



ELSEVIER

Available online at www.sciencedirect.com

Public Health

journal homepage: www.elsevier.com/puhe

Original Research

Short-term effects of social encouragement on exercise behavior: insights from China's Wanbu network



Liuan Wang ^a, Xitong Guo ^{a,*}, Tianshi Wu ^a, Lucheng Lv ^b, Zhiwei Zhang ^c

^a eHealth Research Institute, School of Management, Harbin Institute of Technology, Harbin, China

^b National Science Library, Chinese Academy of Sciences, Beijing, China

^c Department of Statistics, University of California, Riverside, USA

ARTICLE INFO

Article history:

Received 26 August 2016

Received in revised form
17 February 2017

Accepted 3 March 2017

Keywords:

Social media
Social network
Exercise habit
Health behavior
Longitudinal data

ABSTRACT

Objectives: The objective is to explore the short-term effects of social encouragement on exercise behavior in China.

Study design: A longitudinal observational study.

Methods: We collected longitudinal data on exercise and social interactions through public access to the Wanbu network, a large Chinese social network designed to encourage people to walk more. Our data set consisted of 5010 subjects who participated in the network between March 14, 2014, and September 4, 2015, and had at least one social interaction recorded. The data were analyzed using linear regression models relating the number of steps (NS) walked per day to the number of comments (NC), number of thumbs-up (NT), and number of posts (NP) received on the previous day, while adjusting for day of week, quarter of year, and a fixed or random subject effect, with or without a lag term (NS on the previous day) to account for serial correlation.

Results: We found that all three social interactions have positive effects on the next day's exercise level. The estimated effect sizes can be ordered as NT > NC > NP for each of the four models considered. The results also indicate that the participants walked less in the first quarter than in the other three quarters and more on weekdays than on weekends, with Monday being the most active day of a week.

Conclusion: Social encouragement has positive short-term effects on exercise behavior.

© 2017 The Royal Society for Public Health. Published by Elsevier Ltd. All rights reserved.

Introduction

Social media and social networks are playing increasingly important roles in transforming health care and promoting

healthy behavior. In addition to traditional clinic visits, patients can now receive medical advice through telemedicine and online consultation.^{1–5} Patients with similar disease conditions can exchange disease- and treatment-related

* Corresponding author. eHealth Research Institute, School of Management, Harbin Institute of Technology, Room 339, Building 2H, 2 Yikuang Str. Nangang Dist., Harbin, China. Tel.: +86 0451 86414022.

E-mail addresses: wangliuan1973@163.com (L. Wang), xitongguo@hit.edu.cn (X. Guo), wutianshi@hit.edu.cn (T. Wu), lvlc@mail.las.ac.cn (L. Lv), zhiwei_zhang@yahoo.com (Z. Zhang).

<http://dx.doi.org/10.1016/j.puhe.2017.03.004>

0033-3506/© 2017 The Royal Society for Public Health. Published by Elsevier Ltd. All rights reserved.

information as well as social encouragement on platforms such as patientslikeme.com.^{1,6,7} Health-related information (e.g. diet and exercise) is also widely available on general social networks such as Facebook and (in China) WeChat, where people with and without disease can share information, discuss health issues, and encourage each other to develop and maintain a healthy lifestyle.

This research is based on the Wanbu network, a large social network created by the Chinese Center for Disease Control and Prevention. ‘Wanbu’ is a Chinese phrase that literally means ‘ten thousand steps,’ and the Wanbu network is designed to encourage people to walk more. Participants in the Wanbu network are provided with a wrist strap that records the number of steps (NS) walked on each day and allows the user to upload the data in www.wanbu.com.cn, where the data can be summarized and visualized (see Fig. 1). The network also allows participants to exchange information and interact with their friends. Specifically, a participant can post information and respond to (‘like’, comment on, and/or share) other participants’ posts, as illustrated in Fig. 2.

This article aims to shed light on the short-term effects of the aforementioned social interactions on an individual’s daily exercise level. Such interactions can be regarded as expressions of social encouragement. It has been found that social encouragement can help improve the health conditions of patients with mental disease⁸ and certain chronic conditions.^{9,10} Social encouragement has also been found to have positive influence on exercise habits in previous studies that used questionnaires to measure exercise on a weekly basis.^{11–13} To the best of our knowledge, shorter term effects of social encouragement on physical exercise have not been studied yet. Here, we attempt to answer this question using actual exercise data from the Wanbu network.

