What's the Healthiest Day?
Circaseptan (Weekly) Rhythms in Healthy Considerations

John W. Ayers, PhD, MA, Benjamin M. Althouse, PhD, ScM, Morgan Johnson, MPH, Mark Dredze, PhD, Joanna E. Cohen, PhD, MHSc

Background: Biological clocks govern numerous aspects of human health, including weekly clocks—called circaseptan rhythms—that typically include early-week spikes for many illnesses.

Purpose: To determine whether contemplations for healthy behaviors also follow circaseptan rhythms.

Methods: We assessed healthy contemplations by monitoring Google search queries (2005–2012) in the U.S. that included the word *healthy* and were Google classified as health-related (e.g., healthy diet). A wavelet analysis was used in 2013 to isolate the circaseptan rhythm, with the resulting series compared by estimating ratios of relative query volume (healthy versus all queries) each day (e.g., (Monday–Wednesday)/Wednesday).

Results: Healthy searches peaked on Monday and Tuesday, thereafter declining until rebounding modestly on Sunday. Monday and Tuesday were statistically indistinguishable (t=1.22, p=0.22), but their combined mean had 30% (99% CI=29, 32) more healthy queries than the combined mean for Wednesday−Sunday. Monday and Tuesday query volume was 3% (99% CI=2, 5) greater than Wednesday, 15% (99% CI=13, 17) greater than Thursday, 49% (99% CI=46, 52) greater than Friday, 80% (99% CI=76, 84) greater than Saturday, and 29% (99% CI=27, 31) greater than Sunday. We explored media-based (priming) motivations for these patterns and they were consistently rejected.

Conclusions: Just as many illnesses have a weekly clock, so do healthy considerations. Discovery of these rhythms opens the door for a new agenda in preventive medicine, including implications for hypothesis development, research strategies to further explore these rhythms, and interventions to exploit daily cycles in healthy considerations.
(Am J Prev Med 2014;▮(▮):▮▮▮–▮▮▮) © 2014 American Journal of Preventive Medicine

Introduction

Clock-like rhythms are ubiquitous across health.[1] Seasonal variations, such as with mental illness,[2] have been most notable. However, weekly circaseptan rhythms characterized by Monday spikes in high blood pressure,[3] infectious disease,[4] myocardial infarction,[5] sinus tachycardia,[6] and stroke[7] also exist.

From the Graduate School of Public Health (Ayers), San Diego State University, San Diego, California; The Santa Fe Institute (Althouse), Santa Fe, New Mexico; The Mondays Campaign (Johnson), New York, New York; Human Language Technology Center of Excellence (Dredze), Johns Hopkins University; and the Institute for Global Tobacco Control, Johns Hopkins Bloomberg School of Public Health, Johns Hopkins University (Cohen), Baltimore, Maryland

Address correspondence to: John W. Ayers, PhD, MA, 9245 Sky Park Court, Suite 230, San Diego CA 92123. E-mail: ayers.john.w@gmail.com.
0749-3797/$36.00
http://dx.doi.org/10.1016/j.amepre.2014.02.003

Given the week is socially constructed, the likely mechanisms driving circaseptan rhythms in illness are psychosocial and therefore relevant to health behaviors. Moreover, understanding circaseptan rhythms of health behaviors can yield critical public health gains. For instance, government-funded health promotion programs spend $76.2 billion annually,[8] and their cost-effectiveness can be improved by targeting the population on weekday(s) when more individuals are contemplating their health habits.

Because healthy contemplations are at best recorded semi-annually, investigators have focused on annual (e.g., New Year's day)[9] or seasonal (e.g., winter weight gain)[10] rather than weekly rhythms. Nonetheless, a web data revolution is changing preventive medicine by generating real-time health trends, such as those from aggregating Internet search queries.[11–15] In this exploratory report, we describe daily patterns in online search queries to

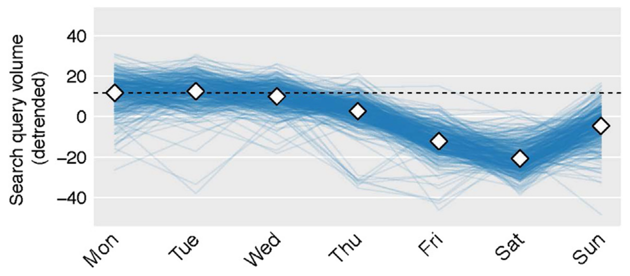

Figure 1. Early-week spikes in "healthy" thinking
Note: Each line is a weekly trend line for all Google queries that included the term *healthy* that were then Google classified as health-related, as estimated from the wavelet transform The diamonds indicate the mean estimates by day of the week, with the corresponding mean for Monday also reflected in a reference line. N=2,906 number of days in the analysis (2005−2012).

uncover circaseptan rhythms, where examining individual's searches reveals both the searcher's contemplations and when they are taking action toward behavior change.

