

Sleep, Mood and Sociability in a Healthy Population

Sai T. Moturu, Inas Khayal, Nadav Aharony, Wei Pan and Alex (Sandy) Pentland

Abstract—Sleep and mood problems have a considerable public health impact with serious societal and significant financial effects. In this work, we study the relationship between these factors in the everyday life of healthy young adults. More importantly, we look at these factors from a social perspective, studying the impact that couples have on each other and the role that face-to-face interactions play. We find that there is a significant bi-directional relationship between mood and sleep. More interestingly, we find that the spouse's sleep and mood may have an effect on the subject's mood and sleep. Further, we find that subjects whose sleep is significantly correlated with mood tend to be more sociable. Finally, we observe that less sociable subjects show poor mood more often than their more sociable contemporaries. These novel insights, especially those involving sociability, measured from quantified face-to-face interaction data gathered through smartphones, open up several avenues to enhance public health research through the use of latest wireless sensing technologies.

I. BACKGROUND AND MOTIVATION

THE effects of social relationships and social support on health, both physical and mental, as well as their role in health promotion have been well-documented over the years [1], [2], [3], [4], [5], [6]. However, the interest in this space has grown in recent years after studies suggesting that social ties (self-reported friends) can have a significant effect on the adoption and spread of health-related behaviors such as obesity [7] and sleep loss [8].

While such studies have provided interesting insights and piqued the interest of the research community, their reliance on self-reported social tie information and longitudinal study

Manuscript received April 15, 2011. Research was partially sponsored by the Army Research Laboratory under Cooperative Agreement Number W911NF-09-2-0053, and by AFOSR under Award Number FA9550-10-1-0122. Views and conclusions in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. Government. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes notwithstanding any copyright notation.

S. T. Moturu is a postdoctoral associate at the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (phone: 919-289-9724; e-mail: smoturu@mit.edu).

I. Khayal is an assistant professor at the Masdar Institute of Science and Technology, Masdar City, Abu Dhabi. She is also a visiting professor at the Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: ikhayal@mit.edu).

N. Aharony is a PhD candidate associate at the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: nadav@media.mit.edu).

W. Pan is a PhD candidate associate at the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: panwei@media.mit.edu).

A. Pentland is the Toshiba Professor of Media, Arts, and Sciences at the Media Lab, Massachusetts Institute of Technology, Cambridge, MA 02139 USA (e-mail: pentland@media.mit.edu).

data collected at static time points over large time periods that does not capture real-world interactions leaves a large scope for richer data collection.

Until the start of this century, most of the data collected on human interactions was through self-reported surveys and experience sampling. More recently, long term monitoring has been implemented using a variety of technologies including video [8], smartphones [9], [10], [11] and wearable sensing devices [12], [13], [14], [15]. These studies clearly depict the importance of dynamic data collected from the real world as opposed to sole reliance on static self-reports. Such data has proven to be critical for the understanding of real-world user behaviors.

In this work, we gather much more dynamic and continuous data from subjects in a co-located community over a period of few months, alleviating some of the shortcomings of the experiments discussed above.

Such dynamic data can be obtained through a combination of wireless sensing and regular surveys. Current smartphones are increasingly used as social sensors [10], [16], [17]. We believe that such rich information of quantified face-to-face social interactions will provide novel insights. Our recent work [16], [18] reflects this belief with observations that such interactions seem to show stronger correlations with behavioral effects including weight gain as opposed to data of self-reported contacts. In addition to wireless sensing, regular surveys can provide useful information that might not be easy to gather automatically. Such surveys can enable us to track behavioral aspects on a daily scale over many months.

In this work, we are interested in studying the bidirectional effects between sleep and mood. The motivation for studying sleep and mood is due to their considerable impact on public health and its associated financial and societal costs.

It is estimated that 50-70 million Americans suffer from a chronic disorder of sleep and wakefulness [19] and sleep problems account for significant direct (an estimated \$14 billion for insomnia [20]) and indirect costs (sleep-related fatigue alone is estimated to cost businesses \$150 billion yearly [19]). Poor sleep has an influence on several comorbid conditions including diabetes, obesity and cardiovascular morbidity, significantly affects behavior and has a strong association with psychiatric or psychological conditions. Further, poor sleep can result in impaired cognitive function, decreased quality of life and job performance, and increased risk of road and industrial accidents [19].

