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Psychological Language on Twitter Predicts County-Level Heart Disease Mortality

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Abstract

Hostility and chronic stress are known risk factors for heart disease, but they are costly to assess on a large scale. We used language expressed on Twitter to characterize community-level psychological correlates of age-adjusted mortality from atherosclerotic heart disease (AHD). Language patterns reflecting negative social relationships, disengagement, and negative emotions—especially anger—emerged as risk factors; positive emotions and psychological engagement emerged as protective factors. Most correlations remained significant after controlling for income and education. A cross-sectional regression model based only on Twitter language predicted AHD mortality significantly better than did a model that combined 10 common demographic, socioeconomic, and health risk factors, including smoking, diabetes, hypertension, and obesity. Capturing community psychological characteristics through social media is feasible, and these characteristics are strong markers of cardiovascular mortality at the community level.

Keywords

heart disease, risk factors, well-being, language, big data, emotions, social media, open data, open materials

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Heart disease is the leading cause of death worldwide (World Health Organization, 2011). Identifying and addressing key risk factors, such as smoking, hypertension, obesity, and physical inactivity, have significantly reduced this risk (Ford & Capewell, 2011). Psychological characteristics, such as depression (Lett et al., 2004) and chronic stress (Menezes, Lavie, Milani, O'Keefe, & Lavie, 2011), have similarly been shown to increase risk through physiological effects (e.g., chronic sympathetic arousal) and deleterious health behaviors (e.g., drinking and smoking). Conversely, positive psychological characteristics, such as optimism (Boehm & Kubzansky, 2012) and social support (Tay, Tan, Diener, & Gonzalez, 2013), seem to decrease risk, most likely through similar pathways.

In its 2020 Strategic Impact Goal Statement, the American Heart Association suggested that to further reduce the risk for heart disease, "population-level strategies are essential to shift the entire distribution of risk" (Lloyd-Jones et al., 2010, p. 589). Like individuals, communities have characteristics, such as norms, social connectedness, perceived safety, and environmental stress, that

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contribute to health and disease (Cohen, Farley, & Mason, 2003). One challenge to addressing community-level psychological characteristics is the difficulty of assessment; traditional approaches that use phone surveys and household visits are costly and have limited spatial and temporal precision (Auchincloss, Gebreab, Mair, & Diez Roux, 2012; Chaix, Merlo, Evans, Leal, & Havard, 2009).

Rich information about the psychological states and behaviors of communities is now available in big social-media data, offering a flexible and significantly cheaper alternative for assessing community-level psychological characteristics. Social-media-based digital epidemiology can support faster response and deeper understanding of public-health threats than can traditional methods. For example, Google has used search queries to measure trends in influenza, providing earlier indication of disease spread than the Centers for Disease Control and Prevention (CDC; Ginsberg et al., 2009). Other studies have used Twitter to track Lyme disease, H1N1 influenza, depression, and other common ailments (Chew & Eysenbach, 2010; De Choudhury, Counts, & Horvitz, 2013; de Quincey & Kostkova, 2009; Paul & Dredze, 2011a, 2011b; Salathé, Freifeld, Mekaru, Tomasulo, & Brownstein, 2013; Seifter, Schwarzwalder, Geis, & Aucott, 2010; St Louis & Zorlu, 2012).

Methods for inferring psychological states through language analysis have a rich history (Pennebaker, Mehl, & Niederhoffer, 2003; Stone, Dunphy, Smith, & Ogilvie, 1966). Traditional approaches use dictionaries—predetermined lists of words—associated with different constructs (e.g., *sad, glum*, and *crying* are part of a negative-emotion dictionary; Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007). *Open-vocabulary* approaches identify predictive words statistically and are not based on traditional predetermined *dictionaries* (Schwartz, Eichstaedt, Kern, Dziurzynski, Ramones, et al., 2013), offering a complementary method of language analysis.

In this study, we analyzed social-media language to identify community-level psychological characteristics associated with mortality from atherosclerotic heart disease (AHD). Working with a data set of 10s of millions of Twitter messages (tweets), we used dictionary-based and open-vocabulary analyses to characterize the psychological language correlates of AHD mortality. We also gauged the amount of AHD-relevant information in Twitter language by building and evaluating predictive models of AHD mortality, and we compared the language models with traditional models that used demographic and socioeconomic risk factors.