Methods

Daily trends for all queries that included the word *healthy* in combination with other terms (e.g., *healthy recipes*) were downloaded from Google's public database for 2005–2012, or 2,906 days (google.com/trends). Non–health-related searches (e.g., *healthy salary*) were omitted by only analyzing search trends that Google classified as health-related.[16]

Changes in raw search volume can be deceptive because all searches might decline during the weekend. Therefore, Google archives return relative search volume (RSV) trends, reflecting the proportion of healthy queries relative to all queries, then normalized on a 0–100 scale representing the highest observed daily search proportion (e.g., RSV=50 is 50% of the highest search proportion).

First, we used the continuous wavelet transform to identify searches' weekly periodic component. Specifically, this approach decomposes the time series into time-frequency space (e.g., RSV per day, week, or year), thus determining the dominant decomposition time variability in the data. This approach was preferred to alternatives (e.g., Fourier) because it produces robust estimates over time that correct for the typical biases in time series designs (e.g., trending) and does not make parametric assumptions.[17] Moreover, the wavelet allows examination of both the intensity and timing of periodic circaseptanality over the entire study period, which is not dually possible with a Fourier decomposition. For a comprehensive analytic treatment of the wavelet transform, see Torrence et al.[18]; for practical examples, see Grenfell[19] and Johansson.[20]

Second, we reconstructed the time series with periodic components <14 days (as identified by the wavelet) after adding back the mean of the time series, as the wavelet is mean-centered. Third, we modeled the difference between Monday and other days as a difference in means, fitting a linear regression with the days of the week as a factor variable (i.e., $\beta_{Tuesday} + \beta_{Wednesday} \ldots + \beta_{Sunday}$).

Fourth, the mean search volume difference between days was described as a percentage increase by division of the regression variables (e.g., percentage difference $= \frac{\beta_{Tuesday}}{\beta_{intercept(Monday)}} \times 100$). For the latter, CIs were estimated by simulating 5,000 bootstrap replicates from the multivariate normal sampling distribution, with the mean equal to the maximum-likelihood point estimates and variance equal to the variance−covariance matrix; that is, $\hat{\beta}_{est} \sim MVN(\hat{\beta}_{mle}, V(\hat{\beta}_{mle}))$, where $\hat{\beta}_{mle}$ is the vector of the regression coefficients and $V(\hat{\beta}_{mle})$ the variance−covariance matrix from the regression. This method allows estimation of the uncertainty in non-standard, interpretable measures (see King et al.[21] for a detailed explanation and statistical justification). Ninety-nine percent CIs are presented based on a Bonferroni correction for six comparisons (7 days, one common reference).[22]

We crawled the U.S. Google News (news.google.com) domain for the same periods, capturing English-language coverage of "healthy" topics in newspapers/magazines and broadcast/cable networks, including online and print content. The number of articles containing *healthy* was divided by the number of articles containing *the* each day, reported per 100,000. We then tested the hypothesis that media were responsible for search patterns[23] by replicating the wavelet analysis for media, and estimating Pearson correlation and a repeated measures ANOVA with within-week clustering for media compared to search trends.[24] All statistical analyses were conducted in R, version 2.15.3.

Results

Healthy queries in the U.S. peaked early in the week, declining through Saturday until modestly rebounding on Sunday (Figure 1). Moreover, search volumes were more consistent by day across weeks than within weeks across days (intraclass correlation, 0.006 vs 0.740), meaning that Mondays are more like other Mondays than the neighboring Sunday or Tuesday.

