SocialText:

A Framework for Understanding the Relationship between Digital Communication Patterns and Mental Health

Sanjana Mendu, Mehdi Boukhechba, Anna Baglione, Sonia Baee, Congyu Wu, Laura Barnes

University of Virginia

Overview

Overview

- **Introduction**
- **Background**
- Framework
- Discussion
- Applications
- Future Work

Introduction

- Approximately 3.2 billion people actively use social media worldwide
- Over 43 million American adults suffer from a mental health or substance abuse condition, and treatment remains difficult to access for many [1]
- The pervasive nature of traditional SMS messaging and the growing popularity of social networking applications have yielded a rich landscape of digital textual communications (DTCs)
- DTCs are particularly promising for addressing the current widespread mental health crisis

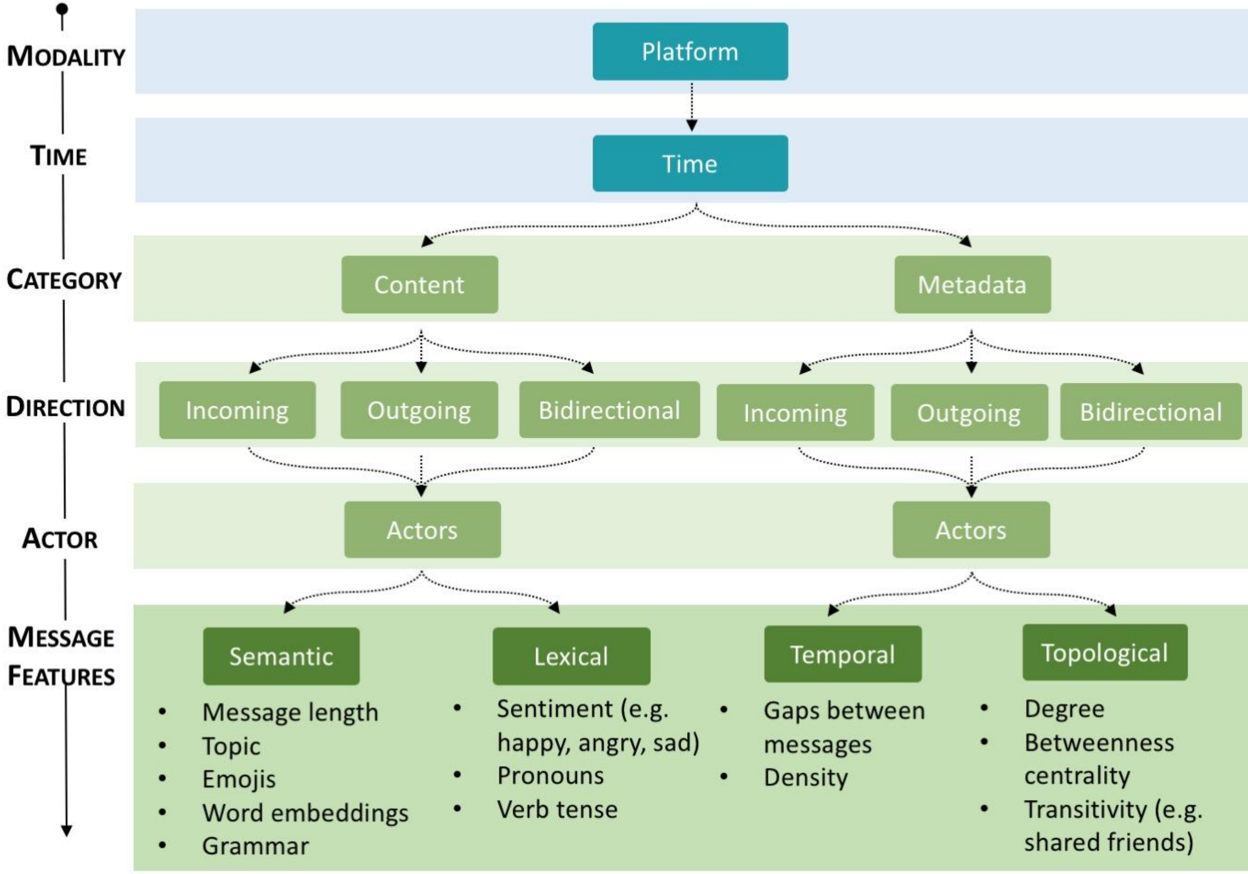
Background

- For individuals facing periods of stress, depression, and loneliness, DTCs provide a window into their mental state, coping behaviors and social support network [2]
- However, despite the richness of their features, DTCs remain largely unexplored in existing mobile sensing frameworks.
- Current approaches to analyzing DTCs for mental health remain largely split along quantitative-qualitative lines
- Combining these methods is important to comprehensively characterize mental health outcomes related to digital text communication