Like sleep, mood disorders also have significant financial

costs. Annual cost estimates for depression and anxiety disorders are over \$100 billion [21]. However, the indirect costs and intangible effects of mood-related problems have a much greater societal impact. While negative affect is frequently associated with risk for illness and mortality, positive affect is associated with lower morbidity and improved health outcomes [22], [23].

In addition to studying the relationship between sleep and mood, we are interested in studying these behaviors from a social perspective. In particular, we wish to study the effects that couples have on each other in terms of these factors and also the role the face-to-face interactions play on them. Hence, we select a co-located family community that allows us to study these aspects in a natural real world setting with healthy young couples going about their everyday lives as they normally would.

II. EXPERIMENT

A. Overview and Participants

Starting March 2010, we initiated a living laboratory conducted with members of a young-family residential living community adjacent to a university in North America. All members of the community are couples, and at least one the members is affiliated with the university, usually as a graduate student. The entire community is composed of over 400 residents, approximately half of which have children, with low- to mid-range household income. The residence has a vibrant community life, with many ties of friendship between its members. The data used for this analysis was collected from 54 participants. Participants provided informed consent as approved by the Committee on the Use of Humans as Experimental Subjects at our institution.

Participants were provided Android smartphones with a proprietary software sensing platform that allowed us to track face-to-face interactions through bluetooth proximity sensing in addition to other behavioral, contextual and communication patterns. Regular surveys were used to obtain additional contextual and behavioral information about participants.

B. Sensing Platform

This is the core of the study's data collection. Android operating system-based mobile phones are used as in-situ social sensors to map users activity features, proximity networks, media consumption, and behavior diffusion patterns. The phones are augmented with our software platform, which periodically senses and records information such as cell tower ID, wireless LAN IDs; proximity to nearby phones and other Bluetooth devices; accelerometer and compass data; call and SMS logs; statistics on installed phone applications, running applications, media files, general phone usage; and other accessible information. Figure 1 depicts an overview of the system architecture.

The phone system also has a survey application. We did not sponsor phone plans or data plans - users received a mobile phone that fit their desired provider, and they were

responsible to port their existing account to it or open a new account. The condition was that the study phone be their primary phone for the duration of the study.

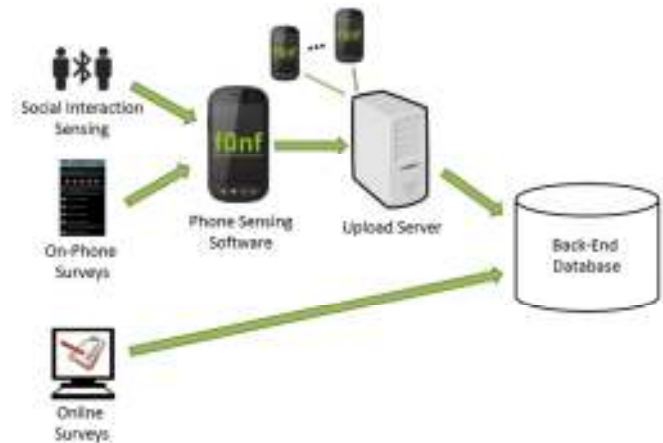


Figure 1. Overview of system architecture

C. Surveys

Subjects complete web-based surveys at regular intervals. Monthly, daily and weekly surveys include questions about relationships and social activities, personality using standard scales like the Big-Five Inventory [24] and behavioral information such as mood, diet, exercise and sleep.

D. Dataset

The dataset used here includes a combination of self-reported survey data and automatically captured face-to-face interactions. This data was collected from the 54 healthy subjects over a period of 4 months. The final dataset included 4602 days of sleep and mood data, a large amount of data for this domain.

The sleep information was self-reported by subjects (the options were provided in hours: <5, 5, 6, 7, 8, 9, >9). Sleep of 7 hours or more is considered 'good' while sleep under 7 hours is considered 'poor'. Users were also asked to select their predominant mood for the day from multiple options. This was ultimately grouped into good mood (Happy or content, Relaxed or peaceful) and poor mood (Stressed or anxious, Angry or frustrated). Finally, the data also included personality information (extraversion, agreeableness, conscientiousness, neuroticism, openness) for the subjects using the Big-Five Inventory.