Relative query volume was significantly different for each comparison except Monday versus Tuesday (t=1.22, p=0.22); thus, Monday and Tuesday were pooled for further analysis. Monday and Tuesday queries were 30% (99% CI=29, 32) greater than the combined Wednesday−Sunday mean. Moreover, healthy queries on Monday and Tuesday were 3% (99% CI=2, 5) greater than Wednesday; 15% (99% CI=13, 17) greater than Thursday; 49% (99% CI=46, 52) greater than Friday; 80% (99% CI=76, 84) greater than Saturday; and 29% (99% CI=27, 31) greater than Sunday.

Media rhythms were substantially different from search rhythms. For example, Monday was not focal for healthy media coverage: Wednesday had about 9% (99% CI=0.4, 18) greater media coverage than Monday. In addition, media trends were only loosely associated with search queries (r=0.34). Lastly, repeated measures ANOVA revealed no effect of news on search after accounting for within-week clustering (F=0.926, p=0.34). Therefore, the likely explanation for circaseptan rhythms in healthy thinking was not media priming.

Discussion

Just as many illnesses have a weekly clock, so may healthy contemplations. Investigators now have evidence to embark on a research agenda to further appreciate and exploit rhythms in health behaviors, including developing new hypotheses, databases, and interventions.

Hypothetically, the observed patterns suggest that health behavior contemplations are not governed by individual psychology, but rather collective behavior patterns. Therefore, the likely mechanistic factors supplanting individual psychology are the socially constructed meanings attributed to the days of the week. First, the beginning of the week may be akin to a mini New Year's day. Second, reengagement with workweek planning may engender health-related planning. Third, healthy rhythms may be a collateral consequence of early-week spikes in poor health. Lastly, poor health choices during the weekend may promote a desire to cleanse come Monday.

Evidence cannot be presented herein to test mechanistic claims, but new databases can shed light on the ubiquity of circaseptan rhythms. Interventionists, for instance, could assess how program enrollment varies daily as a secondary aim, where enrollment may indicate healthy contemplations. Population surveys could include questions about the weekday respondents' desire to initiate a behavior change and why. Use of service data, such as smoking quitlines, may also yield insights.[25]

Nevertheless, the discovery of circaseptan rhythms has strong potential for improving public health, both near- and long-term. Health promotion campaigns could immediately be made more cost effective by targeting the population early in the week rather than uniformly across the week. For instance, mass media campaigns could purchase more advertisements.

A major limitation is that we cannot precisely link our findings to raw search volumes. However, Eysenbach and Köhler estimated that 5% of all global searches are health-related,[26] and in 2012, people searched Google 1.2 trillion times.[27] Thus, a single percentage point difference may represent millions of health queries each day, meaning that a small percentage difference between Wednesday and Monday/Tuesday can have substantial practical implications.

These findings are the initial steps toward understanding recurring weekly rhythms in health contemplations. That weekly clocks also impact precise behaviors seems likely,[28] and we hope our work encourages others to measure and leverage these rhythms in preventive medicine.

We thank Mauricio Santilliana, Keith Schnakenberg, and the Journal's statistical editor for advice on data modeling. This work was supported in part by a cooperative agreement with the Johns Hopkins Bloomberg School of Public Health and the Mondays Campaign. Those responsible for the funding decision had no role in the design and conduct of the study; in the collection, management, analysis, and interpretation of the data; or in the preparation, review, or approval of the manuscript.

JWA holds an equity stake in Directing Medicine LLC and HealthWatcher Inc. He has been a paid advisor/speaker to numerous universities and allied health groups in the past 2 years. BMA holds an equity stake in Directing Medicine LLC and is a paid advisor to HealthWatcher Inc. MJ is the research director at the Mondays Campaign. MD is a paid advisor to Directing Medicine LLC. JEC is a faculty advisor to the Mondays Campaign as part of a collaborative agreement between the Mondays Campaign and the Johns Hopkins Bloomberg School of Public Health.

