data and Methods

The data for this study were gathered with Twitter's free Streaming Application Programming Interface (API) from August 2016 to January 2017. Twitter is a social networking service that allows users to message each other globally and/or directly in short microblogging posts known as tweets. Tweets are constrained to 140 characters at a maximum and allow users to document, share and interact with public and private communities. Twitter's free Streaming API was used to gather tweets because it provides a real-time continuous connection to Twitter and updates on tweets matching search criteria. The Streaming API represents 1% of all tweets and analyses show that this 1% sample is a random representative sample of all tweets (Sloan et al. 2013) Searching for tweets by subject with the Streaming API means that tweets are not filtered by location (conversely, filtering for tweets for location precludes searching for tweets by hashtag). Using Amazon Web Services (AWS) Elastic Computing (EC2) server, I collected English-language tweets almost daily for essentially the entire day[5]. Tweets were gathered, analyzed, and processed with R software (R Core Team 2016); this analysis relied heavily on the `streamR`, `twitteR`, `stringr`, and `wru` packages (Barbera 2014; Gentry 2015; Khanna and Imai 2016; Wickham 2016)

3.1 Physical Activity Attitude Measurement

Initial search terms for physical activity tweets used standards for moderate to vigorous (henceforth, MVPA) created by Godin and Shephard (1985). MVPA are ideal for investigation because these health behaviors are more universally recognized, data generated is less context dependent, and activities are more race-neutral[6]. Additionally, MVPA have near universal recognition through common activities such as walking and biking. The search terms continuously queried on Twitter's Streaming API first included the following specific activities: #biking, #jogging, #pullups, #pushups[7], #running, and #walking. Words or phrases that are preceded by the hashtag symbol (#) create a searchable link to other users that are describing their experience similarly. This shared experience is integral to Twitter and searching for physical activity tweets with the hashtag sharply differentiates users that tried to create a social dialogue about their physical activity instead of incidentally mentioning physical activity keywords (e.g. "running late to work"). Additionally, because individuals can pursue physical activity in facility-based or home-based settings, the following terms

[5]Tweets were not collected during this period when the server was interrupted for maintenance or the stream to Twitter's API timed out unexpectedly.

[6]Data generated describing physical activity are more likely to include context clues like duration while being less inherently context dependent than other health behaviors that impact chronic disease prevalence. For instance, nutrition consumption is much broader in scope and difficult to investigate without some contextual knowledge (e.g., food proportions or servings). Lastly, health behaviors related to physical activity may be more race-neutral than other health behaviors. Guthman (2008) discusses how race affects the alternative food provision market and produces minority exclusion because "these spaces tend to hail white subjects, whites continue to define the rhetoric, spaces, and broader projects" (395). Cultural and socioeconomic boundaries in nutrition discourse suggest that studies into lay nutrition discussion will be segmented by race and class (Lamont and Molnár 2002).

[7]#pushups was ultimately removed from the analysis for reasons discussed in **Section 6. Challenges**

were also added to capture home-based physical activities: #homeworkouts, #bodyweightworkouts, #bodyweightexercises (Foster et al. 2005).

3.2 Predicting Demographic Background

After collecting almost 830,000 tweets from approximately 230,000 users[8] with the relevant search times, two software were used to estimate Twitter users' demographic background. Faceplusplus.com (henceforth Face++) generated demographic estimates of race, gender, and age. Face++ is a computer vision software platform that uses an image to predict age (continuously; with a range) as well as gender and single-race (both categorical; with numeric confidence estimates)[9]. The validity between Face++ demographic estimates has been examined by Bakhshi, Shamma, and Gilbert (2014) and Rhue and Clark (2016) which found greater than 90% agreement between automatic classifications from Face++ software and human classifications from Amazon Mechanical Turk (MTurk)[10]. Additionally, Rhue and Clark (2016) found the confidence level from Face++ estimates mattered as lower confidence estimates were more likely to have disagreement with human classifications suggesting using thresholds with Face++ data instead of all estimates produced by the software. Face++ demographic background estimates have also fared well in social media based studies by Huang, Weber, and Vieweg (2014), Yadav et al. (2014), and Jang et al. (2016). This study also applied a predictor developed by Imai and Khanna (2016) to predict Twitter users' racial backgrounds. These predictions use the Twitter account last name (based on account screen name) and cross-referencing Census data to estimate the user's racial background. A multidimensional view of Twitter users' race is created by supplementing the racial category image Face++ estimates with the surname estimates when available[11].

Twitter users' demographic background was estimated by sending users' profile picture URL to the Face++ API resulting in estimates for 147,178 tweets from 53,910 users. The final analysis was subset to only include tweets with non-missing estimates for relevant demographic characteristics and other exclusionary criteria. These exclusionary criteria included user with estimated age greater than 18 (20,202 observations dropped) and Face ++ race confidence estimate greater than 50% confidence[12] (3,533 observations dropped). The age range for respondents in this study spans ages 18 to 66 and the final analytical sample includes 147,178 tweets from 54,115 users.

Face++ Example

The following example demonstrates the Face++ API estimating the race, gender, and age of W.E.B. DuBois[13] in 1918 (age 50). Face++ estimates that DuBois is black (98.63% confident), male (100% confident), and age 38 (with a range of 10 years)[14]. While the software is accurate (and confident) with the race and gender estimates, the age estimate does not include DuBois' true age (50), although his true age is near the height of the suggested age range (48).

3.3 Analytical Strategy

Main Analysis

[8]193,515 tweets from 3,249 presumably professional accounts were removed. Users were determined to be professional accounts by examining user screen names and users with organizations in their user name (e.g. "News", "Watch Reviews", "Bowling Club", etc.) were removed.

[9]Face++ is moving all operations completely to new API on May 1st 2017 and the current version of the new API does not estimate race nor discuss the details of the new machine learning algorithm approach to detect demographics. This study uses the old Face++ API and the following link describes demographic results produced from that method: http://old.faceplusplus.com/detection_detect/

[10]Researchers are leveraging MTurk, an online marketplace that matches task requesters (researchers) and task completers (subjects), to collect inexpensive, high-quality data (Buhrmester, Kwang, and Gosling 2011).

[11]Imai and Khanna (2016) method is a Bayesian predictor that provides racial background probabilities given last name and geographic location. The entire Bayesian method is only applied on the geolocated supplemental sample while the main analysis uses last name only for racial background predictions.

[12]the minimum gender confidence estimate was limited to 50% by probability

[13]The photo used in this example is a photo of W.E.B. DuBois (aged 50) under Creative Commons license from Wikipedia https://upload.wikimedia.org/wikipedia/commons/1/12/WEB_DuBois_1918.jpg

[14]Go to the old Face ++ API Demo at http://old.faceplusplus.com/demo-detect/ and use the image link from the previous footnote to see Face++ estimates.

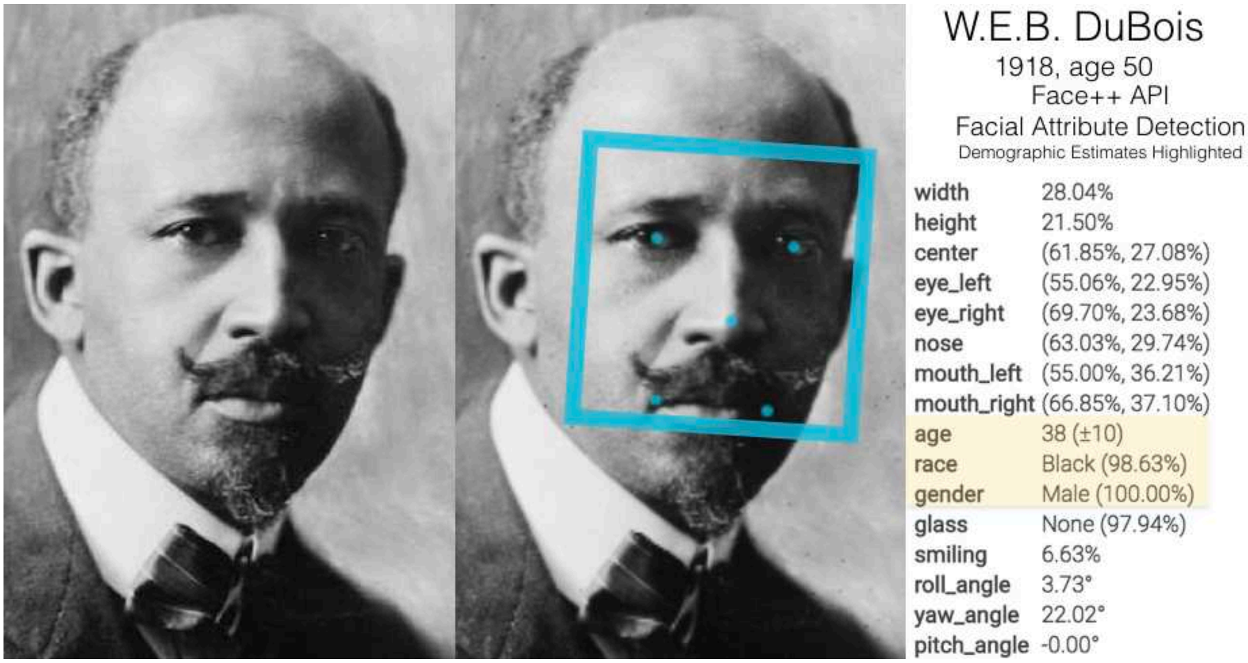


Figure 1: W.E.B. DuBois Face++ API Estimates

This study analyzes physical activity attitudes expressed in tweets with sentiment analysis. Sentiment analysis uses computationally intensive techniques to identify positive, neutral or negative opinions in text (Pak and Paroubek 2010). Computational approaches to opinion, sentiment, and subjectivity in text emerged from natural language processing, computer science field at the intersection of computation and linguistics (Agarwal et al. 2011). Natural language processing is concerned with using computers to understand human text and speech (Chowdhury 2005).

Multiple textual features can be used to investigate tweets sentiment including lexical features, part-of-speech features, n-gram features and micro-blogging features. Lexical features are concerned with sentence level polarity (positive, negative, neutral), part-of speech features include number of verbs, adverbs, adjectives, nouns, and any other parts of speech. Furthermore, n-gram features are a contiguous sequence of n items from a tweet and micro-blogging features capture the presence of positive, negative, and neutral emoticons and abbreviations and the presence of intensifiers (e.g., all-caps and character repetitions). While there are strategic advantages and disadvantages to each textual feature, prior research has established lexical features are a good representation of Twitter sentiment, especially in comparison to other metrics such as part-of-speech features (Kouloumpis, Wilson, and Moore 2011). For an in-depth review of the sentiment analysis and its origins in natural language processing see Pang and Lee (2008).

Sentiment analysis use an opinion lexicon and scoring algorithm to assign a single numeric score to a body of text (here tweets). The opinion lexicon consists of select positive and negative words with predefined scores. The scoring algorithm produces a single sentiment score for a body of text by subtracting the values corresponding to negative words from positive words (positive words score +1, negative words score -1) found in the opinion lexicon[15]. This study uses an opinion lexicon with nearly 6,800 words created by Hu and Liu (2004) and Liu, Hu, and Cheng (2005) and implements the Breen (2012) scoring algorithm. Negative and positive scores correspond to negative and positive opinions; respectively. In this study, the sentiment analysis indicate how positive or negative individuals feel about various physical activities.

