Inferring Sleep Disturbance from Text Messages of Suicide Attempt Survivors:

A Pilot Study

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A Thesis presented to the Graduate Faculty

of the University of Virginia in Candidacy for the Degree of

Master of Arts

Department of Psychology

University of Virginia
December, 2021

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Acknowledgements and Disclosures

This study was funded by University of Virginia Presidential Fellowships in Data Science awarded to Jeffrey J. Glenn and Alicia L. Nobles, and National Institute of Mental Health Grants (R34-MH106770 and R01MH113752) awarded to Bethany A. Teachman. Jeffrey J. Glenn was also supported by the Department of Veterans Affairs Office of Academic Affiliations Advanced Fellowship Program in Mental Illness Research and Treatment. The views expressed in this article are those of the authors and do not necessarily reflect the position or policy of the Department of Veterans Affairs or the U.S. Government. Ilana Ladis is supported by the National Science Foundation Graduate Research Fellowship under grant No. 1842490. Any opinions, findings, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views of the National Science Foundation.

We would like to thank Drs. Lee Ritterband, Melissa Ree, Allison Harvey, Tina Goldstein, and Jessica Hamilton for their assistance in preparing the sleep dictionary used for this study. We would also like to thank Tara Valladares, M.A., Daniel Coppersmith, M.A., and Drs. Jeffrey J. Glenn, Alicia L. Nobles, Laura E. Barnes, and Bethany A. Teachman for their scholarship and intellectual contributions to this study.

Abstract

Sleep disturbance is a modifiable, acute risk factor for suicide, but naturalistic assessment of sleep problems is challenging. Examining communication on digital platforms can help identify phenotypes of sleep disturbance, which may aid in the detection of possible imminent suicide risk. This within-person pilot study examined sleep-related communication and texting patterns in a database of personal text messages (*N* = 86,705) provided by 26 individuals who survived at least one lifetime suicide attempt. Participants provided the dates of past suicide attempts, as well as two-week periods in which they experienced positive mood, depressed mood, or suicidal ideation. Generalized mixed effect models were used to test the association between suicide/mood episode type (e.g., attempt versus ideation) and three outcomes: likelihood of a text including sleep-related content or not, nightly count of texts sent from midnight-5:00 AM, and sum of unique hour bins from midnight - 5:00 AM with any outgoing text. Linguistic Inquiry Word Count was used to identify sleep-related texts, based on a custom dictionary of sleep-related words, phrases, and emojis. Analyses with a sleep dictionary that was manually revised to be more accurate showed that sleep-related communication was more likely during depressed mood episodes than positive mood episodes. Otherwise, there were no significant differences in either the likelihood of sleep-related communication, count of outgoing text messages from midnight – 5:00 AM, or sum of unique hour bins from midnight – 5:00 AM across suicide/mood episode types. Although sleep-related communication may differ as a function of within-person mood level, the present study did not detect differences in sleep-related communication tied to suicidal thoughts or behaviors. Future research with larger datasets and multiple data streams (e.g., call and social media logs) may provide insight into digital communication phenotypes associated with sleep problems and suicidal thoughts and behaviors.

Keywords: suicide, sleep, technology, risk-assessment, digital phenotyping

Inferring Sleep Disturbance from Text Messages of Suicide Attempt Survivors: A Pilot Study

Over the last 20 years, suicide rates have risen in the United States, and suicide remains the nation's tenth leading cause of death (Hedegaard et al., 2018). At the same time, the field of suicide prevention has lagged behind, due in part to the paucity of clearly delineated risk factors and warning signs for *imminent* suicide risk (Franklin et al., 2017). Many longitudinal studies aiming to elucidate risk factors for suicide have taken place over several months or years, with outcomes assessed at only one or a few time points. While this approach has yielded valuable knowledge surrounding general risk factors, it is not as applicable for identifying warning signs that indicate whether someone might attempt suicide *tomorrow* or *next week*. Moreover, though established risk factors (e.g., substance abuse) have clinical utility, they may go undetected, even by conscientious mental health professionals.