Physical proximity data for face-to-face interactions over a one-month period was used to compute a measure of sociability, indicating how sociable an individual was over that time period. It should be noted that this measure only included face-to-face interactions within this community and is assumed to provide a reasonable proxy for sociability.

III. RESULTS AND DISCUSSION

A. Sleep and Mood

We aggregated daily data across all subjects to study the

bidirectional relationship between sleep and mood. Figure 2 depicts the mean sleep and mood of the subjects. We observed that when participants had slept less than 7 hours, the predominant mood observed was poor in nearly 47.3% of the cases. However, when they had slept 7 hours or more, this number dropped to 28.3%. This difference was found to be significant ($p < 0.001$). This result holds even when the husbands and wives are analyzed separately ($p < 0.001$). The odds ratio for poor mood is 2.27 illustrating that it is more likely for nights with poor sleep.

Considering that mood could also affect sleep, we also looked the effect of a day's predominant mood on that night's sleep. We observe that when the predominant mood was poor, the sleep was also poor in 29.8% of the cases. However, when the mood is good, this number drops to 16.5%. This difference was also found to be significant ($p < 0.001$). The odds ratio for poor sleep is 2.14, illustrating that it is more likely after days with a predominantly poor mood.

B. Couples

While the above results from individual data is interesting, the key aspect of this study is the presence of couples. We describe our observations from the couples in this section.

First, we present some overall patterns in these couples. We observe that 1) the wives show poor mood more often than the husbands ($p < 0.0001$), 2) the wives sleep slightly better than their husbands ($p < 0.001$), and 3) there is no significant difference in the sociability of the wives and husbands in this community.

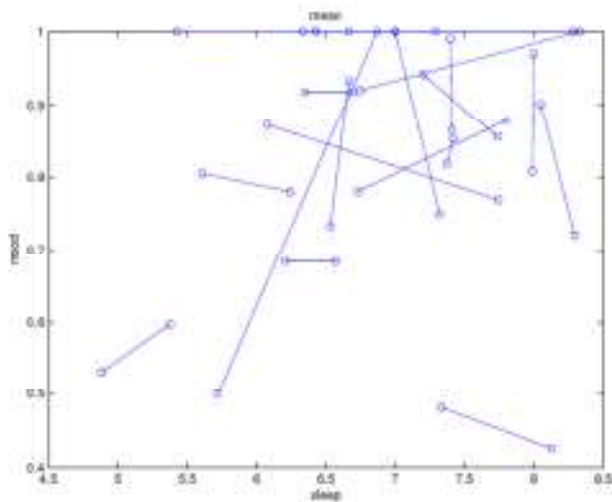


Figure 2. Mean sleep and mood in subjects. Sleep is in hours. Mood is binary (1 indicates good mood and 0 indicates bad mood). Each point on the plot is a subject. Couples are linked with a straight line between the points.

Next, we look at sleep and mood as earlier, aggregating data for couples (as opposed to individuals). The following day's mood was significantly poorer for the spouses of those who slept less than 7 hours (39.8% of the cases) when

compared to those who slept more than 7 hours (25.8%). However, the effect size is slightly lower when compared to the effect of one's own sleep on mood. The odds ratio for poor mood is 1.90 illustrating that it is more likely that an individual has poor mood when their spouse has had poor sleep. Similarly, the night's sleep was significantly poorer for the spouses of those who had predominantly poor mood that day.

The observations so far indicate that an individual's mood could be affected by their sleep as well as their spouse's sleep. To understand these effects we perform a logistic regression analysis using an individual's mood as the dependent variable and their sleep, spouse's sleep and spouse's mood as independent variables. We find that the individual's sleep ($p < 0.001$) and spouse's mood ($p < 0.001$) are significantly predictive of the individual's mood.

Similarly, an individual's sleep could be affected by their mood and their spouse's mood. Using logistic regression as earlier, we find that the individual's mood ($p < 0.001$) and spouse's sleep ($p < 0.001$) are significantly predictive of the individual's mood. Using the same two predictors to predict that dependent variable, we obtain a classification accuracy of 60% in the former case and 71% in the latter, once again depicting the predictive power of these variables.