Method

We collected tweets from across the United States, determined their counties of origin, and derived values for language variables (e.g., the relative frequencies with which people expressed anger or engagement) for each county. We correlated these county-level language measures with county-level age-adjusted AHD mortality rates obtained from the CDC. To gauge the amount of information relevant to heart disease contained in the Twitter language, we compared the performance of prediction models that used Twitter language with the performance of models that contained county-level (a) measures of socioeconomic status (SES; i.e., income and education), (b) demographics (percentages of Black, Hispanic, married, and female residents), and (c) health variables (incidence of diabetes, obesity, smoking, and hypertension). All procedures were approved by the University of Pennsylvania Institutional Review Board.

Data sources

We used data from 1,347 U.S. counties for which AHD mortality rates; county-level socioeconomic, demographic, and health variables; and at least 50,000 tweeted words were available. More than 88% of the U.S. population lives in the included counties (U.S. Census Bureau, 2010).[1]

Twitter data. Tweets are brief messages (no more than 140 characters) containing information about emotions, thoughts, behaviors, and other personally salient information. In 2009 and 2010, Twitter made a 10% random sample of tweets (the "Garden Hose") available for researchers through direct access to its servers. We obtained a sample of 826 million tweets collected between June 2009 and March 2010. Many Twitter users self-reported their locations in their user profiles, and we used this information to map tweets to counties (for details, see the Mapping Tweets to Counties section of the Supplemental Method in the Supplemental Material available online). This resulted in 148 million county-mapped tweets across 1,347 counties.

Heart disease data. Counties are the smallest socio-ecological level for which most CDC health variables and U.S. Census information are available. From the Centers for Disease Control and Prevention (2010b) we obtained county-level age-adjusted mortality rates for AHD, which is represented by code I25.1 in the International Classification of Disease, 10th edition (ICD 10; World Health Organization, 1992). This code has the highest overall mortality rate in the United States (prevalence = 51.5 deaths per 100,000 in 2010). We averaged AHD mortality rates across 2009 and 2010 to match the time period of the Twitter-language data set.

Demographic and health risk factors. We obtained county-level median income and the percentage of married residents from the American Community Survey (U.S. Census Bureau, 2009). We also obtained high school and college graduation rates from this survey, which we used to create an index of educational attainment. We obtained percentages of female, Black, and Hispanic residents from the U.S. Census Bureau (2010). From the Behavioral Risk Factor Surveillance System of the Centers for Disease Control and Prevention (2009, 2010a) we obtained prevalence of self-reported diabetes, obesity, smoking, and hypertension (common cardiovascular risk factors) for which county-level estimates had previously been derived (see Table S1 in the Supplemental Tables of the Supplemental Material for detailed source information).

Analytic procedure

Language variables from Twitter. We used an automatic process to extract the relative frequency of words and phrases (sequences of two to three words) for every county. For example, the relative frequency of the word *hate* ranged from 0.009% to 0.139% across counties (see the Tokenization section of the Supplemental Method).

We then derived two more types of language-use variables from counties' relative word-usage frequencies: variables based on (a) dictionaries and (b) topics. Dictionary-based variables were relative frequencies of psychologically related words from predetermined dictionaries (e.g., positive-emotion words accounted for 4.6% of all words in a county on average). Topic-based variables were the relative usage of 2,000 automatically created topics, which are clusters of semantically related words that can be thought of as latent factors (words can have loadings on multiple topics; see the Topic Extraction section of the Supplemental Method).

We used preestablished dictionaries for anger, anxiety, positive and negative emotions, positive and negative social relationships, and engagement and disengagement (Pennebaker et al., 2007; Schwartz, Eichstaedt, Kern, Dziurzynski, Lucas, et al., 2013). Topics had previously been automatically derived (Schwartz, Eichstaedt, Kern, Dziurzynski, Ramones, et al., 2013).