Supplemental Analysis

[15]Tweets also can include emoticons (emojis) and researchers are developing methods to determine sentiment expressed by these images (Kiritchenko, Zhu, and Mohammad 2014). This study does not analyze emojis

The literature reviewed shows that studies using social media should be aware of potential influences from: managed presentation of self, user selectivity, geographic filters, subject reliability, and demographic reliability. Supplemental analyses explored potential biases from users "curating" digital traces as well as software and computational limitations from Twitter and supporting data sources.

4. Findings

4.1 Summary
Similar to previous studies that use Twitter data, I find that my population is more demographically homogeneous than the United States population-at-large. The summary statistics tables (Table 1 and 2) show that users in my dataset are relatively young adults (average age = 33.01) and the sample is less racially-diverse (83% White, 6% Asian, 10% Black). Additionally, this sample is marginally more male with 49% of the tweets generated by male users. The search terms tracked (e.g.,physical activity may skew young) could also influence the demographic homogeneity displayed in the sample. The findings from the sentiment analysis indicate some demographic variation in health behavior attitudes inconsistent with the first two demographic-based hypotheses. For instance, prior demographic research suggests that men express more positive attitudes towards physical activity than women (hypothesis 1). Analyses revealed that women (0.39) had more positive sentiment scores than men (0.34); furthermore, the intersectional race and gender comparisons revealed important racial differences in attitudes towards physical activity[16]. Research hypothesizes that Whites will have more positive physical activity attitudes than racial minorities (hypothesis 2). Whites (0.37) equally positive attitudes with blacks but more positive attitudes than Asians. Amongst racial minorities, Asian females (0.28) had a less positive attitude towards physical activity than Black females (0.37) (Table 3). These demographic findings are largely consistent with the second demographic hypothesis although Asians having the lowest overall sentiment was not predicted (See Table 7 for hypotheses review). Lastly, the Plot "Race by Gender Distribution of Physical Activity Hashtags" shows hashtag counts by race and gender (Appendix C includes tabular representation of the same data).

Table 1: Summary Statistcs, Part 1

group	total	proportion
White	45183	0.83
Black	3516	0.06
Asian	5416	0.1
Men	26743	0.49
Women	27372	0.51

Table 2: Summary Statistcs, Part 2

race	gender	total	proportion	mean age
White	Male	21854	0.40	36.38
White	Female	23329	0.43	30.54
Black	Male	2289	0.04	33.48
Asian	Male	2600	0.05	32.72
Asian	Female	2816	0.05	28.54
Black	Female	1227	0.02	30.01

[16]Aging research hypothesizes that similar barriers to exercise and increased awareness of exercise benefits may minimize attitudinal variation in older adults relative to younger adults (King 2001; Mathews et al. 2010; Motalebi et al. 2014). This study analyzed demographic group sentiment by United Nations age categories (e.g., 15 to 19, 20 to 24, etc.) and found that older age groups reported the least positive physical attitudes and lower variation in these attitudes. Individuals aged 44-49 were the most positive age group while individuals aged 35-49 tended to be more positive than all other age groups (See Appendix E for full age analysis results).

Table 3: Demographic Counts

category	total
tweets	147178
users	54115
male users	26743
female users	27372
white users	45183
asian users	3516
black users	5416
white male users	21854
black male users	2816
asian male users	2289
white female users	23329
asian female users	1227
black female users	2600

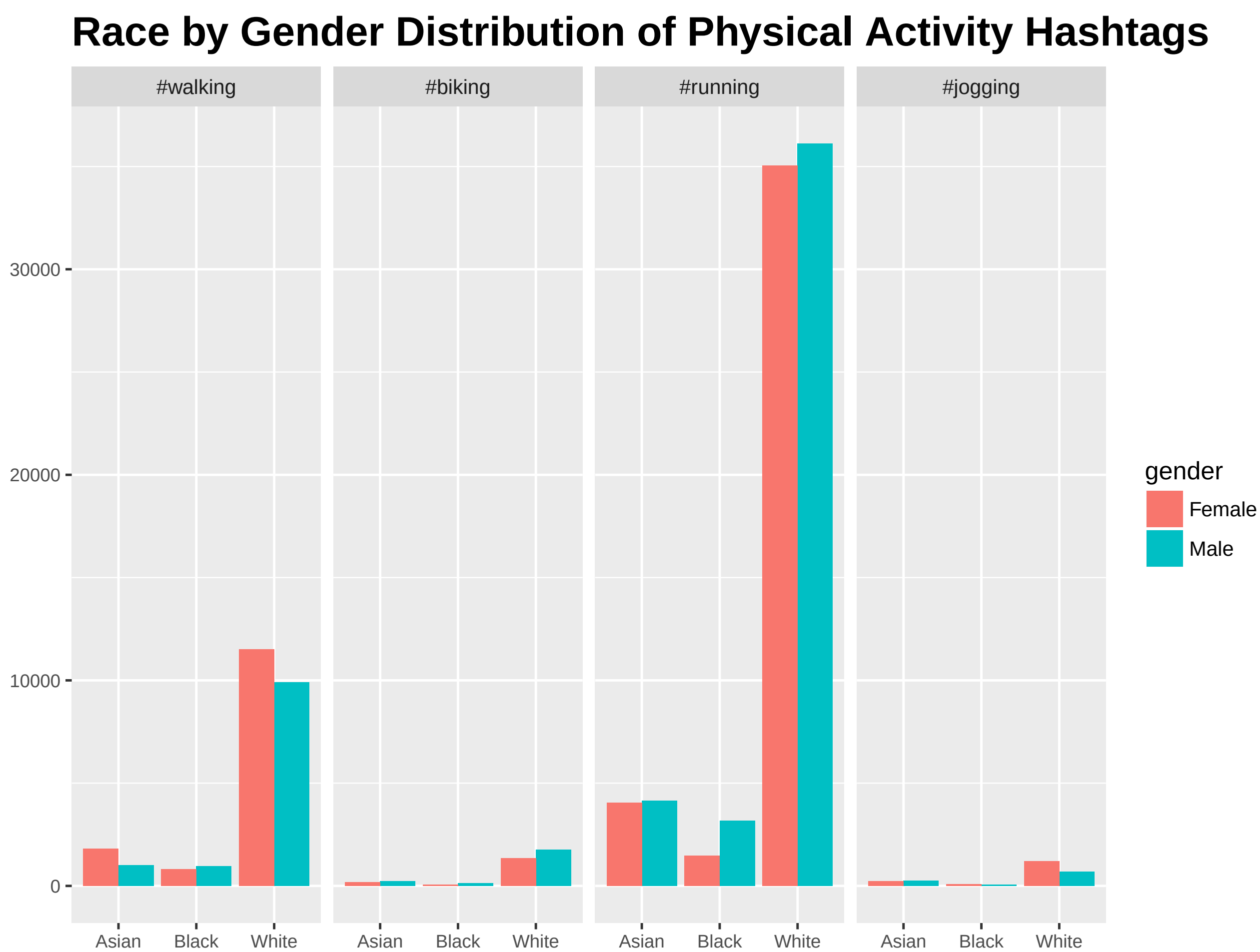
Race by gender analyses revealed that White females report the most positive attitudes (0.41) of any gender and racial group combination. Amongst the remaining females, Asian females (0.29) displayed a more positive attitude towards MVPA than Black females (0.31). Men showed less variation in interactive race-by-gender analyses. For instance, Black males (0.39) had marginally more positive attitudes than White males (0.34) and slightly more positive than Asian males (0.27). Minority women did have an average attitude sentiment more negative than all other race-gender subgroups except for Asian males which partially supports the third demographic hypothesis.

Table 4: Overall Sentiment Scores by Demographic Group

demographic group	mean	st. dev.
Asian	0.28	0.84
Black	0.37	0.86
White	0.37	0.91
Women	0.39	0.94
Men	0.34	0.86

Table 5: Intersectional Analysis of Sentiment Scores

race	gender	mean	sd
Asian	Female	0.29	0.88
Asian	Male	0.27	0.79
Black	Female	0.31	0.84
Black	Male	0.39	0.86
White	Female	0.41	0.95
White	Male	0.34	0.87



4.1 Average Sentiment by Individual Physical Activity

Individual activity analysis reveals variation between demographic groups and physical activities. For instance, racial groups displayed more positive average sentiment on some physical activities than others that may influence the results. Running-related tweets make up 66% of all tweets (92% of all tweets mention #running, #walking, #jogging or #biking) and show key racial and gender differences (See Appendix C for activity counts/proportions disaggregated by demographic group and Appendix D for all activity-specific sentiment scores disaggregated by demographic group). On average, running-related tweets are discussed more positively than non-running tweets. Furthermore, women discuss running more positively than men and White females write more positively about running than all other demographic subgroups. The relationship between running and White female tweets help drive the overall findings that White females have the most positive attitudes towards physical activity. Conversely, Asian men in this sample reported the highest proportion of running tweets relative to their total physical activity tweets while having the lowest average sentiment towards running which drives the finding that Asian males have the least positive overall sentiment towards physical activity. Further examination of tweet sub-samples[17] suggested that the discourse around running is negative because of external considerations (e.g. cold weather, difficult terrain, physical safety concerns, thought about worries while running, etc., See Appendix B for race by gender tweets that discuss these themes) suggesting that attitudes towards running are not reflective of the actual physical activity.

Running tweets vs all others

[17] sub-samples were created by randomly sampling 100 to 1000 tweets within demographic groups

Table 6: Running Sentiment Scores by Demographic Group

race	gender	mean	sd
Asian	Female	0.30	0.89
Asian	Male	0.26	0.75
Black	Female	0.33	0.86
Black	Male	0.27	0.77
White	Female	0.42	0.93
White	Male	0.32	0.85

Table 7: Non-Running Sentiment Scores by Demographic Group

race	gender	mean	sd
Asian	Female	0.26	0.89
Asian	Male	0.27	0.81
Black	Female	0.3	0.84
Black	Male	0.51	0.92
White	Female	0.38	0.96
White	Male	0.34	0.86

Additional textual investigations beyond sentiment scores demonstrated the contrast between some tweets that were physical activity related and those that used physical activity keywords but were not related to physical activity. The following positive and negative tweets from Black females are emblematic of many tweets in the data set, that is, tweets with physical activity keywords and topically discussing physical activity. (See Appendix B; tweets were selected by subsetting the maximum and minimum sentiment scores and filtering in special instances that are discussed in **Section 6. Challenges**)

Example tweets:

Black women:

Positive: "My happy place! Thankful to be back doing what I love. #RUNNING #fitness #gym #love"
Negative: "Looking forward to rest day tomorrow #shealth still sucks .... not as bad as #running."

Table 8: Hypothesis Table

Hypothesis	Finding
1. Men will show more positive attitudes than women	Not supported
2. Blacks and Asians will report less positive attitudes towards physical activity than Whites	Partially supported
3. Black and Asian women will have the least positive attitudes of demographic subgroups	Partially supported

4.2 Supplemental Analysis

Presentation of self

Retweets were more positive than mentions and original tweets for all racial-gender combinations. Mentions were positive than original tweets with the exception of Asian males, Black males, and Black females. These findings suggest that when Twitter users' apply the words of other individuals to describe their attitudes towards physical activity Twitter users' are universally more positive describing physical activity than when these same individuals author tweets to specific individuals or tweet at no one in particular (All supplemental tables are available in Appendix E).