Methods

Data

The Wanbu network currently has over 574,050 registered participants. Through public access to the Wanbu website, a data set was created for 5010 participants who were in the network from March 14, 2014, to September 4, 2015, and had at least one social interaction recorded. The data were downloaded automatically using a Python crawler program which was developed specifically for this purpose. The information collected was limited to exercise and social interactions and did not include any personal information. The data collection procedure was approved by the Institutional Review Board of the Harbin Institute of Technology.

We measure daily exercise level using the NS walked and measure social encouragement using the following daily

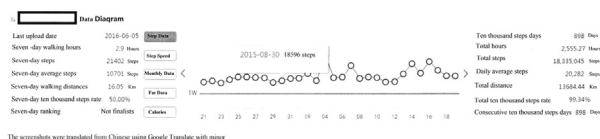


Fig. 1 – An example summary for an individual participant in the Wanbu network.

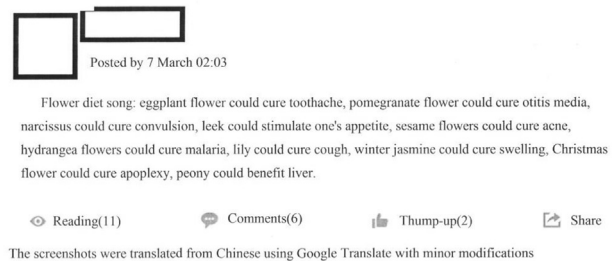


Fig. 2 – An example post by an individual participant in the Wanbu network.

counts: the number of comments (NC) received, number of thumbs-up (NT) received, and number of posts (NP) by friends in the network. NS is an important aspect of physical exercise with profound health implications. For example, increasing daily steps in primary care has been found to be a cost-effective approach toward improving daily physical activity among adults with type-2 diabetes.¹⁴

Analytical approach

Linear regression models were used to relate daily NS to NC, NT, and NP of the previous day, with a fixed or random subject effect to account for the variability between subjects. The models also adjusted for day of week (Sunday through Saturday) and quarter of year. The resulting models can be written as follows:

$$NS_{it} = \beta_0 + \beta_1 NP_{it-1} + \beta_2 NT_{it-1} + \beta_3 NC_{it-1} + \sum_j \phi_j DoW_{ijt} + \sum_j \gamma_j QoY_{ijt} + \phi_i + \varepsilon_{it}$$

where the subscript i denotes subject (1 through 5010), t represents time (day) since March 14, 2014, DoW stands for ‘day of week,’ QoY stands for ‘quarter of year,’ ϕ_i is a fixed or random effect for subject, and ε_{it} is a random error term. Both DoW and QoY are represented by dummy variables; for instance, DoW_{ijt} is a dummy variable indicating that the i th subject’s t th day in the data set is the j th day of a week. If ϕ_i is a random effect, it is assumed to follow a normal distribution with mean zero.

The models described previously address the heterogeneity between subjects but do not consider serial correlation (in the sense that the correlation between two observations from the same subject decreases with the gap time). To account for possible serial correlation, we also fitted dynamic models that include a lag term (i.e. yesterday’s NS) in addition to the terms described previously. In contrast, the models without a lag term will be referred to as static models. All models were fitted using the plm package in R.¹⁵

Results

Table 1 shows summary statistics for the quantitative variables concerned (NS, NC, NT, and NP). In addition, we also show the frequency distributions of NC, NT, and NP in Fig. 3. The participants in our data set walked approximately 15,000 steps a day on average, with a median of about 14,000 steps. The overall frequency of seeing a post was slightly

Table 1 – Summary statistics for quantitative variables.

Variable	Mean	SD
# steps	15,085	8209.65
# posts	0.3467	3.68
# comments	0.00973	0.27
# thumbs-up	0.00964	0.33

SD, standard deviation.

greater than one in three days, and the frequencies of receiving comments and thumbs-up were much lower (about one in 100 days for both measures). Fig. 4 shows bar charts for the average NS in each quarter and on each day of a week as well as within- and between-subject variation. There appears to be a seasonal trend in Fig. 4, with the first quarter being the least active one. Fig. 4 also suggests a weekly pattern in which participants walked more on weekdays than on weekends, with Monday being the most active day of a week.