Because words can have multiple senses, act as multiple parts of speech, and be used in the context of irony or negation, it is important to gauge empirically how well such lists of words measure what is intended (Grimmer & Stewart, 2013). To that end, we had human raters evaluate the dictionaries to determine whether each accurately measured the psychological concept intended. For each of the eight dictionaries, two independent raters examined 200 tweets containing dictionary words and rated whether each dictionary word in the tweets expressed the associated dictionary concept. A third rater was brought in to break ties. Judges rated the dictionaries to have accuracy levels between 55% and 89% (see Table S2 in the Supplemental Tables).[2]

Statistical analysis. Dictionary and topic language variables were correlated with county AHD mortality rates using ordinary least squares linear regression. Each language variable was entered individually into the regression equation and then entered simultaneously with education and income as controls. We tested 2,000 topics, so we applied the Bonferroni correction to the significance threshold (i.e., for the correlation of 1 of 2,000 topics to be significant, its p value would have to be less than .05/2,000, or .000025).

Predictive models. A predictive model of county AHD mortality rates was created using all of the Twitter language variables. That is, we created a single model in which all of the word, phrase, dictionary, and topic frequencies were independent variables and the AHD mortality rate was the dependent variable. We used regularized linear regression (ridge regression) to fit the model (see the Predictive Models section of the Supplemental Method). We also created predictive models of county AHD mortality rates in which the predictors were different combinations of sets of variables: Twitter language, county demographics (percentages of Black, Hispanic, married, and female residents), and socioeconomic (income, education) and health (incidence of diabetes, obesity, smoking, and hypertension) variables.

We avoided distorted results (due to model overfitting—picking up patterns simply by chance) by using a 10-fold cross-validation process that compared model predictions with out-of-sample data. For this analysis, the counties were first randomly partitioned into 10 parts (*folds*). Then, a predictive model was created by fitting the independent variables to the dependent variable (AHD mortality) over 9 of the 10 folds of counties (the *training set*). We then evaluated how well the resulting model predicted the outcomes for the remaining fold (one 10th of the counties; the *hold-out set*). We evaluated the model by comparing its predicted rates with the actual CDC-reported mortality rates using a Pearson product-moment correlation. This procedure was repeated 10 times, allowing each fold to be the hold-out set. The results were averaged together to determine overall prediction performance across all counties for a given model.

To compare predictive performance between two models (e.g., a model based only on Twitter language versus a model based on income and education), we conducted paired t tests comparing the sizes of the standardized residuals of county-level predictions from the models.

Table 1. County-Level Correlations Between Atherosclerotic Heart Disease (AHD) Mortality and Twitter Language Measured by Dictionaries

Language variable	Correlation with AHD mortality
Risk factors	
Anger	.17 [.11, .22]**
Negative relationships	.16 [.11, .21]**
Negative emotions	.10 [.05, .16]**
Disengagement	.14 [.08, .19]**
Anxiety	.05 [.00, .11]†
Protective factors	
Positive relationships[a]	.02 [−.04, .07]
Positive emotions	−.11 [−.17, −.06]**
Engagement	−.16 [−.21, −.10]**

Note: The table presents Pearson *r*s, with 95% confidence intervals in square brackets (*n* = 1,347 counties). The anger and anxiety dictionaries come from the Linguistic Inquiry and Word Count software (Pennebaker, Chung, Ireland, Gonzales, & Booth, 2007); the other dictionaries are our own (Schwartz, Eichstaedt, Kern, Dziurzynski, Lucas, et al., 2013). Positive correlations indicate that higher values for the language variables are associated with greater AHD mortality.
[a]This is the correlation without *love* included in the dictionary. See note 3 at the end of the article and the discussion for more information.
†$p < .10$. **$p < .001$.

Results

Dictionaries

Greater usage of anger, negative-relationship, negative-emotion, and disengagement words was significantly correlated with greater age-adjusted AHD mortality (*r*s = .10–.17; for specific results, including confidence intervals, see Table 1). After controlling for SES (income and education), all five negative language factors (including usage of anxiety words) were significant risk factors for AHD mortality (partial *r*s = .06, 95% confidence interval, or CI = [.00, .11], to .12, 95% CI = [.07, .17]). This suggests that Twitter language captures information not accounted for by SES. Greater use of positive-emotion and engagement words was associated with lower AHD mortality (r = −.11 and r = −.16, respectively). Use of engagement words remained significantly protective after controlling for SES (partial r = −.09, 95% CI = [−.14, −.04]), but use of positive-emotion words became only marginally significant (partial r = −.05, 95% CI = [−.00, −.11]). Usage of positive-relationships words[3] showed a nonsignificant association with AHD mortality (r = .02, 95% CI = [−.04, .07]; see Table 1).

