

## **Loneliness in an Age of Unprecedented Social Connection: Using Data Analytics to Explore the Role of Social Media in Bolstering or Impairing Well-Being**

**Background:** Whether briefly acknowledging a passerby, conversing with a friend over a cup of coffee, or sending quick text messages to friends and colleagues, frequent social interaction in many ways defines the human experience. With the advent of social media, we have more access to others than ever before, so why does loneliness continue to be a pervasive social problem? The **goal of** this proposal is twofold: 1) to investigate the relative value of different kinds of social interactions, both in-person and through social media, in terms of loneliness and well-being and 2) to leverage this knowledge to address loneliness.

Despite lacking the palpability of in-person social interactions, psychological research suggests that social media interactions should elicit very real psychological consequences. Minor similarities such as knowing that someone happens to like the same painting during a laboratory study, can lead to feelings of affiliation and a preference for subsequently socializing with someone [1]. Conversely, even the experience of being excluded from a computer game of catch between two cartoon characters can elicit the hurt feelings and affiliative desires of real social rejection [2]. On a larger scale, **loneliness and rejection are public health issues**. Living alone increases the **mortality rate of seniors by over 20%, which is comparable to smoking and drinking, and higher than obesity**. Loneliness is also associated with **negative health outcomes, including heart disease** [3-5].

Different modes of communication via social media (e.g., likes vs. posts) can be differentiated from each other, as well as from face-to-face conversation, based on the presence or absence of social cues. If the absence of cues, such as facial expressions or real-time responding, makes social media-based interactions less fulfilling, then social media should have negative effects on well-being and one's sense of belonging, as some past studies have found [6]. But, an individual's experience of the social world depends on how the individual *interprets* social situations rather than on objective aspects of a situation [7]. To the extent that people 'fill in' information, e.g. by imagining someone's tone, based on their expectations, **the psychological effects of virtual interactions should vary by person and situation**.

**Research Objective:** With the emergence of smartphones, mobile applications, and wearable devices, people generate tremendous amounts of data in their daily lives, which can be used to track and predict important aspects of the human experience [8, 9, 10], including depression [11, 12] social anxiety [20], life decisions [13], and students' academic performance [14]. Furthermore, prior work exploring social interactions among the lonely has relied on self-report measures, whereby participants recall how they behaved in past social encounters [15]. This can be problematic, as participants may be embarrassed to disclose, or may misremember, the nature of their actual feelings during past interactions. Fortunately, with the advent of wearable Smart Watches and Sensors, we are now able to track **psychophysiological data** from participants, which lies outside of their conscious control. Our study will thus measure both Galvanic Skin Response (GSR) and heart rate--two well-validated measures of stress and arousal [16]--to track participants' levels of anxiety during real social encounters. We propose a novel study bridging across heterogeneous platforms, including mobile phones, wearables, and lab questionnaires to predict, analyze, and ultimately improve the part of people's quality of life affected by day-to-day social interaction.

### **Experimental Methodology:**

80 undergraduates will be recruited for course credit from the psychology department participant pool (a number based on effect sizes in prior studies) [6]. Participation will last 30

days. We will compare responses across the resulting panel data to isolate the effects of different mediums of communication. A phone application (Sensus) will communicate with APIs from social media applications (Facebook and Twitter). By designing the research protocol mounted on Sensus, we will also collect self-report data. In fact, in our previous work, we have already implemented a protocol to collect and analyze the locality and self-report data in Sensus [20]. Furthermore, we will add advanced functionality to the Sensus platform by integrating sound and psychophysiological sensing from the smart watches. Based on past studies, we will contact participants at fixed 2-3 hour intervals determined by participants to avoid contacting participants during classes [6]. These measures collected through Sensus include:

Heart-rate and Galvanic Skin Response (GSR) from Smart Watch provided by the Engineering school: Indicators of arousal, which will be used for the assessment of stress and anxiety.

Psychological questionnaires through Sensus: Brief measures of mood [17] and loneliness [18].

Questionnaires concerning social media use: Participants will be asked questions about the nature and duration of social media usage, e.g. whether they used social media actively by making their own posts or passively by reading posts, whether they liked someone else's post or someone liked theirs, etc. Questionnaires will be targeted based on the activity log and structured like decision trees to minimize length.