Table 2 presents the results of linear regression analyses under the four models described in Analytical approach (with a fixed or random effect for subject, with or without a lag term). The Hausman test¹⁶ indicates that there is no evidence that the random-effect distribution is misspecified ($P = 0.1694$). The results in Table 2 consistently suggest that all three social interactions have positive effects on the next day's exercise level. The estimated effect sizes can be ordered as $NT > NC > NP$ for each of the four models considered. The choice of a fixed or random effect for subject seems to have minimal impact on the estimates of regression coefficients and the associated standard errors. The effects of social interactions tend to become smaller but remain statistically significant, when a lag term is added to the model, suggesting that social interactions might in part act as mediators between exercise levels on the present day and the next day. Despite the quantitative differences resulting from adding a lag term, the results in Table 2 clearly indicate that social

encouragement has positive short-term effects on exercise level.

Table 2 also confirms the seasonal and weekly patterns observed in Fig. 4. The first quarter is apparently the least active quarter of a year for exercise, possibly due to the fact that temperature is lowest in the first quarter in most parts of China. The reduced exercise level on weekends is presumably driven by the need to relax and recover from work stress.

Discussion

This research adds to the existing literature on social media and social networks by shedding light on the short-term effects of social interactions on exercise behavior, which have not been studied before. The main finding, that social interactions help increase an individual's exercise level on the next day, is consistent with previous research on the health benefits of social encouragement.^{6,8,9,12,17,18} This finding suggests that individual exercisers should be encouraged to interact more with their peers in exercise-related social networks such as Wanbu. It is worth noting that only 1.18% (5010/426,000) of the Wanbu participants had any social interactions at all during the study period, which suggests that increased social interactions could have a large positive impact on this community. The health benefits of social encouragement could be further amplified as industry leaders continue to develop new technologies to strengthen and expand the existing capabilities for social interactions.

One limitation of this observational study is the possible existence of unmeasured time-dependent confounders. Our models do include time-dependent covariates such as day of week, quarter of year, and possibly a lag term (NS on the present day), as well as a fixed or random subject effect that 'absorbs' all time-independent confounders. However, there may be other time-dependent confounders that are not included in our data set such as weather conditions and

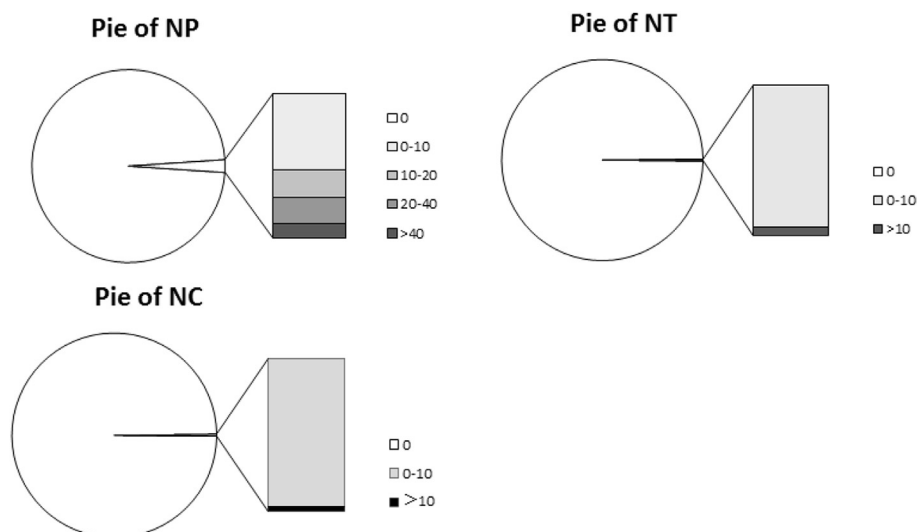


Fig. 3 – Pie graphs of number of posts (NP), number of thumbs-up (NT), and number of comments (NC).