User selectivity

Tweets created by individuals with only tweet in the analysis were more positive towards physical activity for Asian females, Asian males, and Black females; conversely, individuals with multiple tweets were more positive discussing physical activity for Black males, and White males and females.

Demographic reliability

The sensitivity of Face++ racial and gender confidence estimates were also explored. Comparisons were made at the 99th, 95th, 90th, 85th, 80th, and 50th percentile to understand how increasing racial and gender accuracy affected results. These analysis showed that a potential gender effect occurred in the racial estimates. All males were more positive at racial confidence estimates in the 99th percentile than the 50th; conversely, all women were positive at the 50th than 99th percentile. At all percentiles of gender confidence, the results maintained consistency for demographic groups (e.g., White females most positive from 99th to 50th percentile, Asian females and males alternate least positive attitudes across percentiles) .

Subject reliability

Using a new set of physical activity subjects (#mma, #boxing, #basketball, #crossfit, #workout, #weightlifting, #wrestling, #golf, #tennis, #skiing, #horsebackriding, and #yoga), demographic variations in attitudes were assessed. These new hashtags revealed different results from the hashtags in the main analysis. The following findings from the supplemental analysis were not observed in the main analysis: men had more positive attitudes than women (hypothesis 1 disconfirmed), racial minorities reported more positive attitudes than Whites (hypothesis 2 disconfirmed).

Table 9: Supplement: Overall Analysis of Sentiment Scores

demographic group	mean	sd
Asian	0.36	1.01
Black	0.37	0.94
White	0.34	1.01
Female	0.30	0.96
Male	0.40	1.05

Table 10: Supplement: Intersectional Analysis of Sentiment Scores

race	gender	mean	sd
Asian	Female	0.34	1.05
Asian	Male	0.39	0.96
Black	Female	0.43	0.96
Black	Male	0.36	0.93

race	gender	mean	sd
White	Female	0.29	0.95
White	Male	0.41	1.08

Geographic filters

Geo-located tweets within the US were positive than non-US geo-located for Asian males and females, Black females, and White males. The two most positive groups in the main analysis, Black males and White females, have more positive attitudes in the non-US geolocated tweets than the US geo-located tweets. A second geographic filter was created by leveraging the Zillow House Search API[18] to understand the relationship between socio-economic status and attitudes towards physical activity. Home values were grouped into three tiers by determining the home values that corresponds to various income groups (lower-income [household income less than $42,000], middle-income [household income greater than $126,000 > $42,000], high-income [household income greater than $126,000]) and clear SES differences emerged. The high-income homes reported more positive physical activity attitudes for all races except for Asian males. However, the estimates for Asian males in middle- and low-income homes are based on less than 10 individuals (contrastingly, 32 users are in the Asian male high income group). Similarly, the high-income estimate for Black females is based on only one individual. In total, tweets occurring from users associated with high-income home values were on average more positive than tweets from other income backgrounds.

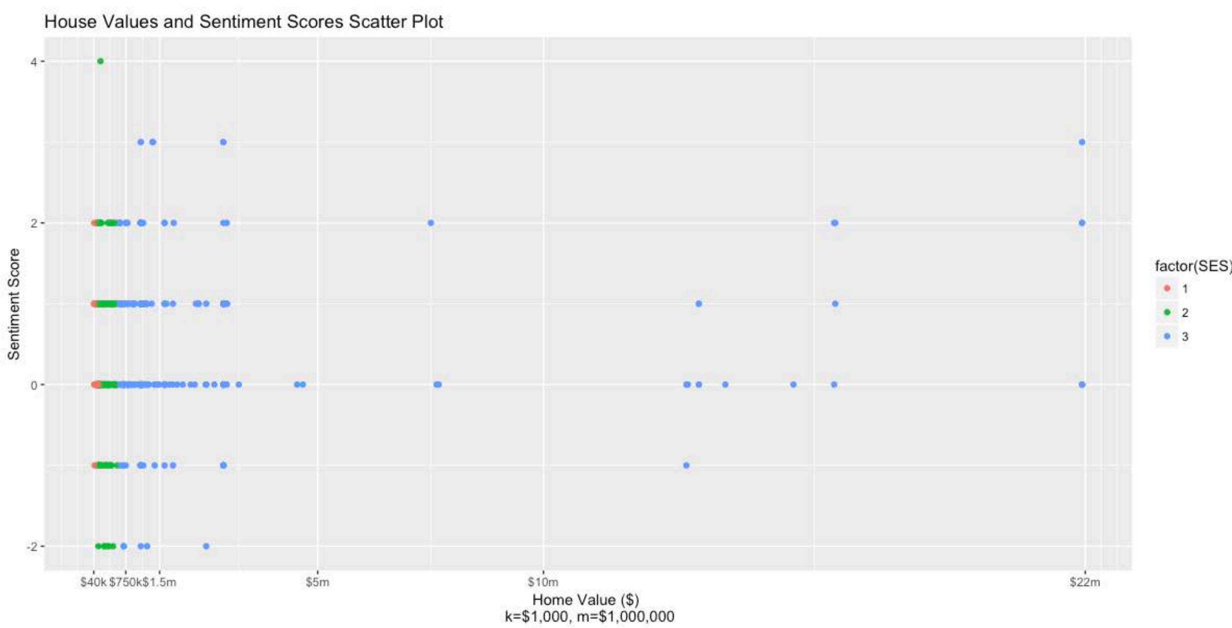


Figure 2: Sentiment Score by House Values Scatter Plot

The various supplemental approaches illustrate the sensitivity of Twitter data to various data and subject limitations. In the supplemental analyses, virtually every sensitivity examined (tweet audience, geographic filters, hashtags, demographic filters, user selectivity) changed the findings from the main analysis in some way. On average, the supplemental analyses minimized the variation between demographic subgroups. The least significant changes were gender confidence filters while the most significant changes were produced by shifting tweet audience (original tweets vs retweets vs mentions) and applying geographic filters. These

[18] Zillow is a real estate marketplace that provides home valuations through the House Search API https://www.zillow.com/howto/api/GetSearchResults.htm. A tweet's geo-location was reverse-geocoded into a street address with the ggmaps package (Kahle and Wickham 2013) and the street addresses were sent to the Zillow API for home value estimates.

supplemental findings suggest that establishing thresholds and filters for "usable data" (e.g., racial confidence thresholds, geographic filters) can improve the accuracy of claims.

Table 11: Supplemental Table

Approach	Overall Findings	Changes to Race Findings	Changes to Gender Findings
Presentation of self	Retweets[19] more positive than original tweets or mentions	All races more positive (no change in order)	Men more positive than women
User selectivity	Individuals with one tweet more positive than users with multiple tweets	No changes	No changes
Subject reliability	Terms that define "physical activity" important	Blacks and Asians more positive than Whites	Men more positive than women
Demographic reliability	No changes from main analysis	All races more positive at the 99th percentile than the 50th	Asian women more positive at the 50th percentile than 99th
Gender reliability	No changes from main analysis	No changes	No changes
Geographic filter (US only tweets)	US tweets different from non US tweets	Blacks and Asians more positive than Whites	No changes
Geographic filter (SES proxy)	Higher value homes associated with more positive sentiment	See Appendix E: small sample sizes	See Appendix E: small sample sizes

5. Conclusion

Some demographic variations MVPA attitudes were observed in this analysis. Tweet sentiment analysis revealed racial differences where Whites and Blacks were equally positive in their discussion of physical activity and more positive than Asians. Gender analysis revealed that women had more positive sentiment than men towards physical activity; the racial and gender results slightly support previous demographic research although the gender findings are more inconsistent than the racial findings. Whites and Blacks had a near equal gender gap in sentiment (.07 and .08) while Asians had the smallest gender gap (.02).

The racial differences in attitudes towards physical activity shown in this study were largely driven by White females and Black males displaying the most positive attitudes towards physical activity. The relatively positive sentiment of Black males relative to White males and females complicates the established relationship between attitudes and physical activity engagement. Attitudinal research suggests that positive health attitudes should correlate with more engagement in physical activity and ultimately lower chronic disease burden; however, results from Black males challenge this established attitudinal relationship. Black males positive attitudes towards physical activity juxtaposed with Black females less positive attitudes adds additional complexity to the attitude-engagement relationship because these subgroups have contrasting attitudes toward physical activity but similar physical activity trends. However, these findings regarding physical activity are sensitive to multiple Twitter data limitations.

[19]retweets: sharing someone else's tweet; tweet: sharing one's own thoughts to all Twitter users; mentions: sharing one's thought with a specific user in mind (can also be visible to other Twitter users) https://support.twitter.com/articles/166337

Supplemental approaches revealed that Twitter data is subject to audience effects (presentation of self), geographic limitations, and subjects reliability. For instance, while the main analysis shows that Black males have a top two average sentiment and Black females have bottom 3 average sentiment, geographic comparisons call this finding into question. In US geo-located tweets, Black females are much more positive than Black males while the inverse is true for the non US geo-located tweets. Future research should strive to incorporate methods that acknowledge the limitations of Twitter that the supplemental analyses demonstrated while also addressing the potential seasonality (e.g., activity preferences and resulting attitudes towards physical activity could change based on time of year). A wider date range in tweets that included several months could remove the potential biases from 5 months.

6. Challenges

While investigating the tweets, multiple potential sources of spuriousness related to Twitter data were identified that suggest further data pre-processing is necessary before calculating sentiment scores. First, specific hashtag searches on Twitter's Streaming API cannot be bound to specific geographic areas. Secondly, due to Twitter's inherent social atmosphere, social phenomena occurring at the same time can appropriate hashtags from other movements. Two hashtags, #pushups and #walking, are emblematic of the locational limitations and discussion conflation that can occur with Twitter data.

#pushups

On October 31st 2016, Imran Khan,leader of the Pakistan Tehreek-i-Insaaf (PTI) party, gained international (viral) attention[20] for doing pushups as a sign of strength before a planned government protest on November 2nd. Imran Khan's followers wrote scathing posts about the Pakistani government and included #pushups in their messages. Given the inability to search for subjects (by hashtag(#) or keyword) and simultaneously limit geographic area, misidentified pushups tweets complicated this study and ultimately all #pushups tweets were removed from the final analysis (See Appendix E for sentiment analysis of removed #pushups tweets).

#walking

Another source of spurious tweets was related to the social interaction that Twitter tries to foster. For instance, viewers of the popular television show Walking Dead use "#walkingdead" to participate in discussions around the television show. However, some Walking Dead viewers used "#walking dead" which is different from "#walkingdead". Because both hashtags to discuss the television show include "#walking", the subject filter gathered these tweets. Ultimately, both instances for referring to the television show Walking Dead were removed from the data. Removing misidentified tweets and applying further scrutiny to the tweet text improves estimates of demographic differences in physical activity.

Third, Twitter users are not obligated to put up a recent or factual photograph as a profile picture. The anonymity provided by the internet makes it easy to pretend to be someone else in online social networks. Users with a fake profile picture could easily confound Face++ demographic background estimates. Fourth, professional organizations communicate with followers via Twitter and early analysis showed that some profile pictures on accounts from these organizations were likely fitness models. These tweets potentially confound the sentiment analysis by providing more positive phrases and increase demographic skewness in representation. However, most individuals are likely to include a picture of their likeness and the analysis removed users with professional organizations in their name. Fifth, this project specified activity terms that were preceded by a hashtag which limits the sample size. While this method was used to exclude incidental physical activity term mentions (e.g. "running late to work"), intentional using physical activity terms without the hashtag symbol leads to substantively relevant tweets being ignored[21].