While sleep and mood have been linked in the past, they have not been studied in healthy couples in the past (to the best of our knowledge). These results are very interesting and present several avenues to study such effects in more detail in the future.

C. Sociability

So far, we've presented results from studying patterns at the aggregate level. Here, we move towards individual patterns. On an aggregate level, we find the sleep and mood were significantly correlated. When we look at these patterns for every individual, we find that some subjects show significant correlations while others do not. Delving deeper, we find that the subjects whose mood was significantly affected by the previous night's sleep tended to have greater sociability ($p = 0.063$). One explanation for this interesting observation could be based on individual personality traits as some traits might make it more likely for a subject to be affected by mood. However, we find no correlation with the Big Five personality traits as we find with the phone-based sociability feature. This could indicate that features derived automatically using smartphones might be useful in detecting such differences. This is in tune with some past observations where it was found retroactively that phone-based features might be useful in early flu detection (Madan et al. 2010b).

Further, we study the relationship between mood and sociability. Using the mood information, we separated the groups into two: 1) those who exhibited primarily good mood (relaxed, calm, happy, content) i.e., on at least 70% of the occasions 2) those who exhibited poor mood (stressed, anxious, frustrated, angry) i.e., on at least 30% of the occasions. We observed that people who fell into the latter

group were significantly less sociable in this community ($p=0.02$). This is an intriguing finding, one that would not have been possible without such quantifiable face-to-face interaction data collected through smartphones. Mood is an important factor that is known to play an important role in several comorbid conditions. Hence, this observation could indicate that greater sociability results in better overall health through improved mood, supporting an oft heard notion about social interactions.

A similar analysis was also conducted using the amount of sleep obtained each night by participants instead of mood. However, no significant correlations were found. Nevertheless, this is in tune with our expectation that day-to-day variations in sleep are not affected by how sociable an individual is.

IV. CONCLUSIONS AND FUTURE WORK

In this work, we study several aspects of the relationships between sleep, mood and sociability using data from a population of healthy couples in a naturalistic setting. We find that there is a significant bidirectional relationship between sleep and mood. More interestingly, we find that the spouse's sleep and mood might affect a subject's mood and sleep respectively. However, the most significant impact to a subject's mood seems to be from their own sleep as well as their spouse's mood.

We also find that a subject's sociability, a measure of how much social interaction they have, seems to be predictive of the individuals who have the most significant correlation between sleep and mood. Further, we find that the more sociable subjects tend to have better mood on average. These intriguing insights are made possible by the novel use of smartphones as social sensors to quantify the amount of face-to-face interactions that subjects have and open up avenues for more health-related studies using such sensing.

The results depicted here open up several questions about the impact of social interactions on sleep and mood, which may be answered through subsequent studies. In particular, we would like to use the rich social interaction data available for this population to gain further insights in this direction. Further, it would also be more useful to gather rich sleep data. We are currently running an experiment gathering rich sleep data (quantifying sleep quality in addition to quantity) using a wireless sensing headband (a commercial product manufactured by Zeo Inc.) to leverage the opportunity of studying sleep in a naturalistic setting. Through this work, we hope to provide novel insights and bring greater interest to the potential for public health research using the latest capabilities in wireless sensing.

ACKNOWLEDGMENT

We would like to thank Cory Ip for significant contributions towards experimental deployment and management. We would also like to thank several undergraduate contributors for their help with the development of the sensing platform.