Topics

We complemented the dictionaries with an open-vocabulary approach, using automatically created topics consisting of semantically coherent groups of words. For each county, we calculated the relative use of each topic, and we correlated topic use with AHD. Figure 1 shows topic composition and correlations for 18 topics whose use was significantly correlated with AHD mortality.[4] The risk factors we observed were themes of hostility and aggression (*shit, asshole, fucking;* *r*s = .18, 95% CI = [.12, .23], to .27, 95% CI = [.22, .32]), hate and interpersonal tension (*jealous, drama, hate;* *r*s = .16, 95% CI = [.11, .21], to .21, 95% CI = [.16, .26]), and boredom and fatigue (*bored, tired, bed;* *r*s = .18, 95% CI = [.12, .23], to .20, 95% CI = [.15, .25]). After controlling for SES, use of seven of the nine risk topics remained significantly correlated with AHD mortality at Bonferroni-corrected levels (partial *r*s = .12, 95% CI = [.07, .17], to .25, 95% CI = [.20, .30], $p < 7 \times 10^{-6}$).

Other topics were protective factors (Fig. 1, bottom panel). Use of topics related to positive experiences (*wonderful, friends, great;* *r*s = −.14, 95% CI = [−.19, −.08], to −.15, 95% CI = [−.21, −.10]) was associated with lower AHD mortality, a finding that mirrors the dictionary-based results. Also associated with lower AHD mortality was use of topics reflecting skilled occupations (*service, skills, conference;* *r*s = −.14, 95% CI = [−.20, −.09], to −.17, 95% CI = [−.22, −.12]) and topics reflecting optimism (*opportunities, goals, overcome;* *r*s = −.12, 95% CI = [−.18, −.07], to −.13, 95% CI = [−.18, −.07]), which has been found to be robustly associated with reduced cardiovascular disease risk at the individual level (Boehm & Kubzansky, 2012; Chida & Steptoe, 2008). After controlling for SES, the correlations between protective topics and AHD mortality remained significant at the traditional .05 level but were no longer significant at Bonferroni-corrected levels.

Prediction

In Figure 2, we compare the predictions of AHD mortality from regression models with different independent variables. Predictive performance was slightly but significantly better for a model combining Twitter and the 10 traditional demographic, SES, and health predictors than for a model that included only the 10 traditional predictors (Twitter plus 10 traditional factors: r = .42, 95% CI = [.38, .46]; 10 traditional factors only: r = .36, 95% CI = [.29, .43]), $t(1346) = −2.22$, p = .026. This suggests that Twitter has incremental predictive validity over and above traditional risk factors. A predictive model using only Twitter language (r = .42, 95% CI = [.38, .45]) performed slightly better than a model using the 10 traditional factors, $t(1346) = −1.97$, p = .049.

To explore these associations in greater detail, we compared the performance of prediction models containing stepwise combinations of Twitter and sets of demographic predictors (percentages of Black, Hispanic, married, and female residents), socioeconomic predictors (income and education), and health predictors (incidence

Fig. 1. Twitter topics most correlated with age-adjusted mortality from atherosclerotic heart disease (significant at a Bonferroni-corrected significance level of $p < 2.5 \times 10^{-5}$). The topics with positive correlations (top) and the topics with negative correlations (bottom) have each been grouped into sets, which are labeled at the left. The size of the word represents its prevalence relative to all words within a given topic (larger = more frequent; for details, see the Supplemental Method).