Overview

- Introduction
- Background
- **Framework**
- Discussion
- Applications
- Future Work

Framework Diagram



Feature Examples

Proportion of platform usage (e.g. Facebook vs. Twitter, mobile vs. desktop)

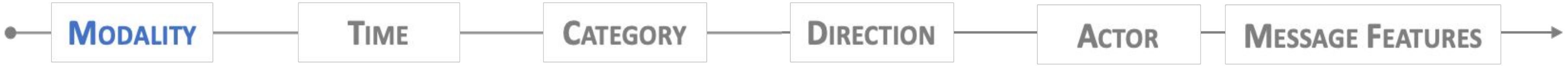
Time of day (e.g. morning, 6-9am), day of week (e.g. Monday, weekday)

Ratio of incoming/outgoing messages

Name, relationship, demographic (e.g. age, gender, nationality, language, ethnicity) of recipients/senders

(Feature examples clustered by type in this layer)

Modality



- The **Modality** layer encompasses software and hardware level differences in methods by which people can engage with digital text communication
- Modalities can be differentiated in terms of the **software** platform (e.g. Facebook, SMS) and/or **hardware** (e.g. laptop, phone) used

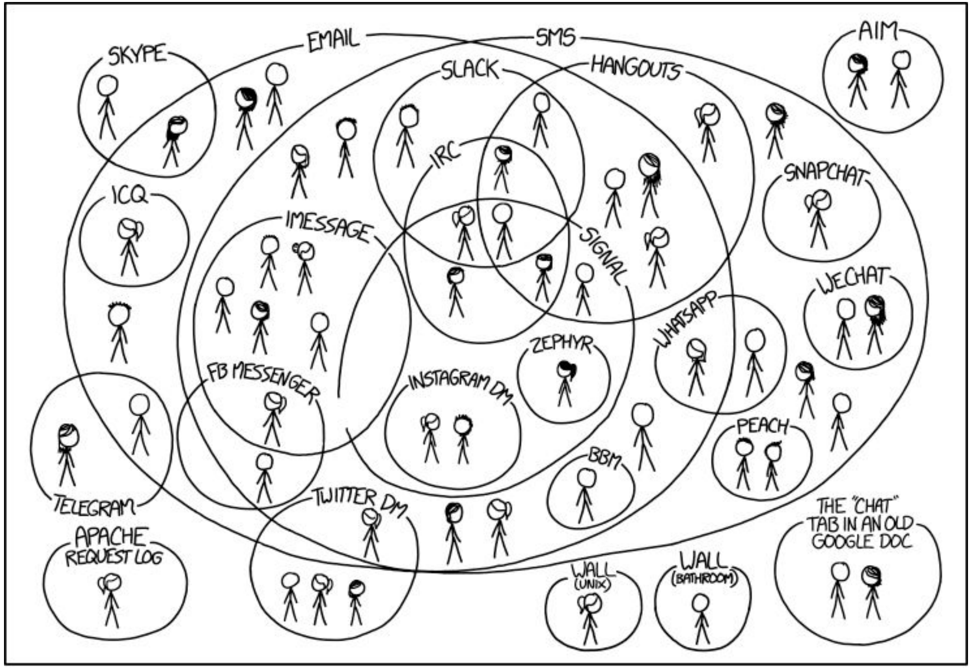
Software

Hardware

Modality

MODALITY → TIME → CATEGORY → DIRECTION → ACTOR → MESSAGE FEATURES

- The **Modality** layer encompasses software and hardware level differences in methods by which people can engage with digital text communication
- Individuals interact with each other differently on different platforms
- Differences in platform **demographics** and **features** can influence social contexts and interactions



I HAVE A HARD TIME KEEPING TRACK OF WHICH CONTACTS USE WHICH CHAT SYSTEMS.

Time

MODALITY — TIME — CATEGORY — DIRECTION — ACTOR — MESSAGE FEATURES

Trait Measures

- Individual-level predispositions
- Usually assessed clinically
- Depression / Anxiety / Personality

Hybrid Measures

- Longitudinal emotional states
- Not quite trait-level stability
- "How did you feel this week?"