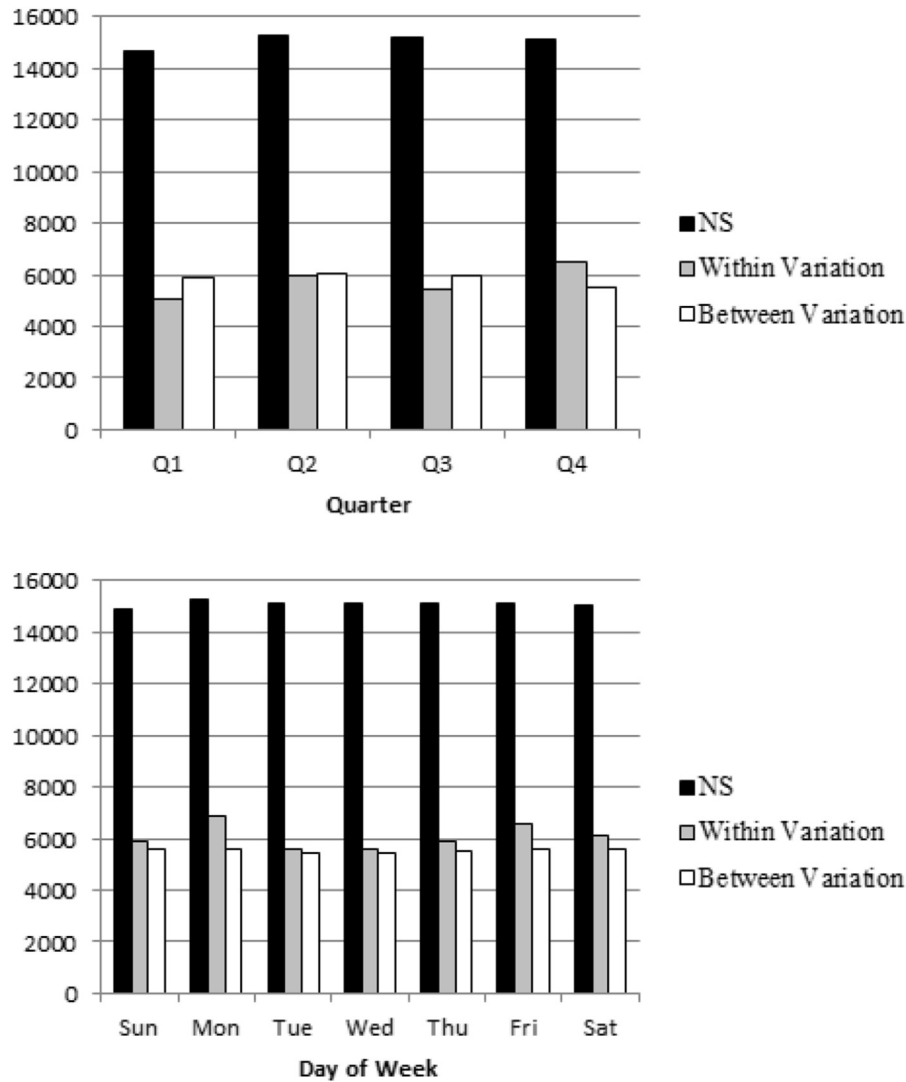


Fig. 4 – Bar charts for the average number of steps (NS) and its variation within and between subjects in each quarter and on each day of a week.

Table 2 – Estimated regression coefficients with standard errors (in parentheses).

Variables	Static models		Dynamic models	
	Fixed effect	Random effect	Fixed effect	Random effect
Intercept	–	13,341.41*** (78.88)	–	6116.30*** (22.46)
Step_Lag_1	–	–	0.42*** (0.0009)	0.56*** (0.008)
# posts	3.88** (1.76)	4.17** (1.76)	0.97 (1.56)	8.89*** (1.37)
# comments	89.74*** (16.29)	90.48*** (16.28)	26.57* (14.49)	45.24*** (14.89)
# thumbs-up	101.40*** (13.32)	102.80*** (13.32)	40.29*** (11.77)	67.80*** (12.15)
Sunday	Reference	–	–	–
Monday	437.86*** (21.38)	436.99*** (21.38)	530.48*** (19.26)	542.35*** (20.15)
Tuesday	292.80*** (21.41)	291.62*** (21.41)	1.97.39*** (19.12)	146.48*** (20.01)
Wednesday	285.75*** (21.36)	284.74*** (21.37)	266.86*** (19.20)	234.16*** (20.09)
Thursday	306.60*** (21.34)	305.48*** (21.34)	271.41*** (19.12)	240.18*** (20.01)
Friday	295.41*** (21.36)	294.26*** (21.36)	223.16*** (19.11)	185.40*** (20.00)
Saturday	156.52*** (21.47)	156.45*** (21.48)	82.52*** (19.25)	58.98*** (20.15)
Quarter 1	Reference	–	–	–
Quarter 2	735.38*** (17.07)	734.01*** (17.06)	422.19*** (15.38)	290.11*** (15.71)
Quarter 3	612.33*** (17.46)	611.32*** (17.46)	337.91*** (15.68)	246.04*** (15.86)
Quarter 4	615.89*** (19.70)	614.36*** (19.69)	373.37*** (17.69)	245.55*** (18.20)

*P < 0.1; **P < 0.05; ***P < 0.01.

special events. Such conditions and events may influence a Wanbu user's exercise behavior as well as social interactions. This limitation could be mitigated in future studies by extensive data collection under prospective designs. Another limitation of the current study is the restriction to a single platform. It is possible that individuals interact with each other on multiple platforms. This limitation can also be addressed with a prospective design that captures social interactions on multiple platforms.