[20] http://timesofindia.indiatimes.com/world/pakistan/Imran-Khan-does-50-push-ups-as-warm-up-for-November-2-Islamabad-protest/articleshow/55153350.cms

[21] Tweets that use a physical activity keyword, but are not contextually related to physical activity such as "#Trump's #lewd and #obscene talk about #woman,making belittling #vulgar #comments,is last straw on back of the #camel.#Running for #POTUS?" are being removed

Additionally, the specific physical activities followed may reflect cultural preferences and/or environmental constraints that potentially limit the analysis. For instance, Bourdieu (1993) argues that working- and middle-class individuals pursue physical activity in which the body is used to conquer others while the upper-class pursue physical activity for fitness, which helps their professional goals. To that end, some hashtags (#running, #jogging, and #biking) may represent physical activity markers biased toward the upper class. Beyond cultural tastes potential influences, multiple public health studies have found income differences in physical activity such as walking and biking related to built environment that could potentially affect conclusions (Brownson et al. 2001; Ewing et al. 2003; Giles-Corti 2002; Gordon-Larsen et al. 2006; Hoehner et al. 2005). Supplemental analyses explored the variation in attitudes towards a broader physical activity set[22] and used socio-economic status proxies.

Lastly, Twitter is notorious for activity from "socialbot" (also known as "bot") accounts, pre-programmed interactive scripts that appear as humans and "cyborgs" either bot-assisted human or human-assisted bot (Chu et al. 2012; Rouse 2013). Through tailored algorithms, bots and cyborgs can become influential by acquiring numerous followers that retweet content; the extent to which bots are on Twitter and other social media is uncertain (Ferrara et al. 2016; Messias et al. 2013). Its entirely possible that tweets from bots are included in this analysis. Gender dynamics regarding bots may also complicate this analysis. While Freitas et al. (2014) found that there is no significant gender difference in popularity acquired by socialbots in the aggregate, gender was influential for socially connected users posting on the same topic. Additionally, Shafahi, Kempers, and Afsarmanesh (2016) show that content (especially retweeted and duplicated tweets) originating from female twitter bots is shared more frequently than male bots suggesting that retweeted content from profiles with female pictures have a greater bot likelihood. I will identify and remove bot tweets to improve conclusions about attitudinal variation by using the BotOrNot Service developed by Davis et al. (2016). This open source service leverages Twitter users' recent account history to predict the likelihood the user is a bot.

Ongoing improvements to the project include using approaches created by Barbera (2014) and Vicente, Batista, and Carvalho (2016) to further leverage profile data to examine linguistic and demographic concerns. Barbera has produced materials to gather entire timeline data for users. Entire timeline data could clarify the relationship between the Twitter user's language in general and their language when discussing physical activity. For instance, negative tweets about physical activity could illustrate user's negative language in general and not negative attitudes about physical activity per se. Additionally, Vicente et al. (2016) has introduced a text mining approach with an individual's Twitter user name and screen name to aid in gender detection. Incorporating these two approaches will clarify sentiment analysis results and demographic background conclusions.

[22] New search terms such as #boxing, #basketball, #crossfit, #weightlifting, #golf, and #tennis were not added midstream during data collection to maintain continuity.

Appendix A

Examples of Physical Activity Survey Items

Affuso et al. (2011):

1) In order to relieve stress and maintain your health, how important is it for you personally to exercise—is it very important, somewhat important, not very important, or unimportant?; 2) In order to relieve stress and maintain your health, how important is it for you personally to get enough rest and relaxation—is it very important, somewhat important, not very important, or unimportant?; 3) Do you feel there are enough places in your neighborhood to be physically active, such as recreation centers, fitness centers, outdoor space, etc.?; 4) Do you think it is possible for a person to be overweight and still be healthy, or does being overweight mean a person is unhealthy?; 5) Do you agree or disagree with this statement: Exercise is necessary to be healthy.; 6) Do you think that being overweight can increase a person's risk of getting a disease like cancer, or not? Physical Activity participation—During the past month, other than your regular job, did you participate in any physical activities or exercise such as running, aerobics, golf, gardening, or walking for exercise? (pg. 3)

Bozionelos and Bennett (1999):

> "Participants were required to indicate their level of agreement or disagreement with two statements (e.g. for me to participate in regular exercise during the next three weeks is …, etc.), using a seven-point Likert scale used on all the [Theory of Planned Behavior] items except intentions, on three bipolar adjective pairs for each statement (i.e. good/bad, harmful/beneficial and pleasant/unpleasant). The item responses were summed and divided by six to provide a total attitude score" (pg. 520)

Appendix B

Example tweets:

Black women:

Positive: "My happy place! Thankful to be back doing what I love. #RUNNING #fitness #gym #love"
Negative: "Looking forward to rest day tomorrow #shealth still sucks …. not as bad as #running."

White women:

Positive: "what better way to get #motivated clear the mind and improve #wellbeing #walking for health"
Negative: "So I am naive, insecure, fearful, and resent men #darkness #chase #running #rape"

Asian women:

Positive: ""Happiness lies in the joy of achievement and the thrill of creative effort." ~Franklin D. Roosevelt #nopainnogain #itri #running #fitness"
Negative: "Running in cold weather = the worst. Layering up because it's cold, then get boiling hot and can't breathe because the airs so cold #running"

Black men:

Positive: "Nice cool morning and I can't run yet but love seeing others out enjoying it #running #swimbikerun #training #rehab"
Negative: "Shin splints hurt to bad! Just can't get my run in. #running #hurt #fitness"

White men:

Positive: "Today. Be happy. Be joyful. Rejoice. #run #running #runner #rejoice #happy #instahappy #love"
Negative: "My #running is getting worse as I age. So slow! More painful. I still give it what I have which is an aged shuffle!"

Asian men:

Positive: "Walking is great. Walking and talking with a good friend: Bliss #walking #health #disruptsittingtime"
Negative: "Thinking of worries, frustrations & anger, while #running a hard 4km by the sea, watching the"

Appendix C

Activity-specific Counts by Demographic Group

Table 12: Activity Counts and Proportions by Demographic Group

race	gender	#pullups	total	hashtags	counts	prop
Asian	Female	28	7507	#walking	1803	0.24
Asian	Male	42	6864	#walking	1013	0.15
Black	Female	10	2963	#walking	808	0.27
Black	Male	73	6038	#walking	959	0.16
White	Female	199	60824	#walking	11513	0.19
White	Male	327	62982	#walking	9908	0.16
Asian	Female	28	7507	#running	4054	0.54
Asian	Male	42	6864	#running	4149	0.60
Black	Female	10	2963	#running	1470	0.50
Black	Male	73	6038	#running	3173	0.53
White	Female	199	60824	#running	35050	0.58
White	Male	327	62982	#running	36115	0.57
Asian	Female	28	7507	#jogging	236	0.03
Asian	Male	42	6864	#jogging	252	0.04
Black	Female	10	2963	#jogging	91	0.03
Black	Male	73	6038	#jogging	58	0.01
White	Female	199	60824	#jogging	1199	0.02
White	Male	327	62982	#jogging	699	0.01
Asian	Female	28	7507	#biking	175	0.02
Asian	Male	42	6864	#biking	228	0.03
Black	Female	10	2963	#biking	55	0.02
Black	Male	73	6038	#biking	145	0.02
White	Female	199	60824	#biking	1348	0.02
White	Male	327	62982	#biking	1771	0.03
Asian	Female	28	7507	#homeworkouts	8	0.00
Asian	Male	42	6864	#homeworkouts	1	0.00
Black	Female	10	2963	#homeworkouts	1	0.00
Black	Male	73	6038	#homeworkouts	4	0.00
White	Female	199	60824	#homeworkouts	69	0.00
White	Male	327	62982	#homeworkouts	29	0.00
Asian	Female	28	7507	#bodyweightexercises	0	0.00
Asian	Male	42	6864	#bodyweightexercises	1	0.00
Black	Female	10	2963	#bodyweightexercises	1	0.00
Black	Male	73	6038	#bodyweightexercises	0	0.00
White	Female	199	60824	#bodyweightexercises	3	0.00
White	Male	327	62982	#bodyweightexercises	22	0.00
Asian	Female	28	7507	#bodyweightworkouts	0	0.00
Asian	Male	42	6864	#bodyweightworkouts	1	0.00
Black	Female	10	2963	#bodyweightworkouts	0	0.00
Black	Male	73	6038	#bodyweightworkouts	0	0.00
White	Female	199	60824	#bodyweightworkouts	1	0.00
White	Male	327	62982	#bodyweightworkouts	17	0.00

Table 13: Activity Counts by Demographic Group

race	gender	#walking	#biking	#running	#jogging	#pullups	#homeworkouts
Asian	Female	1803	175	4054	236	28	8
Asian	Male	1013	228	4149	252	42	1
Black	Female	808	55	1470	91	10	1
Black	Male	959	145	3173	58	73	4
White	Female	11513	1348	35050	1199	199	69
White	Male	9908	1771	36115	699	327	29

Appendix D

Activity-specific Sentiment Scores

#running

race	gender	mean	sd
Asian	Female	0.30	0.89
Asian	Male	0.26	0.75
Black	Female	0.33	0.86
Black	Male	0.27	0.77
White	Female	0.42	0.93
White	Male	0.32	0.85

#walking

race	gender	mean	sd
Asian	Female	0.17	0.77
Asian	Male	0.21	0.78
Black	Female	0.19	0.70
Black	Male	0.63	0.97
White	Female	0.26	0.90
White	Male	0.25	0.78

#jogging

race	gender	mean	sd
Asian	Female	0.22	0.86
Asian	Male	0.32	0.79
Black	Female	0.18	0.84
Black	Male	0.33	0.82
White	Female	0.16	0.96
White	Male	0.48	1.08

#biking

race	gender	mean	sd
Asian	Female	0.39	0.97
Asian	Male	0.43	0.90
Black	Female	0.07	1.08
Black	Male	0.47	0.73
White	Female	0.37	0.99
White	Male	0.47	0.96

#pullups

race	gender	mean	sd
Asian	Female	0.65	0.83
Asian	Male	0.32	0.81
Black	Female	0.28	0.89
Black	Male	0.25	0.76
White	Female	0.64	0.79
White	Male	0.40	0.88

#homeworkouts

race	gender	mean	sd
Asian	Female	-0.78	0.44
Asian	Male	0.00	NA
Black	Female	0.00	NA
Black	Male	-0.20	0.45
White	Female	0.30	0.77
White	Male	0.25	0.69

#bodyweightexercises

race	gender	mean	sd
Asian	Male	0.50	0.71
Black	Female	-1.00	NA
White	Female	0.33	0.49
White	Male	0.19	0.40

#bodyweightworkouts

race	gender	mean	sd
Asian	Male	0.00	NA
Black	Male	0.00	NA
White	Female	0.15	0.55
White	Male	0.00	0.00