State Measures

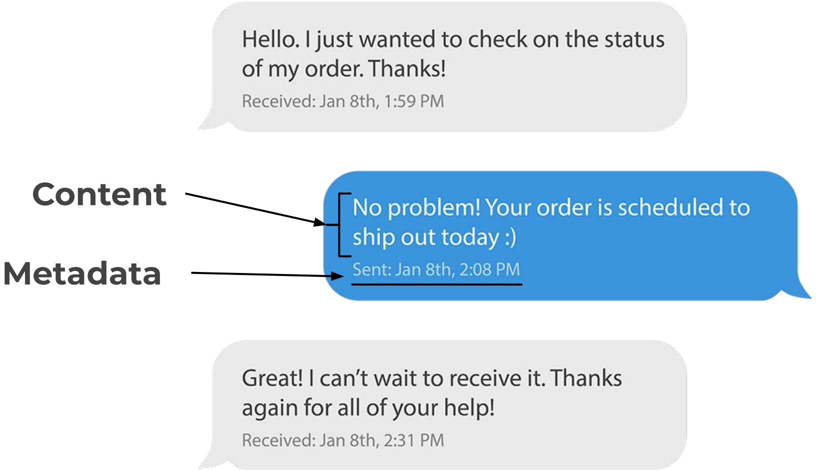
- Momentary feelings
- Current mood, affect, etc.
- "How do you feel right now?"

- The **Time** layer defines the time window of interest (i.e. hour, day, week)
- Time is an important factor for mental health, as different temporal contexts may yield different insights
- Researchers can use time windows that match the target mental health outcome

Category

MODALITY — TIME — CATEGORY — DIRECTION — ACTOR — MESSAGE FEATURES

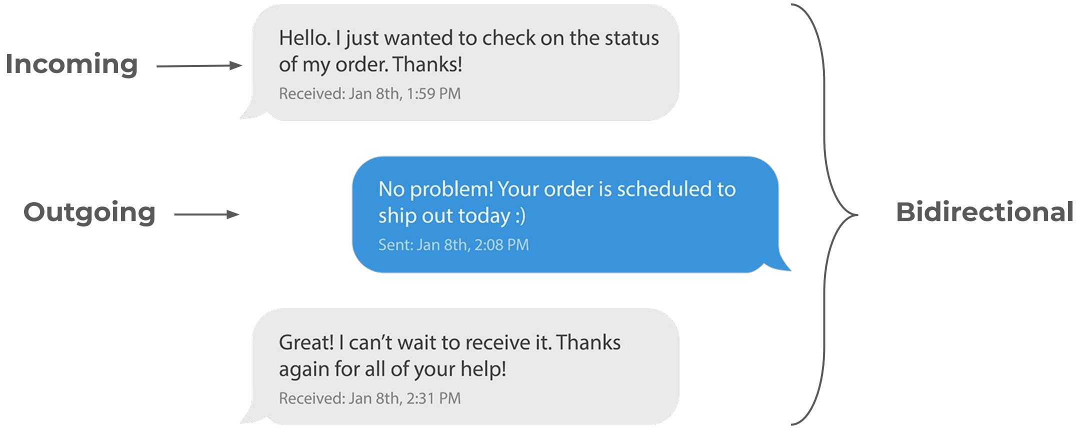
- **Content** features describe patterns from the textual content of the digital messages.
- **Metadata** features describe how individuals use DTC platforms in terms of metadata (i.e. timestamp, direction (incoming/outgoing), recipients).
- **Independent** analysis is valuable but limited
- **Interconnections** have rarely been explored
- Framework structure allows for **both** independent and interconnected approaches



Direction

Modality — Time — Category — **Direction** — Actor — Message Features →

- The **Direction** layer defines the sender and recipient of a DTC
- In this framework, we categorize DTC direction as either:
  - **Incoming** - participant **received** message from someone else
  - **Outgoing** - participant **sent** message to someone else
  - **Bidirectional** - complete conversational set of DTCs **exchanged**