References

1. Dunlap JC, Loros JJ, DeCoursey PJ, eds. Chronobiology: biological timekeeping. Sunderland MA: Sinauer Associates, 2004.
2. Ayers JW, Althouse BM, Allem JP, Rosenquist JN, Ford DE. Seasonality in seeking mental health information on Google. Am J Prev Med 2013;44(5):520–5.
3. Murakami S, Otsuka K, Kubo Y, et al. Repeated ambulatory monitoring reveals a Monday morning surge in blood pressure in a community-dwelling population. Am J Hypertens 2004;17(12 Pt 1): 1179–83.
4. Brillman JC, Burr T, Forslund D, Joyce E, Picard R, Umland E. Modeling emergency department visit patterns for infectious disease complaints: results and application to disease surveillance. BMC Med Inform Decis Mak 2005;5:4.
5. Evans C, Chalmers J, Capewell S, et al. "I don't like Mondays"-day of the week of coronary heart disease deaths in Scotland: study of routinely collected data. BMJ 2000;320(7229):218–9.
6. Chen Y, Chen W. Detection of circaseptan rhythm and the "Monday effect" from long-term pulse rate dynamics. Conf Proc IEEE Eng Med Biol Soc 2011:3780–3.
7. Manfredini R, Casetta I, Paolino E, et al. Monday preference in onset of ischemic stroke. Am J Med 2001;111(5):401–3.
8. Forsberg V, Fichtenberg C. The prevention and public health fund: a critical investment in our nation's physical and fiscal health. Washington DC: American Public Health Association, Center for Public Health Policy, 2012.
9. Gritz ER, Carr CR, Marcus AC. Unaided smoking cessation: great American smokeout and New Year's day quitters. J Psychosoc Oncol 1989;6:217–34.
10. Yanovski JA, Yanovski SZ, Sovik KN, Nguyen TT, O'Neil PM, Sebring NG. A prospective study of holiday weight gain. N Engl J Med 2000;342(12):861–7.
11. Ayers JW, Ribisl KM, Brownstein JS. Tracking the rise in popularity of electronic nicotine delivery systems (electronic cigarettes) using search query surveillance. Am J Prev Med 2011;40(4):448–53.
12. Ayers JW, Althouse BM, Allem JP, Ford DE, Ribisl KM, Cohen JE. A novel evaluation of World No Tobacco day in Latin America. J Med Internet Res 2012;14(3):e77.
13. Noar SM, Ribisl KM, Althouse BM, Willoughby JF, Ayers JW. Using digital surveillance to examine the impact of public figure pancreatic cancer announcements on media and search query outcomes. J Natl Cancer Inst Monogr 2013;2013(47):188–94.

14. Ayers JW, Althouse BM, Allem JP, et al. Novel surveillance of psychological distress during the great recession. J Affect Disord 2012;142(1—3):323–30.
15. Althouse BM, Allem JP, Childers MA, Dredze M, Ayers JW. Population health concerns during the U.S.' great recession. Am J Prev Med 2014;46(2):166–70.
16. Cook S, Conrad C, Fowlkes AL, Mohebbi MH. Assessing Google flu trends performance in the U.S. during the 2009 influenza virus A (H1N1) pandemic. PLoS One 2011;6(8):e23610.
17. Percival DB, Walden AT. Wavelet methods for time series analysis. Cambridge: Cambridge University Press, 2000.
18. Torrence C, Compo GP. A practical guide to wavelet analysis. Bull Am Meteorol Soc 1998;79:61–78.
19. Grenfell BT, Bjørnstad ON, Kappey J. Travelling waves and spatial hierarchies in measles epidemics. Nature 2001;414(6865):716–23.
20. Johansson E. Wavelet theory and some of its applications. Lulea. Sweden: Department of Mathematics, Luleå University of Technology, 2005.
21. King G, Tomz M, Wittenberg J. Making the most of statistical analyses: improving interpretation and presentation. Am J Pol Sci 2000;44: 341–55.
22. Bland JM, Altman DG. Multiple significance tests: the Bonferroni method. BMJ 1995;310(6973):170.
23. Scheufele DA, Tewksbury D. Framing, agenda setting, and priming: the evolution of three media effects models. J Comm 2007;57:9–20.
24. Hastie T, Tibshirani R, Friedman JH. The elements of statistical learning: data mining, inference, and prediction. New York NY: Springer, 2009.
25. Rossetti MD, Trzcinski GF, Syverud SA. Emergency department simulation and determination of optimal attending physician staffing schedules. Sim Conf Proc 1999;2:1532–40.
26. Eysenbach G, Köhler C. Health-related searches on the Internet. JAMA 2004;291(24):2946.
27. Google. 2012 Search Trends. google.com/zeitgeist/2012.
28. Ayers JW, Althouse BM, Johnson M, Cohen JE. Circaseptan (weekly) rhythms in smoking cessation considerations. JAMA Intern Med 2014;174(1):146–8.