Appendix E

Presentation of self

Mention tweets

race	gender	mean	sd
Asian	Female	0.34	0.87
Asian	Male	0.28	0.79
Black	Female	0.27	0.81
Black	Male	0.38	0.83
White	Female	0.48	0.93
White	Male	0.37	0.85

Retweeted tweets

race	gender	mean	sd
Asian	Female	0.45	1.05
Asian	Male	0.44	1.00
Black	Female	0.46	0.99
Black	Male	0.62	0.99
White	Female	0.53	1.00
White	Male	0.55	1.01

Original tweets

race	gender	mean	sd
Asian	Female	0.22	0.89
Asian	Male	0.27	0.77
Black	Female	0.37	0.90
Black	Male	0.38	0.89
White	Female	0.33	0.96
White	Male	0.30	0.87

Geographic filters

US geolocated tweets

race	gender	mean	sd
Asian	Female	0.36	0.84
Asian	Male	0.33	0.78
Black	Female	0.67	0.98
Black	Male	0.35	0.78
White	Female	0.34	0.86
White	Male	0.32	0.86

non-US geolocated tweets

race	gender	mean	sd
Asian	Female	0.24	0.69
Asian	Male	0.24	0.69
Black	Female	0.26	0.89
Black	Male	0.52	0.80
White	Female	0.42	0.91
White	Male	0.28	0.82

US geolocated tweets (SES proxy)

High-income homes

race	gender	mean	sd
Asian	Female	0.50	0.65
Asian	Male	0.28	0.75
Black	Female	1.00	NA
Black	Male	0.38	0.52
White	Female	0.51	1.00
White	Male	0.42	0.93

Middle-income homes

race	gender	mean	sd
Asian	Female	-0.50	0.71
Asian	Male	1.00	0.00
Black	Female	0.50	0.55
Black	Male	0.20	0.56
White	Female	0.30	0.83
White	Male	0.15	0.78

Low-income homes

race	gender	mean	sd
Asian	Male	0.88	0.83
Black	Female	0.57	0.98
Black	Male	0.25	0.46
White	Female	0.60	0.84
White	Male	0.19	0.46

User selectivity

Users with multiple tweets

race	gender	mean	sd
Asian	Female	0.22	0.83
Asian	Male	0.23	0.71
Black	Female	0.25	0.74
Black	Male	0.42	0.84
White	Female	0.37	0.92
White	Male	0.30	0.81

Users with one tweet

race	gender	mean	sd
Asian	Female	0.38	0.94
Asian	Male	0.33	0.88
Black	Female	0.39	0.95
Black	Male	0.33	0.87
White	Female	0.44	0.97
White	Male	0.40	0.94

Subject reliablity

demographic group	mean	sd
Asian	0.36	1.01
Black	0.37	0.94
White	0.34	1.01
Female	0.30	0.96
Male	0.40	1.05

race	gender	mean	sd
Asian	Female	0.34	1.05
Asian	Male	0.39	0.96
Black	Female	0.43	0.96
Black	Male	0.36	0.93
White	Female	0.29	0.95
White	Male	0.41	1.08

Demographic reliability

Racial reliability

99th percentile

race	gender	mean	sd
Asian	Female	0.20	0.95
Asian	Male	0.33	0.77
Black	Female	0.29	0.83

race	gender	mean	sd
Black	Male	0.39	0.87
White	Female	0.39	0.93
White	Male	0.34	0.87

95th percentile

race	gender	mean	sd
Asian	Female	0.33	0.98
Asian	Male	0.26	0.76
Black	Female	0.32	0.83
Black	Male	0.48	0.91
White	Female	0.40	0.94
White	Male	0.35	0.87

90th percentile

race	gender	mean	sd
Asian	Female	0.30	0.91
Asian	Male	0.28	0.76
Black	Female	0.30	0.81
Black	Male	0.50	0.91
White	Female	0.40	0.94
White	Male	0.34	0.87

85th percentile

race	gender	mean	sd
Asian	Female	0.30	0.90
Asian	Male	0.28	0.76
Black	Female	0.30	0.83
Black	Male	0.45	0.89
White	Female	0.39	0.95
White	Male	0.35	0.87

80th percentile

race	gender	mean	sd
Asian	Female	0.28	0.87
Asian	Male	0.27	0.75
Black	Female	0.29	0.83
Black	Male	0.45	0.87
White	Female	0.39	0.94
White	Male	0.34	0.87

50th percentile

race	gender	mean	sd
Asian	Female	0.29	0.88
Asian	Male	0.27	0.79
Black	Female	0.31	0.84
Black	Male	0.39	0.86
White	Female	0.41	0.95
White	Male	0.34	0.87

Gender reliability

99th percentile

race	gender	mean	sd
Asian	Female	0.27	0.88
Asian	Male	0.28	0.78
Black	Female	0.31	0.90
Black	Male	0.42	0.87
White	Female	0.40	0.94
White	Male	0.33	0.87

95th percentile

race	gender	mean	sd
Asian	Female	0.25	0.86
Asian	Male	0.27	0.78
Black	Female	0.31	0.85
Black	Male	0.40	0.87
White	Female	0.40	0.94
White	Male	0.33	0.86

90th percentile

race	gender	mean	sd
Asian	Female	0.25	0.86
Asian	Male	0.26	0.77
Black	Female	0.31	0.85
Black	Male	0.39	0.86
White	Female	0.40	0.94
White	Male	0.33	0.86

85th percentile

race	gender	mean	sd
Asian	Female	0.25	0.86
Asian	Male	0.27	0.77

race	gender	mean	sd
Black	Female	0.32	0.86
Black	Male	0.39	0.86
White	Female	0.40	0.94
White	Male	0.33	0.86

80th percentile

race	gender	mean	sd
Asian	Female	0.26	0.86
Asian	Male	0.27	0.77
Black	Female	0.31	0.85
Black	Male	0.39	0.85
White	Female	0.40	0.95
White	Male	0.33	0.86

50th percentile

race	gender	mean	sd
Asian	Female	0.29	0.88
Asian	Male	0.27	0.79
Black	Female	0.31	0.84
Black	Male	0.39	0.86
White	Female	0.41	0.95
White	Male	0.34	0.87

Age analysis

age_groups	race	gender	mean	sd
15_19	Asian	Female	0.39	0.88
15_19	Asian	Male	0.37	0.76
15_19	Black	Female	0.14	0.67
15_19	Black	Male	0.40	0.81
15_19	White	Female	0.27	0.94
15_19	White	Male	0.36	0.95
20_24	Asian	Female	0.24	0.90
20_24	Asian	Male	0.21	0.85
20_24	Black	Female	0.30	0.84
20_24	Black	Male	0.33	0.78
20_24	White	Female	0.34	0.90
20_24	White	Male	0.31	0.86
25_29	Asian	Female	0.36	0.91
25_29	Asian	Male	0.21	0.75
25_29	Black	Female	0.27	0.86
25_29	Black	Male	0.34	0.75
25_29	White	Female	0.36	0.96
25_29	White	Male	0.32	0.86
30_34	Asian	Female	0.28	0.89
30_34	Asian	Male	0.28	0.75
30_34	Black	Female	0.32	0.85
30_34	Black	Male	0.26	0.82
30_34	White	Female	0.42	0.96
30_34	White	Male	0.34	0.86
35_39	Asian	Female	0.20	0.93
35_39	Asian	Male	0.30	0.77
35_39	Black	Female	0.42	0.93
35_39	Black	Male	0.36	0.83
35_39	White	Female	0.45	0.96
35_39	White	Male	0.33	0.87
40_44	Asian	Female	0.28	0.88
40_44	Asian	Male	0.38	0.88
40_44	Black	Female	0.45	0.72
40_44	Black	Male	0.47	0.88
40_44	White	Female	0.40	0.91
40_44	White	Male	0.35	0.86
45_49	Asian	Female	0.48	0.86
45_49	Asian	Male	0.31	0.78
45_49	Black	Female	0.67	0.82
45_49	Black	Male	0.66	1.06
45_49	White	Female	0.67	0.91
45_49	White	Male	0.34	0.81
50_54	Asian	Female	0.06	0.48
50_54	Asian	Male	0.25	0.80
50_54	Black	Female	0.23	0.91
50_54	Black	Male	0.82	1.05
50_54	White	Female	0.43	0.88
50_54	White	Male	0.36	0.86
55_59	Asian	Female	0.21	0.65
55_59	Asian	Male	0.26	0.66

age_groups	race	gender	mean	sd
55_59	Black	Female	0.36	0.49
55_59	Black	Male	0.32	0.79
55_59	White	Female	0.34	0.93
55_59	White	Male	0.37	0.85
60_64	Asian	Female	0.38	0.90
60_64	Asian	Male	0.37	0.79
60_64	Black	Female	0.09	0.94
60_64	Black	Male	0.12	0.63
60_64	White	Female	0.36	0.94
60_64	White	Male	0.31	0.81
65_69	Asian	Female	0.11	0.93
65_69	Asian	Male	0.09	0.45
65_69	Black	Female	0.20	0.45
65_69	Black	Male	0.17	0.58
65_69	White	Female	0.51	0.87
65_69	White	Male	0.34	0.86

#pushups

race	gender	mean	sd
Asian	Female	-0.07	1.16
Asian	Male	-0.16	1.18
Black	Female	0.39	1.03
Black	Male	0.05	1.11
White	Female	0.14	1.16
White	Male	-0.14	1.25

References

Abiteboul, Serge. 1997. "Querying Semi-Structured Data." Greece.

Affuso, Olivia, Tiffany L. Cox, Nefertiti H. Durant, and David B. Allison. 2011. "Attitudes and Beliefs Associated with Leisure-Time Physical Activity Among African American Adults." *Ethnicity & Disease* 21(1):63–67.

Agarwal, Apoorv, Boyi Xie, Ilia Vovsha, Owen Rambow, and Rebecca Passonneau. 2011. "Sentiment Analysis of Twitter Data." Pp. 30–38 in *Proceedings of the workshop on languages in social media, LSM '11*. Portland, Oregon: Association for Computational Linguistics. Retrieved (http://dl.acm.org/citation.cfm?id=2021109.2021114).

Airhihenbuwa, Collins O., Shiriki Kumanyika, Tanya D. Agurs, and Agatha Lowe. 1995. "Perceptions and Beliefs About Exercise, Rest, and Health Among African-Americans." *American Journal of Health Promotion* 9(6):426–29. Retrieved August 10, 2016 (http://ajhpcontents.org/doi/abs/10.4278/0890-1171-9.6.426).

Ajzen, Icek. 1991. "The Theory of Planned Behavior." *Organizational behavior and human decision processes* 50(2):179–211. Retrieved August 10, 2016 (http://www.sciencedirect.com/science/article/pii/074959789190020T).

Ajzen, Icek and Christine Timko. 1986. "Correspondence Between Health Attitudes and Behavior." *Basic and Applied Social Psychology* 7(4):259–76. Retrieved August 10, 2016 (http://www.tandfonline.com/doi/abs/10.1207/s15324834basp0704_2).

Arseniev-Koehler, Alina, Hedwig Lee, Tyler McCormick, and Megan A. Moreno. 2016. "#Proana: Pro-Eating Disorder Socialization on Twitter." *Journal of Adolescent Health* 58(6):659–64. Retrieved March 6, 2017 (http://linkinghub.elsevier.com/retrieve/pii/S1054139X16000598).