Microphone: will indicate communication in person. No recordings for privacy reasons.

GPS Data: will measure movement, which may be an indicator of a social, active lifestyle.

Activity Logs: Will include participants' activities in texting and social media applications (e.g. Facebook, twitter). The latter will be downloaded through the provided APIs to help us target questions asked through the Sensus app.

Phone log: will indicate how much time participants are spending talking on the phone.

Text Analysis: Looking at positive, negative, and social connection words used by participants during their everyday social media interactions to see how participants feel as they are using social media. This measure will also allow us to assess intervention effectiveness.

These individual difference variables will be collected at the beginning and end of the study:

Demographics: Age, sex, race, socioeconomic status, marital status, political orientation, etc.

Individual Differences: Standard social anxiety, personality, self-esteem, and depression scales.

### **Research Hypotheses:**

- Unambiguous social cues in social media, such as 'likes' and 'retweets' will make individuals feel less lonely and happier regardless of mental health and whether someone gives or receives the cue.
- Ambiguous social cues, such as purely substantive text, will provide well-being and reduce loneliness for healthy individuals, but not anxious or unhappy individuals who will interpret ambiguous cues more negatively.
- People will seek out social media when lonely, regardless of mental health status.
- Specific usages of social media, like 'retweets' and 'likes', can be therapeutic, as indicated by global, long-term reductions in participants' GSR and heart rates.

### **Data Analysis:**

We will use data analytic techniques to explore the patterns of people's loneliness using their daily life data from both real-time and offline tracking. Based on that analysis, we will generate anti-loneliness interventions using social media to improve well-being and reduce loneliness.

Our analysis will have 5 steps:

1. Visualization: to develop appropriate models to verify our pre-formed hypothesis.

2. Feature selection: to understand people's loneliness behavior deeply, we will use generic algorithms (e.g. Mutual information, Chi-square, Principle Component Analysis) to select features that reveal human loneliness patterns. For example, the frequency of using social media, the frequency of receiving or sending Unambiguous social cues in social media.

3. Data mining and machine learning: we will apply data mining and machine learning techniques to the data at both individual and aggregated levels using mood, physiological, social media, social interaction and location statistics. Classification and prediction models will be developed by using state-of-the-art algorithms (e.g., Linear Discriminant Analysis, Support Vector Machine) too.

4. Anti-loneliness intervention generation: As an applied focus, we will generate an anti-loneliness intervention based on analyses from the procedures above. This intervention will be relevant to social media and face-to-face social interactions.

5. Evaluation: Cross-validation will be used to the models built in 3 and to further verify the predictors of both the preliminary hypothesis and new feature patterns. To evaluate the intervention, we will track the loneliness scales of participants and evaluate the changes of their subject well-being in practice.

**Novel Features and Broader Impacts of the Proposed Project:** We expect the present investigation to inform, and perhaps transform, our understanding of social media and its relationship to loneliness and well-being. Previous studies have mainly been small-scale studies confined to lab settings, divorced from the real world, that have ignored individual differences among participants. In contrast, our project will employ a large-scale, data science approach to examine the collective impact of the ways individuals connect with each other. Rather than restricting ourselves to Facebook, we will comparatively examine multiple social media platforms (e.g., Twitter, Reddit) and direct in-person contact. In addition to survey measures, we will also incorporate objective indicators of social connection: phone logs, microphone data, GPS, and physiological data, as participants are naturally immersed in their social worlds. We will also collect individual difference measures (chronic loneliness, social anxiety, etc.), which will allow us to examine differential patterns of social network activity between different types of individuals. **More importantly, this will enable us to identify the social strategies that best predict well-being, belonging, and a happy life.** More broadly, we aim to **incorporate our findings into a potential low-cost, therapeutic intervention to bolster belonging and well-being in populations particularly vulnerable to loneliness.** Ng, Oishi, and colleagues, for example, have found that college students often report high levels of loneliness and mental health issues, due to moving away from home and losing their social network [19, 21].