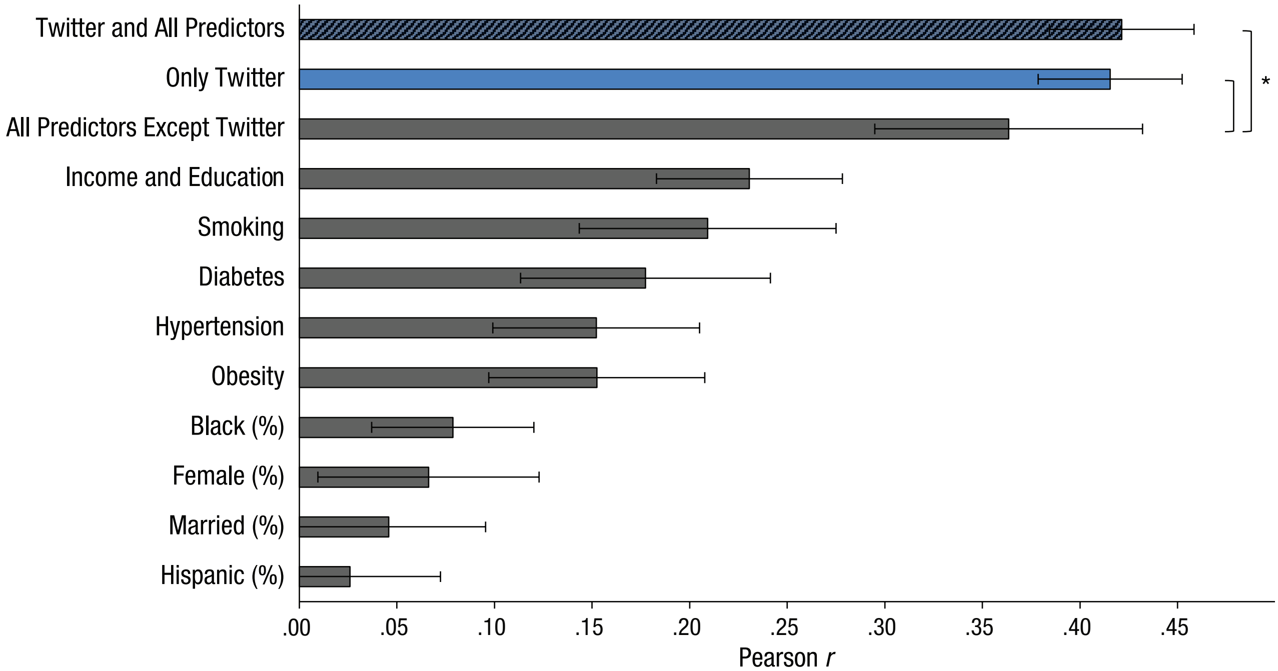

Fig. 2. Performance of models predicting age-adjusted mortality from atherosclerotic heart disease (AHD). For each model, the graph shows the correlation between predicted mortality and actual mortality reported by the Centers for Disease Control and Prevention. Predictions were based on Twitter language, socioeconomic status, health, and demographic variables singly and in combination. Higher values mean better prediction. The correlation values are averages obtained in a cross-validation process used to avoid distortion of accuracy due to chance (overfitting; for details, see the text). Error bars show 95% confidence intervals. Asterisks indicate significant differences between models ($^*p < .05$).

of diabetes, obesity, smoking, and hypertension; see Table S4 in the Supplemental Tables). For all combinations of sets of traditional predictors, adding Twitter language significantly improved predictive performance, $t(1346) > 3.00$, $p < .001$. Adding traditional sets of predictors to Twitter language did not significantly improve predictive performance.

Taken together, these results suggest that the AHD-relevant variance in the 10 predictors overlaps with the AHD-relevant variance in the Twitter language features. Twitter language may therefore be a marker for these variables and in addition may have incremental predictive validity. Figure 3 shows CDC-reported AHD mortality averaged across 2009 and 2010 and Twitter-predicted mortality for the densely populated counties in the northeastern United States; a high degree of agreement is evident.

Discussion

Our study had three major findings. First, language expressed on Twitter revealed several community-level psychological characteristics that were significantly associated with heart-disease mortality risk. Second, use of negative-emotion (especially anger), disengagement, and negative-relationship language was associated with increased risk, whereas positive-emotion and engagement language was protective. Third, our predictive results suggest that the information contained in Twitter language fully accounts for—and adds to—the AHD-relevant information in 10 representatively assessed demographic, socioeconomic, and health variables. Taken together, our results suggest that language on Twitter can provide plausible indicators of community-level psychosocial health that may complement other methods of studying the impact of place on health used in epidemiology (cf. Auchincloss et al., 2012) and that these indicators are associated with risk for cardiovascular mortality.