Author statements

Contributors

XG, LW, and ZZ conceived of the study. LW and LL collected the data. ZZ and TW advised on, and LW performed statistical analysis. ZZ and LW drafted the manuscript, and XG commented and advised on the drafts. All authors read and approved the final manuscript.

Ethical approval

This study was approved by the Institutional Review Board at the School of Management, Harbin Institute of Technology. The data were analyzed anonymously in this study.

Funding

This study is an independent research supported by the National Natural Science Foundation of China Grants (71622002, 71531007, 71471048, 71471049, 71401046, and 71490720).

Competing interests

None declared.

REFERENCES

1. Ba S, Wang L. Digital health communities: the effect of their motivation mechanisms. *Decis Support Syst* 2013;**55**(4):941–7.
2. Maeen S, Zykov S. Towards social network–integrated E-health: identify user attitudes. *Procedia Comput Sci* 2015;**55**:1174–82.
3. Yang H, Guo X, Wu T. Exploring the influence of the online physician service delivery process on patient satisfaction. *Decis Support Syst* 2015;**78**:113–21.
4. Yang H, Guo X, Wu T, Ju X. Exploring the effects of patient-generated and system-generated information on patients' online search, evaluation and decision. *Electron Commer Res Appl* 2015;**14**(3):192–203.
5. Goh JM, Gao G, Agarwal R. The creation of social value: can an online health community reduce rural–urban health disparities? *MIS Q* 2016;**40**(1):247–63.
6. Yan L, Tan Y. Feeling blue? Go online: an empirical study of social support among patients. *Inf Syst Res* 2014;**25**(4):690–709.
7. Yan L, Peng J, Tan Y. Network dynamics: how can we find patients like us? *Inf Syst Res* 2015;**26**(3):496–512.
8. dos Santos LM, dos Santos DN, Rodrigues LC, Barreto ML. Maternal mental health and social support: effect on childhood atopic and non-atopic asthma symptoms. *J Epidemiol Community Health* 2012;**66**(11):1011–6.
9. Gallant MP. The influence of social support on chronic illness self-management: a review and directions for research. *Health Educ Behav* 2003;**30**(2):170–95.
10. Leung L. Loneliness, social support, and preference for online social interaction: the mediating effects of identity experimentation online among children and adolescents. *Chin J Commun* 2011;**4**(4):381–99.
11. Darlow SD, Xu X. The influence of close others' exercise habits and perceived social support on exercise. *Psychol Sport Exerc* 2011;**12**(5):575–8.
12. Resnick B, Orwig D, Magaziner J, Wynne C. The effect of social support on exercise behavior in older adults. *Clin Nurs Res* 2002;**11**(1):52–70.
13. So W-Y, Swearingin B, Robbins J, Lynch P, Ahmedna M. Relationships between body mass index and social support, physical activity, and eating habits in African American university students. *Asian Nurs Res* 2012;**6**(4):152–7.
14. Johnson S, Lier D, Soprovich A, Mundt C, Johnson JA. How much will we pay to increase steps per day? Examining the cost-effectiveness of a pedometer-based lifestyle program in primary care. *Prev Med Rep* 2015;**2**:645–50.
15. Croissant Y, Millo G. Panel data econometrics in R: the plm package. *J Stat Softw* 2008;**27**(2):1–43.
16. Hausman JA. Specification tests in econometrics. *Econometrica* 1978;**46**(6):1251–71.
17. Eriksson E, Lauri S. Informational and emotional support for cancer patients' relatives. *Eur J Cancer Care* 2000;**9**(1):8–15.
18. Hakulinen C, Pulkki-Råback L, Jokela M, E Ferrie J, Aalto AM, Virtanen M, et al. Structural and functional aspects of social support as predictors of mental and physical health trajectories: Whitehall II cohort study. *J Epidemiol Community Health* 2016;**70**(7):710–5.