REFERENCES

- [1] L. Berkman, "Assessing the physical health effects of social networks and social support", *Annual Review of Public Health*, vol. 5, no. 1, pp 413–432, 1984.
- [2] L. Berkman, "The role of social relations in health promotion", *Psychosomatic Medicine*, vol. 57, no 3, pp 245, 1995.
- [3] L. Berkman, T. Glass, I. Brissette, and T. Seeman, "From social integration to health: Durkheim in the new millennium", *Social Science & Medicine*, vol. 51, no. 6, pp 843–857, 2000.
- [4] M. Marmot, and R. Wilkinson, *Social determinants of health*, Oxford University Press, 2005.
- [5] S. Cohen, B. H. Gottlieb, and L. G. Underwood, "Social relationships and health", *American Psychologist*, vol. 59, pp 676–684, 2004.
- [6] K. Rook, "The negative side of social interaction: Impact on psychological well-being", *Journal of Personality and Social Psychology*, vol. 46, no. 5, p. 1097, 1984.
- [7] N. Christakis, and J. Fowler, "The spread of obesity in a large social network over 32 years", *New England Journal of Medicine*, vol. 357, no. 4, pp 370, 2007.
- [8] S. C. Mednick, N. A. Christakis, and J. H. Fowler, "The spread of sleep loss influences drug use in adolescent social networks", *PLoS One*, vol. 5, no. 3, pp e9775, 2010.
- [9] D. Roy, R. Patel, P. DeCamp, R. Kubat, M. Fleischman, B. Roy, N. Mavridis, S. Tellex, A. Salata, J. Guinness, M. Levit, and P. Gorniak, "The human speechome project", *Lecture Notes in Computer Science*, vol. 4211, pp 192, 2006.
- [10] N. Eagle, and A. Pentland, "Social network computing", *Lecture notes in computer science*, pp 289–296, 2003.
- [11] N. Eagle, and A. Pentland, "Reality mining: sensing complex social systems", *Personal and Ubiquitous Computing*, vol. 10, no. 4, pp 255–268, 2006.
- [12] N. Eagle, A. Pentland, and D. Lazer, "Inferring friendship network structure by using mobile phone data", *Proceedings of the National Academy of Sciences*, vol. 106, no. 36, pp 15274, 2009.
- [13] A. Pentland, "Socially aware computation and communication", *In Proceedings of the 7th international conference on Multimodal interfaces*, 2005.
- [14] T. Choudhury, M. Philipose, D. Wyatt, and J. Lester, "Towards activity databases: Using sensors and statistical models to summarize peoples lives", *IEEE Data Engineering Bulletin*, vol. 29, no. 1, pp 49–58, 2006.
- [15] D. Olguin Olguin, P. Gloor, and A. Pentland, A, "Wearable Sensors for Pervasive Health-care Management", 2009.
- [16] D. Olguin Olguin, B. Waber, T. Kim, A. Mohan, K. Ara, and A. Pentland, "Sensible organizations: Technology and methodology for automatically measuring organizational behavior", *IEEE Transactions on Systems, Man, and Cybernetics-B*, 2009.
- [17] A. Madan, S. T. Moturu and A. Pentland, "Social Sensing: Obesity, unhealthy eating and exercise in face-to-face networks", *In Proceedings of Wireless Health '10*, 2010.
- [18] N. Aharony, W. Pan, C. Ip, I. Khayal and A. Pentland, "The Social fMRI: Measuring, Understanding and Designing Social Mechanisms in the Real World", *In Proceedings of the 13th ACM International Conference on Ubiquitous Computing*, 2011.
- [19] A. Madan, M. Cebrian, A. Pentland, "Social Sensing for Epidemiological Behavior Change", *In Proceedings of ACM Ubicomp 2010*.
- [20] H. Colten, and B. Altevogt, *Sleep disorders and sleep deprivation: an unmet public health problem*. National Academies Press, 2006.
- [21] J. Walsh, "Clinical and socioeconomic correlates of insomnia", *Journal of Clinical Psychiatry*, vol. 65, no. 8, pp 13-19, 2004.
- [22] R. C. Kessler, and P. E. Greenberg, "The economic burden of anxiety and stress disorders", *Neuropsychopharmacology: The Fifth Generation of Progress*, pp 981-992, 2002.
- [23] S. Cohen, and S. D. Pressman, "Positive Affect and Health", *Current Directions in Psychological Science*, vol. 15, no. 3, pp 122, 2006.
- [24] A. Steptoe, L. O'Donnell, M. Marmot, and J. Wardle, "Positive affect and psychosocial processes related to health", *British Journal of Psychology*, vol. 99, no. 2, pp 211-227, 2008.
- [25] O. P. John, S. Srivastava, "The Big-Five trait taxonomy: History, measurement, and theoretical perspectives", 1999.