Direction

MODALITY — TIME — CATEGORY — **DIRECTION** — ACTOR — MESSAGE FEATURES

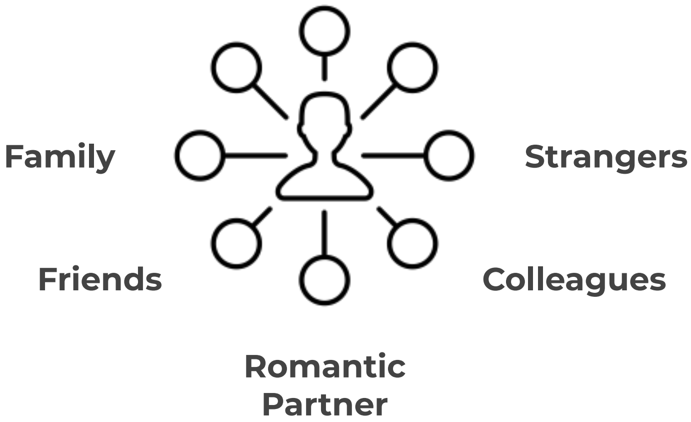
- The **Direction** layer defines the sender and recipient of a DTC
- **Bidirectional** features reveal **discussion quality** and **conversation dynamics**
- **Outgoing** features reveal individuals' **communication styles** via digital text messaging media
- **Incoming** features reveal communication patterns of an individual's **social circle** and overall **social connectedness**

Actor

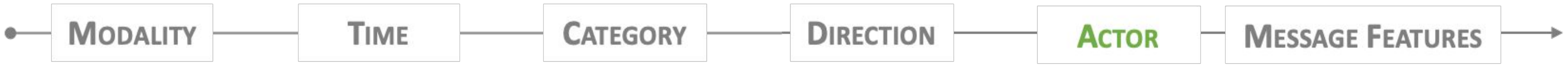
MODALITY — TIME — CATEGORY — DIRECTION — **ACTOR** — MESSAGE FEATURES

- The **Actor** layer distinguishes social relationships between senders and recipients
- These relationships can be characterized by ...
  - the **number** of actors in a conversation
  - the **social dynamics** between different actors
  - conversation-specific **communication styles**

Social Network



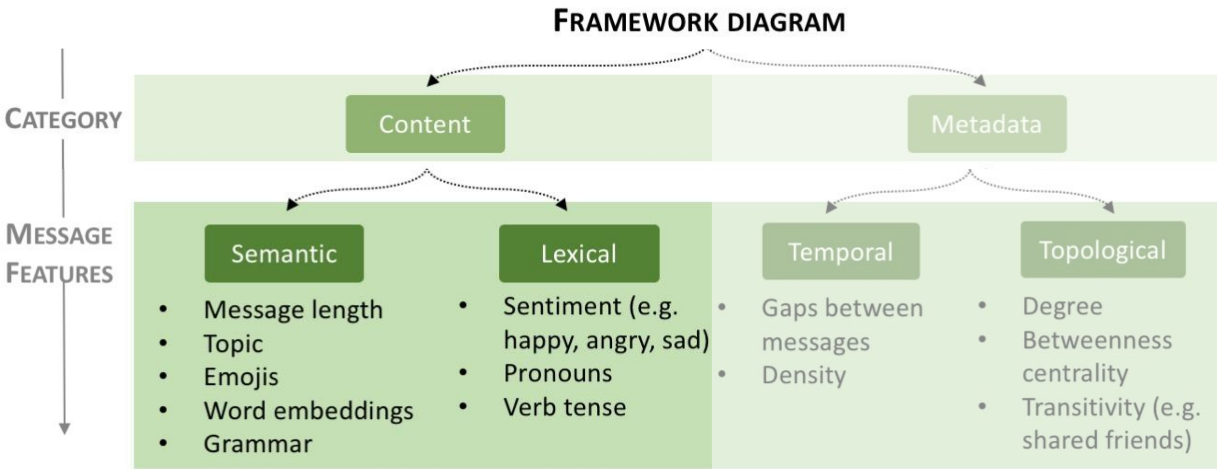
Actor



- The **Actor** layer distinguishes social relationships between senders and recipients
- Differentiate between different types of interactions
  - Group vs. Individual
  - Socially Close vs. Socially Distant
- Features related to **conversation participants**, not the messages themselves fall out of this layer

Message Features: *Content*

- **Content**-based message features reveal social insights from the content of DTC messages
- **Semantic** features describe the relationship between different linguistic structures and their effect on the overall social dynamics of a conversation
- **Lexical** features describe the vocabulary that actors use to communicate with each other