Azjen, Icek. 1985. "From Intentions to Actions: A Theory of Planned Behavior." in *Action control: From cognition to behavior*, *Springer series in social psychology*, edited by J. Kuhl and J. Beckmann. Berlin: Springer.

Bakhshi, Saeideh, David A. Shamma, and Eric Gilbert. 2014. "Faces Engage Us: Photos with Faces Attract More Likes and Comments on Instagram." Pp. 965–74 in. ACM Press. Retrieved February 17, 2017 (http://dl.acm.org/citation.cfm?doid=2556288.2557403).

Baptiste-Roberts, Kesha et al. 2007. "Family History of Diabetes, Awareness of Risk Factors, and Health Behaviors Among African Americans." *American Journal of Public Health* 97(5):907–12. Retrieved August 10, 2016 (http://ajph.aphapublications.org/doi/abs/10.2105/AJPH.2005.077032).

Barbera, Pablo. 2014. *streamR: Access to Twitter Streaming API via R.* Retrieved (https://CRAN.R-project.org/package=streamR).

Bourdieu, Pierre. 1993. "How Can One Be a Sports Fan." *The cultural studies reader* 2:427–40.

Boyington, J. E. A., D. L. Howard, and D. N. Holmes. 2008. "Self-Rated Health, Activities of Daily Living, and Mobility Limitations Among Black and White Stroke Survivors." *Journal of Aging and Health* 20(8):920–36. Retrieved August 10, 2016 (http://jah.sagepub.com/cgi/doi/10.1177/0898264308324643).

Bozionelos, G. and P. Bennett. 1999. "The Theory of Planned Behaviour as Predictor of Exercise: The Moderating Influence of Beliefs and Personality Variables." *Journal of Health Psychology* 4(4):517–29. Retrieved August 22, 2016 (http://hpq.sagepub.com/cgi/doi/10.1177/135910539900400406).

Breen, Jeffrey Oliver. 2012. "Mining Twitter for Airline Consumer Sentiment." *Practical text mining and statistical analysis for non-structured text data applications* 133.

Brenes, Gretchen A., Michael J. Strube, and Martha Storandt. 1998. "An Application of the Theory of Planned Behavior to Exercise Among Older Adults1." *Journal of Applied Social Psychology* 28(24):2274–90. Retrieved August 22, 2016 (http://doi.wiley.com/10.1111/j.1559-1816.1998.tb01371.x).

Brownson, Ross C., Elizabeth A. Baker, Robyn A. Housemann, Laura K. Brennan, and Stephen J. Bacak.

2001. “Environmental and Policy Determinants of Physical Activity in the United States.” *American Journal of Public Health* 91(12):1995–2003. Retrieved February 17, 2017 (http://ajph.aphapublications.org/doi/10.2105/AJPH.91.12.1995).

Buhrmester, Michael, Tracy Kwang, and Samuel D. Gosling. 2011. “Amazon’s Mechanical Turk: A New Source of Inexpensive, yet High-Quality, Data?” *Perspectives on Psychological Science* 6(1):3–5. Retrieved February 21, 2017 (http://journals.sagepub.com/doi/10.1177/1745691610393980).

Cavallo, David N. et al. 2012. “A Social Media–Based Physical Activity Intervention.” *American Journal of Preventive Medicine* 43(5):527–32. Retrieved October 31, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S074937971200520X).

Cesare, Nina, Tyler McCormick, Emma S. Spiro, and Emilio Zagheni. 2016. “Promises and Pitfalls of Using Digital Traces for Demographic Research.” *SSRN Electronic Journal*. Retrieved October 23, 2016 (http://www.ssrn.com/abstract=2839585).

Chowdhury, Gobinda G. 2005. “Natural Language Processing.” *Annual Review of Information Science and Technology* 37(1):51–89. Retrieved November 7, 2016 (http://doi.wiley.com/10.1002/aris.1440370103).

Chu, Zi, Steven Gianvecchio, Haining Wang, and Sushil Jajodia. 2012. “Detecting Automation of Twitter Accounts: Are You a Human, Bot, or Cyborg?” *IEEE Transactions on Dependable and Secure Computing* 9(6):811–24. Retrieved February 15, 2017 (http://ieeexplore.ieee.org/document/6280553/).

Clark, Daniel O. and Faryle Nothwehr. 1999. “Exercise Self-Efficacy and Its Correlates Among Socioeconomically Disadvantaged Older Adults.” *Health Education & Behavior* 26(4):535–46. Retrieved August 10, 2016 (http://heb.sagepub.com/content/26/4/535.short).

Cossrow, Nicole and Bonita Falkner. 2004. “Race/Ethnic Issues in Obesity and Obesity-Related Comorbidities.” *The Journal of Clinical Endocrinology & Metabolism* 89(6):2590–4. Retrieved November 13, 2016 (http://press.endocrine.org/doi/10.1210/jc.2004-0339).

Courneya, Kerry S., Ronald C. Plotnikoff, Stephen B. Hotz, and Nicholas J. Birkett. 2000. “Social Support and the Theory of Planned Behavior in the Exercise Domain.” *American Journal of Health Behavior* 24(4):300–308. Retrieved August 24, 2016 (http://openurl.ingenta.com/content/xref?genre=article&issn=1087-3244&volume=24&issue=4&spage=300).

Courtenay, Will H., Donald R. McCreary, and Joseph R. Merighi. 2002. “Gender and Ethnic Differences in Health Beliefs and Behaviors.” *Journal of health psychology* 7(3):219–31. Retrieved August 10, 2016 (http://hpq.sagepub.com/content/7/3/219.short).

Crenshaw, Kimberle. 1991. “Mapping the Margins: Intersectionality, Identity Politics, and Violence Against Women of Color.” *Stanford Law Review* 43(6):1241. Retrieved October 24, 2016 (http://www.jstor.org/stable/1229039?origin=crossref).

Crespo, Carlos J., Ellen Smit, Ross E. Andersen, Olivia Carter-Pokras, and Barbara E. Ainsworth. 2000. “Race/Ethnicity, Social Class and Their Relation to Physical Inactivity During Leisure Time: Results from the Third National Health and Nutrition Examination Survey, 1988–1994.” *American journal of preventive medicine* 18(1):46–53. Retrieved August 10, 2016 (http://www.sciencedirect.com/science/article/pii/S0749379799001051).

Davis, Clayton Allen, Onur Varol, Emilio Ferrara, Alessandro Flammini, and Filippo Menczer. 2016. “BotOrNot: A System to Evaluate Social Bots.” Pp. 273–74 in. ACM Press. Retrieved February 15, 2017 (http://dl.acm.org/citation.cfm?doid=2872518.2889302).

De Choudhury, Munmun. 2014. “Opportunities of Social Media in Health and Well-Being.” *XRDS: Crossroads, The ACM Magazine for Students* 21(2):23–27. Retrieved August 10, 2016 (http://dl.acm.org/citation.cfm?doid=2701297.2676570).

De Choudhury, Munmun, Scott Counts, and Eric Horvitz. 2013. “Social Media as a Measurement Tool of Depression in Populations.” Pp. 47–56 in *Proceedings of the 5th annual ACM web science conference*. ACM.

Retrieved August 10, 2016 (http://dl.acm.org/citation.cfm?id=2464480).

De Choudhury, Munmun, Michael Gamon, Aaron Hoff, and Asta Roseway. 2013. "'Moon Phrases': A Social Media Faciliated Tool for Emotional Reflection and Wellness." Pp. 41–44 in *2013 7th international conference on pervasive computing technologies for healthcare and workshops*. IEEE. Retrieved August 10, 2016 (http://ieeexplore.ieee.org/xpls/abs_all.jsp?arnumber=6563900).

De Choudhury, Munmun, Sanket Sharma, and Emre Kiciman. 2016. "Characterizing Dietary Choices, Nutrition, and Language in Food Deserts via Social Media." Pp. 1155–68 in. ACM Press. Retrieved August 10, 2016 (http://dl.acm.org/citation.cfm?doid=2818048.2819956).

Dietz, W. H. 1998. "Health Consequences of Obesity in Youth: Childhood Predictors of Adult Disease." *Pediatrics* 101(3):518–25.

Dos Reis, Virgile Landeiro and Aron Culotta. 2015. "Using Matched Samples to Estimate the Effects of Exercise on Mental Health from Twitter." Pp. 182–88 in *Proceedings of the twenty-ninth AAAI conference on artificial intelligence*. Retrieved August 10, 2016 (http://www.cs.iit.edu/~culotta/pubs/virgile15using.pdf).

Dwyer, John J. M. et al. 2006. "Adolescent Girls' Perceived Barriers to Participation in Physical Activity." *Adolescence* 41(161):75–89.

Egede, Leonard E. and Ramita J. Bonadonna. 2003. "Diabetes Self-Management in African Americans: An Exploration of the Role of Fatalism." *The Diabetes Educator* 29(1):105–15.

Eichstaedt, Johannes C. et al. 2015. "Psychological Language on Twitter Predicts County-Level Heart Disease Mortality." *Psychological science* 26(2):159–69. Retrieved August 10, 2016 (http://pss.sagepub.com/content/26/2/159.short).

Ewing, Reid, Tom Schmid, Richard Killingsworth, Amy Zlot, and Stephen Raudenbush. 2003. "Relationship Between Urban Sprawl and Physical Activity, Obesity, and Morbidity." *American Journal of Health Promotion* 18(1):47–57. Retrieved February 17, 2017 (http://ajhpcontents.org/doi/abs/10.4278/0890-1171-18.1.47).

Eyler, Amy A. et al. 1998. "Physical Activity and Minority Women: A Qualitative Study." *Health Education & Behavior* 25(5):640–52. Retrieved August 10, 2016 (http://heb.sagepub.com/content/25/5/640.short).

Eyler, Amy E. et al. 2002. "Correlates of Physical Activity Among Women from Diverse Racial/Ethnic Groups." *Journal of Women's Health & Gender-Based Medicine* 11(3):239–53.

Ferrara, Emilio, Onur Varol, Clayton Davis, Filippo Menczer, and Alessandro Flammini. 2016. "The Rise of Social Bots." *Communications of the ACM* 59(7):96–104. Retrieved February 15, 2017 (http://dl.acm.org/citation.cfm?doid=2963119.2818717).

Foster, Charles, Melvyn Hillsdon, Margaret Thorogood, Asha Kaur, and Thamindu Wedatilake. 2005. "Interventions for Promoting Physical Activity." in *Cochrane database of systematic reviews*, edited by The Cochrane Collaboration. Chichester, UK: John Wiley & Sons, Ltd. Retrieved October 27, 2016 (http://doi.wiley.com/10.1002/14651858.CD003180.pub2).

Freitas, Carlos A., Fabrício Benevenuto, Saptarshi Ghosh, and Adriano Veloso. 2014. "Reverse Engineering Socialbot Infiltration Strategies in Twitter." *CoRR* abs/1405.4927. Retrieved (http://arxiv.org/abs/1405.4927).

French, David P. et al. 2005. "The Importance of Affective Beliefs and Attitudes in the Theory of Planned Behavior: Predicting Intention to Increase Physical Activity1." *Journal of Applied Social Psychology* 35(9):1824–48. Retrieved September 22, 2016 (http://doi.wiley.com/10.1111/j.1559-1816.2005.tb02197.x).