Our findings point to a community-level psychological risk profile similar to risk profiles that have been observed at the individual level. County-level associations between AHD mortality and use of negative-emotion words (relative risk,[5] or RR, = 1.22), anger words (RR = 1.41), and anxiety words (RR = 1.11) were comparable to individual-level meta-analytic effect sizes for the association between AHD mortality and depressed mood (RR = 1.49; Rugulies, 2002), anger (RR = 1.22; Chida & Steptoe, 2009), and anxiety (RR = 1.48; Roest, Martens, de Jonge, & Denollet, 2010).

Although less is known at the individual level about the protective effects of positive psychological variables than about the risk associated with negative variables, our findings align with a growing body of research supporting the

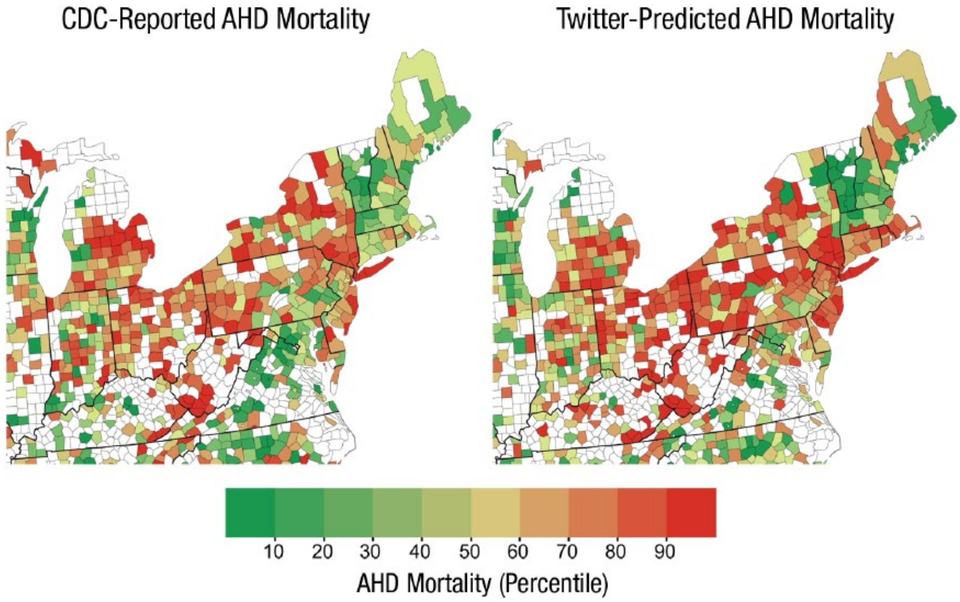

Fig. 3. Map of counties in the northeastern United States showing age-adjusted mortality from atherosclerotic heart disease (AHD) as reported by the Centers for Disease Control and Prevention (CDC; left) and as estimated through the Twitter-language-only prediction model (right). The out-of-sample predictions shown were obtained from the cross-validation process described in the text. Counties for which reliable CDC or Twitter language data were unavailable are shown in white.

cardiovascular health benefits of psychological well-being (Boehm & Kubzansky, in press). Engagement, which has long been considered an important component of successful aging (Rowe & Kahn, 1987), emerged as the strongest protective factor in our study. Use of positive-emotion words was also protective, which is in line with numerous findings that positive emotions convey protection from illness and disease (e.g., Howell, Kern, & Lyubomirsky, 2007; Pressman & Cohen, 2005). Fredrickson, Mancuso, Branigan, and Tugade (2000) have argued that positive emotions may undo the negative cardiovascular aftereffects of anxiety-induced cardiovascular reactivity. Optimism has been shown to have relatively robust association with reduced risk of cardiovascular events at the individual level (Boehm & Kubzansky, 2012; Chida & Steptoe, 2008). We did not have a predefined optimism dictionary, but our topic analyses seem to have identified this as a protective factor (as indicated by results for topics containing *opportunities, goals, overcome*; Fig. 1, bottom). This demonstrates the value of data-driven language analyses.

Overall, our topic findings were similar to and converged with our theory-based dictionary results (cross-correlations are given in Table S3 in the Supplemental Tables). Although theory-based analyses can be more easily tied to existing literature, topic analyses provide a richer portrait of specific behaviors and attitudes (e.g., cursing, frustration, being tired) that correspond to broad psychological characteristics (e.g., anger or stress) associated with an increased risk for AHD mortality. Data-driven analyses, such as our topic analyses, may help identify novel psychological, social, and behavioral correlates of disease.