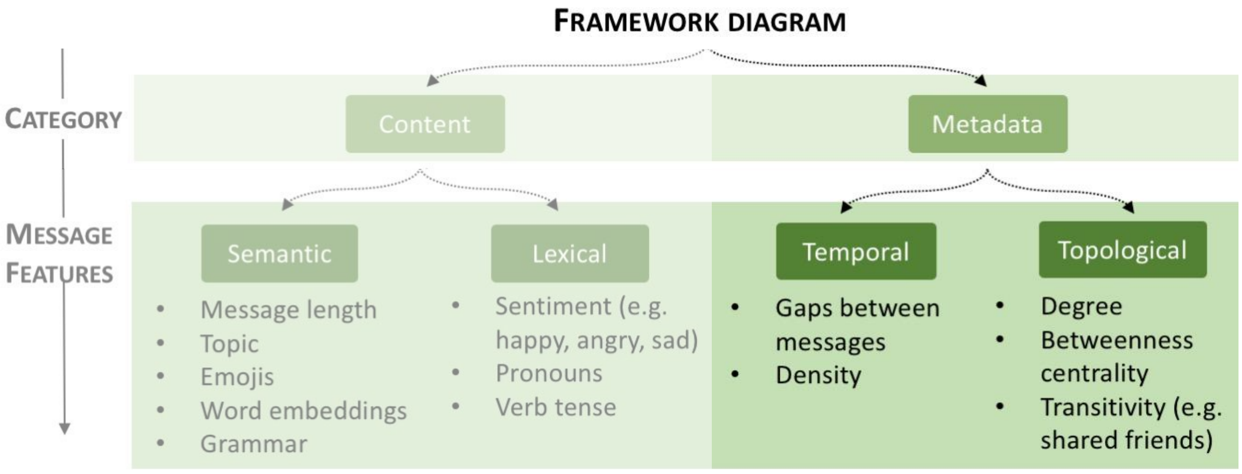
Feature Extraction Methods

Semantic:
- Word Embedding
  - Term Frequency-Inverse Document Frequency (TF-IDF)
  - Word2Vec
- Topic Modeling

Lexical:
- Linguistic Inquiry and Word Count (LIWC)
- Sentiment Analysis
- Functional Language (e.g. pronouns)

Message Features: *Metadata*

- **Metadata** message features primarily relate to the temporal and topological dynamics of social interactions
- **Temporal** features describe message dynamics with respect to time
- **Topological** features describe the connections between actors in terms of messages shared



<u>Feature Extraction Methods</u>

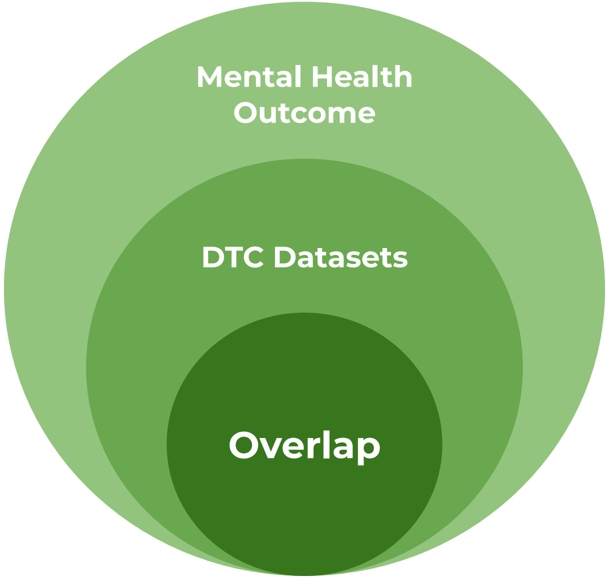
Temporal:
- Gaps
- Density

Topological:
- Network Scale
  - Egocentric, Local & Global
- Degree (i.e. level of social connectedness)
- Betweenness centrality
- Transitivity