Gentry, Jeff. 2015. *twitteR: R Based Twitter Client*. Retrieved (https://CRAN.R-project.org/package=twitteR).

Giles-Corti, B. 2002. "Socioeconomic Status Differences in Recreational Physical Activity Levels and Real and Perceived Access to a Supportive Physical Environment." *Preventive Medicine* 35(6):601–11. Retrieved

February 17, 2017 (http://linkinghub.elsevier.com/retrieve/pii/S0091743502911151).

Giles-Corti, Billie and Robert J. Donovan. 2002. "The Relative Influence of Individual, Social and Physical Environment Determinants of Physical Activity." *Social Science & Medicine (1982)* 54(12):1793–1812.

Godin, G. and R. J. Shephard. 1985. "A Simple Method to Assess Exercise Behavior in the Community." *Canadian Journal of Applied Sport Sciences. Journal Canadien Des Sciences Appliquées Au Sport* 10(3):141–46.

Godin, G., P. Valois, R. J. Shephard, and R. Desharnais. 1987. "Prediction of Leisure-Time Exercise Behavior: A Path Analysis (LISREL V) Model." *Journal of Behavioral Medicine* 10(2):145–58.

Gordon-Larsen, Penny, Melissa C. Nelson, Phil Page, and Barry M. Popkin. 2006. "Inequality in the Built Environment Underlies Key Health Disparities in Physical Activity and Obesity." *Pediatrics* 117(2):417–24.

Gore, Ross Joseph, Saikou Diallo, and Jose Padilla. 2015. "You Are What You Tweet: Connecting the Geographic Variation in America's Obesity Rate to Twitter Content" edited by D. Meyre. *PLOS ONE* 10(9):e0133505. Retrieved August 10, 2016 (http://dx.plos.org/10.1371/journal.pone.0133505).

Grieser, M. et al. 2006. "Physical Activity Attitudes, Preferences, and Practices in African American, Hispanic, and Caucasian Girls." *Health Education & Behavior* 33(1):40–51. Retrieved August 10, 2016 (http://heb.sagepub.com/cgi/doi/10.1177/1090198105282416).

Guthman, Julie. 2008. "'If They Only Knew': Color Blindness and Universalism in California Alternative Food Institutions." *The Professional Geographer* 60(3):387–97. Retrieved August 10, 2016 (http://www.tandfonline.com/doi/abs/10.1080/00330120802013679).

Hagger, Martin S., Nikos L. D. Chatzisarantis, Trudi Culverhouse, and Stuart J. H. Biddle. 2003. "The Processes by Which Perceived Autonomy Support in Physical Education Promotes Leisure-Time Physical Activity Intentions and Behavior: A Trans-Contextual Model." *Journal of Educational Psychology* 95(4):784–95. Retrieved August 10, 2016 (http://doi.apa.org/getdoi.cfm?doi=10.1037/0022-0663.95.4.784).

Hagger, Martin S., Nikos L.D. Chatzisarantis, and Stuart J.H. Biddle. 2002. "A Meta-Analytic Review of the Theories of Reasoned Action and Planned Behavior in Physical Activity: Predictive Validity and the Contribution of Additional Variables." *Journal of Sport and Exercise Psychology* 24(1):3–32. Retrieved August 23, 2016 (http://journals.humankinetics.com/doi/10.1123/jsep.24.1.3).

Harden, A. 2004. "Applying Systematic Review Methods to Studies of People's Views: An Example from Public Health Research." *Journal of Epidemiology & Community Health* 58(9):794–800. Retrieved August 10, 2016 (http://jech.bmj.com/cgi/doi/10.1136/jech.2003.014829).

Haskell, William L. et al. 2007. "Physical Activity and Public Health: Updated Recommendation for Adults from the American College of Sports Medicine and the American Heart Association." *Medicine & Science in Sports & Exercise* 39(8):1423–34. Retrieved August 23, 2016 (http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-200708000-00027).

Hawn, C. 2009. "Take Two Aspirin and Tweet Me in the Morning: How Twitter, Facebook, and Other Social Media Are Reshaping Health Care." *Health Affairs* 28(2):361–68. Retrieved August 10, 2016 (http://content.healthaffairs.org/cgi/doi/10.1377/hlthaff.28.2.361).

Hayes, Sean, Peter Crocker, and Kent Kowalski. 1999. "Gender Differences in Physical Self-Perceptions, Global Self-Esteem and Physical Activity: Evaluation of the Physical Self-Perception Profile Model." *Journal of Sport Behavior* 22(1):1–14.

He, Qian, Emmanuel Agu, Diane Strong, Bengisu Tulu, and Peder Pedersen. 2013. "Characterizing the Performance and Behaviors of Runners Using Twitter." Pp. 406–14 in. IEEE. Retrieved August 10, 2016 (http://ieeexplore.ieee.org/lpdocs/epic03/wrapper.htm?arnumber=6680503).

Hendelman, D., K. Miller, C. Baggett, E. Debold, and P. Freedson. 2000. "Validity of Accelerometry for the Assessment of Moderate Intensity Physical Activity in the Field:" *Medicine & Science in Sports &*

Exercise 32(Supplement):S442–S449. Retrieved August 22, 2016 (http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00005768-200009001-00002).

Henderson, Karla A. and Barbara E. Ainsworth. 2003. “A Synthesis of Perceptions About Physical Activity Among Older African American and American Indian Women.” *American Journal of Public Health* 93(2):313–17.

Hoehner, Christine M., Laura K. Brennan Ramirez, Michael B. Elliott, Susan L. Handy, and Ross C. Brownson. 2005. “Perceived and Objective Environmental Measures and Physical Activity Among Urban Adults.” *American Journal of Preventive Medicine* 28(2):105–16. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0749379704003034).

Hogan, B. 2010. “The Presentation of Self in the Age of Social Media: Distinguishing Performances and Exhibitions Online.” *Bulletin of Science, Technology & Society* 30(6):377–86. Retrieved November 6, 2016 (http://bst.sagepub.com/cgi/doi/10.1177/0270467610385893).

Hu, Minqing and Bing Liu. 2004. “Mining and Summarizing Customer Reviews.” P. 168 in. ACM Press. Retrieved February 21, 2017 (http://portal.acm.org/citation.cfm?doid=1014052.1014073).

Huang, Wenyi, Ingmar Weber, and Sarah Vieweg. 2014. “Inferring Nationalities of Twitter Users and Studying Inter-National Linking.” Pp. 237–42 in. ACM Press. Retrieved February 17, 2017 (http://dl.acm.org/citation.cfm?doid=2631775.2631825).

Im, Eun-Ok et al. 2013. “Racial/Ethnic Differences in Midlife Women’s Attitudes Toward Physical Activity.” *Journal of Midwifery & Women’s Health* 58(4):440–50. Retrieved August 21, 2016 (http://doi.wiley.com/10.1111/j.1542-2011.2012.00259.x).

Im, Eun-Ok et al. 2010. “‘A Waste of Time’: Hispanic Women’s Attitudes Toward Physical Activity.” *Women & Health* 50(6):563–79. Retrieved August 22, 2016 (http://www.tandfonline.com/doi/abs/10.1080/03630242.2010.510387).

Im et al. 2012. “A National Internet Survey on Midlife Women’s Attitudes Toward Physical Activity.” *Nursing Research* 61(5):342–52. Retrieved August 21, 2016 (http://content.wkhealth.com/linkback/openurl?sid=WKPTLP:landingpage&an=00006199-201209000-00005).

Im, Wonshik Chee, Hyun-Ju Lim, Yi Liu, and Hee Kyung Kim. 2008. “Midlife Women’s Attitudes Toward Physical Activity.” *Journal of Obstetric, Gynecologic & Neonatal Nursing* 37(2):203–13. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0884217515300630).

Im, O. K. Ham, E. Chee, and W. Chee. 2015. “Physical Activity and Depressive Symptoms in Four Ethnic Groups of Midlife Women.” *Western Journal of Nursing Research* 37(6):746–66. Retrieved August 21, 2016 (http://wjn.sagepub.com/cgi/doi/10.1177/0193945914537123).

Im et al. 2012. “‘Physical Activity as a Luxury’: African American Women’s Attitudes Toward Physical Activity.” *Western Journal of Nursing Research* 34(3):317–39. Retrieved August 21, 2016 (http://wjn.sagepub.com/cgi/doi/10.1177/0193945911400637).

Imai, Kosuke and Kabir Khanna. 2016. “Improving Ecological Inference by Predicting Individual Ethnicity from Voter Registration Records.” *Political Analysis* 24(2):263–72. Retrieved February 17, 2017 (https://www.cambridge.org/core/product/identifier/S1047198700010962/type/journal_article).

Jang, Jin Yea, Kyungsik Han, Dongwon Lee, Haiyan Jia, and Patrick C. Shih. 2016. “Teens Engage More with Fewer Photos: Temporal and Comparative Analysis on Behaviors in Instagram.” Pp. 71–81 in. ACM Press. Retrieved February 17, 2017 (http://dl.acm.org/citation.cfm?doid=2914586.2914602).

Johnson, Mark R. D. 2000. “Perceptions of Barriers to Healthy Physical Activity Among Asian Communities.” *Sport, Education and Society* 5(1):51–70. Retrieved November 8, 2016 (http://www.tandfonline.com/doi/abs/10.1080/135733200114433).

Kahle, David and Hadley Wickham. 2013. “Ggmap: Spatial Visualization with Ggplot2.” *The R Journal*

5(1):144–61. Retrieved (http://journal.r-project.org/archive/2013-1/kahle-wickham.pdf).

Kandula, Namratha R. and Diane S. Lauderdale. 2005. "Leisure Time, Non-Leisure Time, and Occupational Physical Activity in Asian Americans." *Annals of Epidemiology* 15(4):257–65. Retrieved November 8, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S1047279704002443).

Kaplan, Andreas M. and Michael Haenlein. 2010. "Users of the World, Unite! The Challenges and Opportunities of Social Media." *Business Horizons* 53(1):59–68. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0007681309001232).

Khanna, Kabir and Kosuke Imai. 2016. *Wru: Who Are You? Bayesian Prediction of Racial Category Using Surname and Geolocation*. Retrieved (https://CRAN.R-project.org/package=wru).

King, A. C. 2001. "Interventions to Promote Physical Activity by Older Adults." *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences* 56(Supplement 2):36–46. Retrieved August 10, 2016 (http://biomedgerontology.oxfordjournals.org/cgi/doi/10.1093/gerona/56.suppl_2.36).

Kiritchenko, Svetlana, Xiaodan Zhu, and Saif M. Mohammad. 2014. "Sentiment Analysis of Short Informal Texts." *J. Artif. Int. Res.* 50(1):723–62. Retrieved (http://dl.acm.org/citation.cfm?id=2693068.2693087).

Kouloumpis, Efthymios, Theresa Wilson, and Johanna Moore. 2011. "Twitter Sentiment Analysis: The Good the Bad and the Omg!" Pp. 538–41 in *Roceedings of the fifth international AAAI conference on weblogs and social media*. Association for the Advancement of Artificial Intelligence.

Krause, N. M. and G. M. Jay. 1994. "What Do Global Self-Rated Health Items Measure?" *Medical Care* 32(9):930–42.