In recognition of these concerns, there has been a proliferation of research aiming to examine fluctuations in suicidal thoughts and behaviors (STBs) on a more temporally sensitive level. These studies have leveraged real-time monitoring approaches, including active (e.g., experience sampling) and passive (e.g., analysis of motion data) assessment to monitor changes in suicidality and its correlates as they occur *in situ*. Remarkably, much of this work has revealed that suicidal thoughts often develop and subside rather quickly (e.g., within an hour) and can vary substantially even over the course of a single day (Kleiman & Nock, 2018). These findings underscore the potential benefits of identifying temporally sensitive risk indicators to aid in the detection and prevention of STBs. This work has the potential to inform how and when interventions for STBs can be useful, through identification of both group-level and idiographic trends and risk status markers. In line with these goals, the present study sought to examine whether naturalistic text messaging patterns intimating sleep disturbance – a known risk factor for STBs (Liu et al., 2020)– differ across levels of suicide-risk severity using a within-subjects design among individuals who survived at least one lifetime suicide attempt.

Sleep Disturbance and Suicide Risk

Insomnia and sleep disturbances[1] more broadly have emerged as modifiable, independent risk factors for suicidal ideation, attempts, and completed suicide (Liu et al., 2020). Yet, most studies have examined sleep disturbance and STBs cross-sectionally, precluding the identification of causal risk factors (Liu et al., 2020). Furthermore, many studies that used longitudinal designs examined the relationship between sleep disturbance and STBs in the long-term, with a follow-up period of several months or years (Kearns et al., 2020). Thus, most studies have been unable to draw conclusions about how sleep disturbance and STBs are related in the short-term (e.g., within days or weeks). Studies that have examined proximal effects of sleep disturbance on STBs at the idiographic level have found some evidence for a unidirectional relationship, in which sleep disturbance appears to precede STBs. For example, Littlewood et al. (2019) found that poor sleep quality and short sleep duration predicted greater severity of next-day suicidal ideation in adults with a major depressive episode. Similar patterns have been found in younger adults with a suicide attempt history; namely, increased objective and subjective measures of sleep disturbance predicted increases in suicidal ideation at 7- and 21-day follow-up periods (Bernert et al., 2017). Finally, one study in which individuals with lifetime suicidal behavior completed six surveys over the course of 15 days found that previous insomnia levels predicted increases in suicidal ideation at subsequent time points, but suicidal ideation did not predict subsequent insomnia symptoms (Zuromski et al., 2017).

There is thus some evidence that sleep problems can be considered prospective, near-term risk factors for STBs. It is far more ethically challenging, however, to examine how sleep disturbance manifests in the period leading up to an actual suicide attempt, though retrospective

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[1] Though much research has focused on insomnia (which refers to difficulties with falling or staying asleep), sleep disturbance is a broader construct that encompasses other sleep-related issues, such as persistent nightmares and hypersomnia (i.e., excessive sleepiness). Given the present study did not specifically assess insomnia, but rather inferred individuals' sleep/wake patterns from digital data, "sleep disturbance" was used primarily in this paper to refer to the constructs of interest. Prior empirical studies that specifically assessed insomnia were described accordingly.

reporting has provided some clues. Based on multiple third-party informant interviews with family and friends, adolescents who died by suicide had higher rates of sleep disturbance in the week leading up to their suicide, relative to last-week sleep disturbance assessed in living control participants (Goldstein et al., 2008). Similarly, sleep disturbance was more prevalent among Japanese adults who died by suicide (also based on information provided by third-party informants), relative to living age and gender-matched control participants, even when adjusting for the presence of psychological disorders (Kodaka et al., 2014). These findings suggest that it is possible to discern nomothetic differences in the association between sleep disturbance and suicide-related outcomes (Goldstein et al., 2008; Kodaka et al., 2014). However, these studies are limited by their reliance on third-party informants and do not clarify whether and how sleep disturbance changes *within* a person in the short-term window leading up to a suicide attempt. This is important because between-groups analyses raise concerns about third variable explanations given there is obviously not random assignment to suicide attempt group. The present study begins to address these gaps by inferring sleep disturbance directly from the text messages of individuals who made (non-lethal) suicide attempt(s), versus relying on third-party informants. Additionally, we partition suicide risk across a severity spectrum, to more finely differentiate the imminent period prior to an attempt from other types of periods (e.g., those characterized by depressed mood, but not suicidal ideation, or by suicidal ideation but no attempt).