Overview

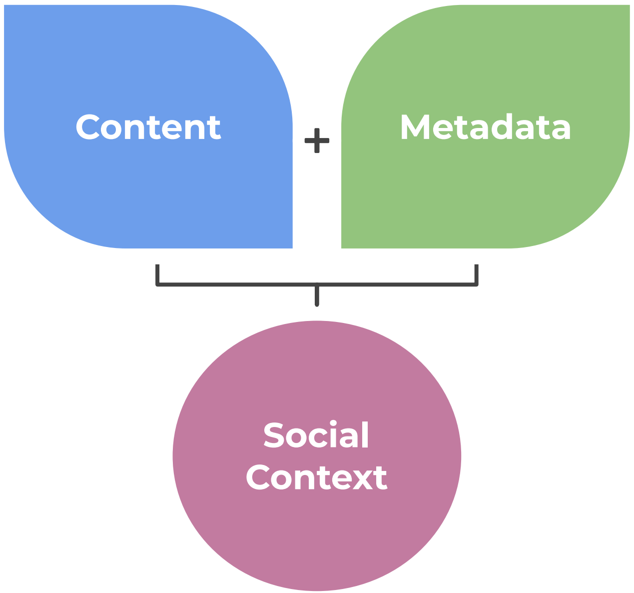
Understanding Current Approaches

- Many researchers have investigated the relationship between **DTC interactions and mental health**
- SocialText can effectively **characterize** these studies irrespective of study design
- SocialText reveals important methodological **overlaps** in the existing literature
    - SMS & Depression [3] / Suicidality [4]
- Researchers can use SocialText to streamline the process of creating **new methodological approaches** from the leading existing approaches



Bridging the Gaps

- There is a clear gap between using **metadata** and **content** features in **mobile sensing for mental health** contexts
- Content and metadata features alone can be informative for predicting mental health outcomes [5,6]
- SocialText unites **content** and **metadata** message features together in a single hierarchy, making it easier for researchers to leverage all features in combination
- Thus, SocialText can assist researchers in developing more **comprehensive** mental health models from DTC data



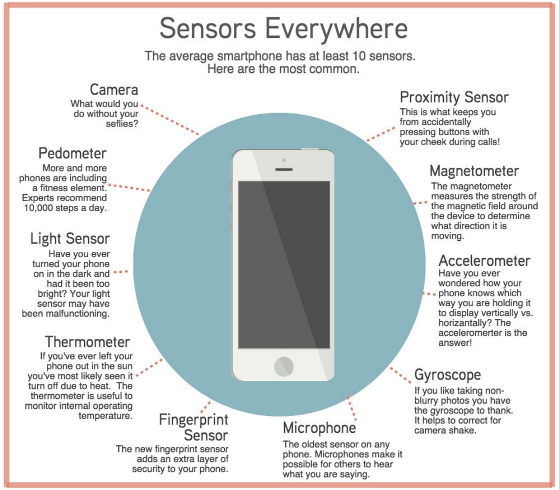
Overview

Mental Health & DTCs

- DTCs afford **rich features** related to social context but remain **largely unexplored** in existing mobile sensing frameworks
- Previous approaches to analyzing DTC features address quantitative and qualitative separately
- SocialText is a **novel framework** that defines a hierarchical structure for extracting features from DTC datasets
- Each layer highlights features that can be derived from **raw sensor data** and used to identify **social context**
- Thus, researchers can leverage SocialText to better predict mental health outcomes from DTCs

Future Work

- **Validating SocialText** using DTC data from ongoing studies:
    - Monitoring **loneliness** in college students
    - Evaluating an mHealth intervention for **social anxiety**
- Contextualize DTC features using **multimodal sensor data**



Thank You

Questions?

References

1. T. Nguyen, M. Hellebuyck, M. Halpern, and D. Fritze, The State of Mental Health in America 2018, 2018.
2. D. C. Mohr, M. Zhang, and S. M. Schueller, “Personal Sensing: Understanding Mental Health Using Ubiquitous Sensors and Machine Learning,” Annual Review of Clinical Psychology, vol. 13, no. 1, pp. 23–47, May 2017.
3. J. D. Elhai, M. F. Tiamiyu, J. W. Weeks, J. C. Levine, K. J. Picard, and B. J. Hall, “Depression and emotion regulation predict objective smartphone use measured over one week,” Personality and Individual Differences, vol. 133, pp. 21–28, Oct. 2018.
4. A. L. Nobles, J. J. Glenn, K. Kowsari, B. A. Teachman, and L. E.Barnes, “Identification of imminent suicide risk among young adults using text messages,” in Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems. ACM, 2018, p. 413.
5. R. Gopalakrishna Pillai, M. Thelwall, and C. Orasan, “Detection of stress and relaxation magnitudes for tweets,” in Companion of the The Web Conference 2018 on The Web Conference 2018. International World Wide Web Conferences Steering Committee, 2018, pp. 1677–1684.
6. Burke, M., & Kraut, R.E, “Using facebook after losing a job: differential benefits of strong and weak ties,” CSCW, 2013.