Krämer, Nicole C. and Stephan Winter. 2008. "Impression Management 2.0: The Relationship of Self-Esteem, Extraversion, Self-Efficacy, and Self-Presentation Within Social Networking Sites." *Journal of Media Psychology* 20(3):106–16. Retrieved November 6, 2016 (http://econtent.hogrefe.com/doi/abs/10.1027/1864-1105.20.3.106).

Lamont, Michèle and Virág Molnár. 2002. "The Study of Boundaries in the Social Sciences." *Annual Review of Sociology* 28(1):167–95. Retrieved August 10, 2016 (http://www.annualreviews.org/doi/10.1146/annurev.soc.28.110601.141107).

Lavizzo-Mourey, R. et al. 2001. "Attitudes and Beliefs About Exercise Among Elderly African Americans in an Urban Community." *Journal of the National Medical Association* 93(12):475–80.

Lee, I. M. and R. S. Paffenbarger. 2000. "Associations of Light, Moderate, and Vigorous Intensity Physical Activity with Longevity. the Harvard Alumni Health Study." *American Journal of Epidemiology* 151(3):293–99.

Liu, Bing, Minqing Hu, and Junsheng Cheng. 2005. "Opinion Observer: Analyzing and Comparing Opinions on the Web." P. 342 in. ACM Press. Retrieved February 21, 2017 (http://portal.acm.org/citation.cfm?doid=1060745.1060797).

Mabry, Iris et al. 2003. "Physical Activity Attitudes of African American and White Adolescent Girls." *Ambulatory Pediatrics* 3(6):312–16.

Mathews, Anna E. et al. 2010. "Older Adults' Perceived Physical Activity Enablers and Barriers: A Multicultural Perspective." *Journal of Aging and Physical Activity* 18(2):119–40.

McCormick, T. H., H. Lee, N. Cesare, A. Shojaie, and E. S. Spiro. 2015. "Using Twitter for Demographic and Social Science Research: Tools for Data Collection and Processing." *Sociological Methods & Research*. Retrieved August 28, 2016 (http://smr.sagepub.com/cgi/doi/10.1177/0049124115605339).

Mcguire, M., P. Hannan, D. Neumarksztainer, N. Cossrow, and M. Story. 2002. "Parental Correlates of Physical Activity in a Racially/Ethnically Diverse Adolescent Sample." *Journal of Adolescent Health* 30(4):253–61. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S1054139X01003925).

Messias, Johnnatan, Lucas Schmidt, Ricardo Oliveira, and Fabrício Benevenuto. 2013. "You Followed My

Bot! Transforming Robots into Influential Users in Twitter." *First Monday* 18(7). Retrieved February 15, 2017 (http://firstmonday.org/ojs/index.php/fm/article/view/4217).

Motalebi, Seyedeh Ameneh, Jamileh Amirzadeh Iranagh, Abbas Abdollahi, and Lim. 2014. "Applying of Theory of Planned Behavior to Promote Physical Activity and Exercise Behavior Among Older Adults." *Journal of Physical Education and Sport* 14(4):562–68.

Müller, Oliver, Iris Junglas, Jan vom Brocke, and Stefan Debortoli. 2016. "Utilizing Big Data Analytics for Information Systems Research: Challenges, Promises and Guidelines." *European Journal of Information Systems* 25(4):289–302. Retrieved November 12, 2016 (http://link.springer.com/10.1057/ejis.2016.2).

Nguyen, Quynh C. et al. 2016. "Leveraging Geotagged Twitter Data to Examine Neighborhood Happiness, Diet, and Physical Activity." *Applied Geography* 73:77–88. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0143622816301394).

Pak, Alexander and Patrick Paroubek. 2010. "Twitter as a Corpus for Sentiment Analysis and Opinion Mining." in *Proceedings of the international conference on language resources and evaluation.* Valleta, Malta.

Pang, Bo and Lillian Lee. 2008. "Opinion Mining and Sentiment Analysis." *Foundations and Trends® in Information Retrieval* 2(1):1–135. Retrieved November 7, 2016 (http://www.nowpublishers.com/article/Details/INR-011).

Papacharissi, Zizi. 2012. "Without You, I'm Nothing: Performances of the Self on Twitter." *International Journal of Communication* 6. Retrieved (http://ijoc.org/index.php/ijoc/article/view/1484).

Park, Kunwoo, Ingmar Weber, Meeyoung Cha, and Chul Lee. 2016. "Persistent Sharing of Fitness App Status on Twitter." Pp. 183–93 in. ACM Press. Retrieved August 10, 2016 (http://dl.acm.org/citation.cfm?doid=2818048.2819921).

Pate, R. R. et al. 1995. "Physical Activity and Public Health. a Recommendation from the Centers for Disease Control and Prevention and the American College of Sports Medicine." *JAMA* 273(5):402–7.

Paul, Michael and Mark Dredze. 2011. "You Are What You Tweet: Analyzing Twitter for Public Health"." Pp. 265–72 in *Proceedings of the fifth international AAAI.* Retrieved (http://www.aaai.org/ocs/index.php/ICWSM/ICWSM11/paper/view/2880).

Popay, J., A. Rogers, and G. Williams. 1998. "Rationale and Standards for the Systematic Review of Qualitative Literature in Health Services Research." *Qualitative Health Research* 8(3):341–51.

R Core Team. 2016. *R: A Language and Environment for Statistical Computing.* Vienna, Austria: R Foundation for Statistical Computing. Retrieved (https://www.R-project.org/).

Rhue, Lauren and Jessica Clark. 2016. "Who Gets Started on Kickstarter? Racial Disparities in Crowdfunding Success." *SSRN Electronic Journal.* Retrieved February 17, 2017 (http://www.ssrn.com/abstract=2837042).

Rouse, M. 2013. "What Is Socialbot? - Definition from WhatIs.com." Retrieved February 15, 2017 (http://whatis.techtarget.com/definition/socialbot).

Scanfeld, Daniel, Vanessa Scanfeld, and Elaine L. Larson. 2010. "Dissemination of Health Information Through Social Networks: Twitter and Antibiotics." *American Journal of Infection Control* 38(3):182–88. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0196655310000349).

Schwarz, Susan Wile and Jason Peterson. 2010. *Adolescent Obesity in the United States: Facts for Policymakers.* New York: Columbia University. National Center for Children in Poverty, Mailman School of Public Health, Columbia University. Retrieved (http://hdl.handle.net/10022/AC:P:10726).

Shafahi, Mohammad, Leon Kempers, and Hamideh Afsarmanesh. 2016. "Phishing Through Social Bots on Twitter." Pp. 3703–12 in. IEEE. Retrieved February 15, 2017 (http://ieeexplore.ieee.org/document/

7841038/).

Siddiqi, Z., J. A. Tiro, and K. Shuval. 2011. "Understanding Impediments and Enablers to Physical Activity Among African American Adults: A Systematic Review of Qualitative Studies." *Health Education Research* 26(6):1010–24. Retrieved August 10, 2016 (http://www.her.oxfordjournals.org/cgi/doi/10.1093/her/cyr068).

Sloan, Luke et al. 2013. "Knowing the Tweeters: Deriving Sociologically Relevant Demographics from Twitter." *Sociological Research Online* 18(3). Retrieved February 21, 2017 (http://www.socresonline.org.uk/18/3/7.html).

Smedley, Brian, Adrienne Stith, and Alan Nelson. 2003. *Unequal Treatment Confronting Racial and Ethnic Disparities in Healthcare.* Washington: National Academies Press. Retrieved August 10, 2016 (http://public.eblib.com/choice/publicfullrecord.aspx?p=3378816).

Smith, Aaron and Joanna Brenner. 2012. "Twitter Use 2012." *Pew Internet & American Life Project* 4.

Stephens, Thomas, David Jacobs Jr., and Craig White. 1985. "A Descriptive Epidemiology of Leisure-Time Physical Activity."*Public health reports* 100(2):147–58.

Streiner, David L., Geoffrey R. Norman, and John Cairney. 2015. *Health Measurement Scales: A Practical Guide to Their Development and Use.* Fifth edition. Oxford: Oxford University Press.

Tammelin, Tuija, Simo Näyhä, Andrew P. Hills, and Marjo Riitta Järvelin. 2003. "Adolescent Participation in Sports and Adult Physical Activity." *American Journal of Preventive Medicine* 24(1):22–28.

Trost, Stewart G., Neville Owen, Adrian E. Bauman, James F. Sallis, and Wendy Brown. 2002. "Correlates of Adults' Participation in Physical Activity: Review and Update." *Medicine and Science in Sports and Exercise* 34(12):1996–2001.

Tucker, Jared M., Gregory J. Welk, and Nicholas K. Beyler. 2011. "Physical Activity in U.S. Adults." *American Journal of Preventive Medicine* 40(4):454–61. Retrieved August 10, 2016 (http://linkinghub.elsevier.com/retrieve/pii/S0749379711000122).

Turner-McGrievy, G. M. et al. 2013. "Comparison of Traditional Versus Mobile App Self-Monitoring of Physical Activity and Dietary Intake Among Overweight Adults Participating in an mHealth Weight Loss Program." *Journal of the American Medical Informatics Association* 20(3):513–18. Retrieved August 10, 2016 (http://jamia.oxfordjournals.org/cgi/doi/10.1136/amiajnl-2012-001510).

Unger, Jennifer B. et al. 2004. "Acculturation, Physical Activity, and Fast-Food Consumption Among Asian-American and Hispanic Adolescents." *Journal of Community Health* 29(6):467–81. Retrieved November 8, 2016 (http://link.springer.com/10.1007/s10900-004-3395-3).

Versey, H. Shellae. 2014. "Centering Perspectives on Black Women, Hair Politics, and Physical Activity." *American Journal of Public Health* 104(5):810–15. Retrieved August 10, 2016 (http://ajph.aphapublications.org/doi/abs/10.2105/AJPH.2013.301675).

Vicente, Marco, Fernando Batista, and Joao Paulo Carvalho. 2016. "Creating Extended Gender Labelled Datasets of Twitter Users." Pp. 690–702 in *Information processing and management of uncertainty in knowledge-based systems*, vol. 611, edited by J. P. Carvalho et al. Cham: Springer International Publishing. Retrieved February 17, 2017 (http://link.springer.com/10.1007/978-3-319-40581-0_56).

Voas, David. 2014. "Towards a Sociology of Attitudes." *Sociological Research Online* 19(1). Retrieved October 14, 2016 (http://www.socresonline.org.uk/19/1/12.html).

Westerterp, Klaas R. and Guy Plasqui. 2004. "Physical Activity and Human Energy Expenditure." *Current Opinion in Clinical Nutrition and Metabolic Care* 7(6):607–13.

Wickham, Hadley. 2016. *Stringr: Simple, Consistent Wrappers for Common String Operations.* Retrieved (https://CRAN.R-project.org/package=stringr).

Wilcox, S., C. Castro, A. C. King, R. Housemann, and R. C. Brownson. 2000. "Determinants of Leisure

Time Physical Activity in Rural Compared with Urban Older and Ethnically Diverse Women in the United States." *Journal of Epidemiology and Community Health* 54(9):667–72.

Yadav, Daksha, Richa Singh, Mayank Vatsa, and Afzel Noore. 2014. "Recognizing Age-Separated Face Images: Humans and Machines" edited by E. Vul. *PLoS ONE* 9(12):e112234. Retrieved February 17, 2017 (http://dx.plos.org/10.1371/journal.pone.0112234).