When analyses use theory-based dictionaries, results can be driven by a few frequent but ambiguous words. For example, greater use of words in the original positive-relationships dictionary (Schwartz, Eichstaedt, Kern, Dziurzynski, Ramones, et al., 2013) was surprisingly associated with increased risk, as was the use of its most frequent word, *love*. *Love* accounted for more than a third of the total usage of the positive-relationships dictionary (5.3 million occurrences of *love* compared with 15.0 million occurrences of all words in the dictionary), which means that *love* drove the results for this dictionary. Reading through a random sample of tweets containing *love* revealed them to be mostly statements about loving things, not people.[6] Excluding *love* from the dictionary reduced the correlation between use of the words in the positive-relationships dictionary and AHD mortality (r = .08, 95% CI = [.03, .13]) to nonsignificance (r = .02, 95% CI = [−.04, .07]).

These results demonstrate the pitfalls of interpreting dictionary-based results at face value and underscore the importance of interpreting such results in light of the most frequent words contained in the dictionaries, which can drive the overall dictionary results in unexpected ways. For transparency, in Table S6 in the Supplemental

Tables, we have provided the correlations with AHD mortality for the 10 most frequently used words in each of the eight dictionaries. These findings also highlight the value of triangulating language analyses across different levels of analysis (words, topics, and dictionaries) for arriving at more robust interpretations.

Given that the typical Twitter user is younger (median age = 31 years; Fox, Zickurh, & Smith, 2009) than the typical person at risk for AHD, it is not obvious why Twitter language should track heart-disease mortality. The people tweeting are not the people dying. However, the tweets of younger adults may disclose characteristics of their community, reflecting a shared economic, physical, and psychological environment. At the individual level, psychological variables and heart-disease risk are connected through multiple pathways, including health behaviors, social relationships, situation selection, and physiological reactivity (Friedman & Kern, 2014). These pathways occur within a broader social context that directly and indirectly influences an individual's life experiences. Local communities create physical and social environments that influence the behaviors, stress experiences, and health of their residents (Diez Roux & Mair, 2010; Lochner, Kawachi, Brennan, & Buka, 2003). Epidemiological studies have found that the aggregated characteristics of communities, such as social cohesion and social capital, account for a significant portion of variation in health outcomes, independently of individual-level characteristics (Leyland, 2005; Riva, Gauvin, & Barnett, 2007), such that the combined psychological character of the community is more informative for predicting risk than are the self-reports of any one individual. The language of Twitter may be a window into the aggregated and powerful effects of the community context.

Our study has several limitations. Tweets constitute a biased sample in two ways. First, they may reflect social-desirability biases, because people manage their online identities (Rost, Barkhuus, Cramer, & Brown, 2013). Second, Twitter users are not representative of the general population. The Twitter population tends to be more urban and to have higher levels of education (Mislove, Lehmann, Ahn, Onnela, & Rosenquist, 2011). In 2009, the median age of Twitter users (Fox et al., 2009) was 5.8 years below the U.S. median age (U.S. Census Bureau, 2010). Nonetheless, our Twitter-based prediction model outperformed models based on classical risk factors in predicting AHD mortality; this suggests that, despite the biases, Twitter language captures as much unbiased AHD-relevant information about the general population as do traditional, representatively assessed predictors.

Another limitation is that our findings are cross-sectional; future research should address the stability of psychological characteristics of counties across time. Also, we relied on AHD mortality rates reported by the CDC, which draws on the underlying cause of death recorded on death certificates; however, the coding on death certificates may be inconsistent (Pierce & Denison, 2010). Finally, associations between language and mortality do not point to causality; analyses of language on social media may complement other epidemiological methods, but the limits of causal inferences from observational studies have been repeatedly noted (e.g., Diez Roux & Mair, 2010).