Using an interdisciplinary approach will allow Brandon Ng, a social neuroscientist, and Adi Shaked, a social psychologist, to carve the social word at its joints, while Yu Huang's engineering background provides the mathematical expertise for evaluating our complex, cross-platform hypotheses and to mine the data for new relationships beyond the original hypotheses. This proposal represents a unique opportunity to answer otherwise elusive questions concerning the extent to which social media can be a surrogate for live interactions, and can be a useful first step toward leveraging social media in a therapeutic capacity. Furthermore, the short time scales along which interventions can be introduced, implemented, and measured can lead to improvements, both theoretically and in the real-world, at exponentially faster rates than what would traditionally be possible in lab settings. Social media, which has been blamed for the erosion of human sociality, may yet be the tool that transforms what a BBC documentary recently described as "The Age of Loneliness" into "The Age of Social Connection".

## References:

- [1] Tajfel, H., & Billic, M. (1974). Familiarity and categorization in intergroup behavior. *Journal of Experimental Social Psychology*, 10(2), 159-170.
- [2] Williams, K. D., Cheung, C. K., & Choi, W. (2000). Cyberostracism: effects of being ignored over the Internet. *Journal of Personality and Social Psychology*, 79(5), 748-762.
- [3] House, J. S., Landis, K. R., & Umberson, D. (1988). Social relationships and health. *Science*, 241(4865), 540-545.
- [4] Holt-Lunstad, J., Smith, T. B., & Layton, J. B. (2010). Social relationships and mortality risk: a meta-analytic review. *PLoS Med*, 7(7), e1000316.
- [5] Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and Social Isolation as Risk Factors for Mortality A Meta-Analytic Review. *Perspectives on Psychological Science*, 10(2), 227-237.
- [6] Kross, E., Verduyn, P., Demiralp, E., Park, J., Lee, D. S., Lin, N., ... & Ybarra, O. (2013). Facebook use predicts declines in subjective well-being in young adults. *PloS one*, 8(8), e69841.
- [7] Shaked, A. & Clore, G.L. (in press). Breaking the World to Make it Whole Again: Attribution in the Construction of Emotion. *Emotion Review*.
- [8] <http://www.digitaltrends.com/mobile/informate-report-social-media-smartphone-use/>
- [9] <http://www.cnn.com/2015/11/03/health/teens-tweens-media-screen-use-report/>
- [10] Andreas M. Kaplan, Michael Haenlein, Users of the world, unite! The challenges and opportunities of Social Media, *Business Horizons*, Volume 53, Issue 1, January–February 2010, Pages 59-68, ISSN 0007-6813, <http://dx.doi.org/10.1016/j.bushor.2009.09.003>.
- [11] Canzian, Luca, and Mirco Musolesi. "Trajectories of depression: unobtrusive monitoring of depressive states by means of smartphone mobility traces analysis." *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2015.
- [12] De Choudhury, Munmun, et al. "Predicting Depression via Social Media." *ICWSM*. 2013.
- [13] Saeb, Sohrab, et al. "Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: an exploratory study." *Journal of medical Internet research* 17.7 (2015).
- [14] Wang, Rui, et al. "Studentlife: assessing mental health, academic performance and behavioral trends of college students using smartphones." *Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing*. ACM, 2014.
- [15] Gardner, W. L., Pickett, C. L., & Brewer, M. B. (2000). Social exclusion and selective memory: How the need to belong influences memory for social events. *Personality and Social Psychology Bulletin*, 26(4), 486-496.
- [16] Golland, Y., Keissar, K., & Levit-Binnun, N. (2014). Studying the dynamics of autonomic activity during emotional experience. *Psychophysiology*, 51(11), 1101-1111.
- [17] Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: the PANAS scales. *Journal of personality and social psychology*, 54(6), 1063-1070.
- [18] Russell, D., Peplau, L. A., & Ferguson, M. L. (1978). Developing a measure of loneliness. *Journal of personality assessment*, 42(3), 290-294.

**[19] Oishi, S., Kesebir, S., Miao, F. F., Talhelm, T., Endo, Y., Uchida, Y., ... & Norasakkunkit, V. (2013). Residential mobility increases motivation to expand social network: But why?. *Journal of Experimental Social Psychology*, 49(2), 217-223.**

**[20] Assessing Social Anxiety using GPS Trajectories and Point-Of-Interest Data. (2016)[Under Review].**

**[21] Ng, B.W., Oishi, S., & Morris, J.P (2016). Will anybody love me?: Dynamic neural mechanisms underlying the effects of residential mobility on social perception. Unpublished manuscript.**