Traditional approaches for collecting psychosocial data from large representative samples, such as the Behavioral Risk Factor Surveillance System of the CDC and Gallup polls, tend to be expensive, are based on only thousands of people, and are often limited to a minimal, predefined list of psychological constructs. A Twitter-based system to track psychosocial variables is relatively inexpensive and can potentially generate estimates based on 10s of millions of people with much higher resolution in time and space. It is comparatively easy to create dictionaries automatically for different psychological or social constructs so that novel hypotheses can be tested. Our approach opens the door to a new generation of psychological informational epidemiology (Eysenbach, 2009; Labarthe, 2010) and could bring researchers closer to understanding the community-level psychological factors that are important for the cardiovascular health of communities and should become the focus of intervention.

Author Contributions

J. C. Eichstaedt led the project. J. C. Eichstaedt and H. A. Schwartz conceived of the study. H. A. Schwartz, J. C. Eichstaedt, G. Park, S. Jha, M. Agrawal, L. A. Dziurzynski, and M. Sap handled data acquisition and processing, development of the prediction models, and data analyses. J. C. Eichstaedt, M. L. Kern, H. A. Schwartz, and G. Park drafted the manuscript. D. R. Labarthe, R. M. Merchant, L. H. Ungar, and M. E. P. Seligman provided critical revisions. C. Weeg and E. E. Larson helped acquire, process, and analyze county-level information. All authors approved the final version of the manuscript for submission. L. H. Ungar and M. E. P. Seligman contributed equally to this article.

Declaration of Conflicting Interests

The authors declared that they had no conflicts of interest with respect to their authorship or the publication of this article.

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Supplemental Material

Additional supporting information can be found at http://pss.sagepub.com/content/by/supplemental-data

Open Practices

All data and materials have been made publicly available via the Open Science Framework and can be accessed at https://osf.io/rt6w2/. The complete Open Practices Disclosure for this article can be found at http://pss.sagepub.com/content/by/supplemental-data. This article has received badges for Open Data and Open Materials. More information about the Open Practices badges can be found at https://osf.io/tvyxz/wiki/view/ and http://pss.sagepub.com/content/25/1/3.full.

Notes

1. Analyses using the available heart disease, demographic, and socioeconomic information for the excluded counties revealed that, compared with the counties in the final sample, the excluded counties had smaller populations (median county population of 12,932 in 1,796 excluded counties vs. 78,265 in included counties), higher rates of AHD (Hedges's g = 0.48, 95% confidence interval, or CI = [0.38, 0.57]; n = 597 excluded counties with data available), lower income (g = −0.42, 95% CI = [−0.53, −0.32]; n = 496), and lower levels of education (g = −0.61, 95% CI = [−.72, −.51]; n = 496). The included and excluded counties did not differ in median age (g = 0.003, 95% CI = [−0.08, 0.08]; n = 1,004).
2. The anxiety and positive-relationships dictionaries were rated as having the lowest accuracies (55.0% and 55.5% respectively; see Table S2 in the Supplemental Tables), whereas the accuracy of the other dictionaries was markedly higher (average accuracy = 82.1%). Cross-correlations of dictionaries (see Table S3 in the Supplemental Tables) revealed that the frequency of use of the positive-relationships and anxiety dictionaries were unexpectedly positively correlated with the frequencies of use of all other dictionaries.
3. The word *love* was removed from the dictionary because it accounted for more than a third of the occurrences of words from this dictionary, and including it distorted the results (see Discussion, and note 6).
4. For ease of interpretation, we have grouped these topics into seemingly related sets and added labels to summarize our sense of the topics. These labels are open to interpretation, and we present for inspection the most prevalent words within the topics. County-level topic- and dictionary-frequency data can be downloaded from https://osf.io/rt6w2/files/.
5. To compare our findings with published effect sizes, we converted correlation coefficients to relative risk values following the method of Rosenthal and DiMatteo (2001).
6. In addition to having this word-sense ambiguity, mentions of *love* may signify a different kind of Twitter use in lower-SES areas. A factor analysis of the words in the positive-relationships dictionary revealed two factors with opposing correlations with SES. A general social factor (*friends, agree, loved*) correlated with higher SES (r = .14), and a partnership factor (*relationship, boyfriend, girlfriend*) correlated with lower SES (r = −.43), as well as higher AHD mortality (r = .18). Usage of the word *love* loaded much higher on this second factor than on the first one (see Table S5 in the Supplemental Tables). This finding may be an indication that in lower-SES areas, users share more about personal relationships on Twitter, which distorts the results obtained when using the original positive-relationships dictionary.

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