Inferring Sleep Disturbance from Digital Communication Data

One relatively unexplored method for capturing sleep-related problems is to examine the ways in which people communicate with others about their sleep issues. A study using linguistic inquiry software found that individuals frequently disclose their insomnia symptoms publicly on Twitter, with an emphasis on sharing their personal experiences with insomnia and coping strategies (Jamison-Powell et al., 2012). As put forth by Jamison-Powell and colleagues (2012), the recurrent theme of sharing personal experiences and advice suggests that Twitter may be serving a sort of “support group function,” connecting people who are struggling with insomnia. This is in line with recently observed trends of increased sharing about mental health problems and peer-to-peer support on public forums such as Reddit (Gkotsis et al., 2016) and other social media sites (Naslund et al., 2016). However, no study to date has examined how sleep-related communication occurs in private communication (e.g., via text message), due to the near non-existence of such data streams (Resnik et al., 2021). Nevertheless, such data could provide valuable insight into whether trends observed in public forums reflect a broader tendency to communicate about sleep problems as a sort of a communal coping mechanism.

Analyzing message content can provide a useful window into the way people are thinking, but the interpretation of text and linguistic features remains subjective in important ways. Sarcasm is a prime example of how the semantic elements of a message can be distorted (e.g., by leading a sentiment analysis algorithm to mistake negatively-valanced messages as positive). For this reason, it is beneficial to not only probe the *content* of messages but also their objective, temporal patterns (e.g., number of texts sent in a given time period). This is highly feasible when messages are accompanied by precise timestamps and dates, as is the case with text messages and social media posts. For example, one study found that users who self-identified as having sleep issues on Twitter tweeted significantly more than a control group of Twitter users during the hours of midnight – 6:00 AM, despite being less active on the platform in general (McIver et al., 2015). A similar study found that late-night tweeting in professional basketball players was associated with within-person reductions in next-day game performance (Jones et al., 2019). These proof-of-concept studies demonstrate that it is possible to differentiate subgroups of interest (e.g., insomnia vs. no insomnia) based on technology usage patterns, and use information scraped from publicly available social media timestamps to predict intraindividual changes in behavior.

The few studies that have leveraged objective digital communication on *private* data streams found that night time phone use and text messaging is common, particularly among adolescents (Schoeni et al., 2015; Troxel et al., 2015). This is particularly relevant here, given the majority of texts analyzed for this study were from when participants were adolescents, even though all were at least 18 at the time of study participation. Findings of frequent objective nighttime phone use align with the majority of survey-based research on adolescent phone use at night (Lemola et al., 2015). High school and college students are frequently awoken by notifications throughout the night (Dowdell & Clayton, 2019; Fobian et al., 2016; Shoval et al., 2020), and college students in particular exhibit substantial smartphone activity (including outgoing text messages) during their self-reported sleep windows (Rod et al., 2018). Objective smartphone data can thus, at the very least, indicate that somebody is awake. Closer examination of phone use could provide insight into more nuanced behaviors. For example, several outgoing text messages might indicate a greater degree of stimulation in comparison to checking one's phone quickly before going back to bed. To this end, the present study was well-poised to examine detailed digital communication dynamics. Collecting incoming and outgoing texts allowed us to examine *what time* and at *what rate* participants sent and received texts. Furthermore, we operationalized "digital communication" in multiple ways. We examined the *total* number of texts sent when individuals were expected to be sleeping, in addition to the *spread* of sent texts over a given night (e.g., all within a single hour vs. distributed across many hours). To our knowledge, this is the first study to examine whether suicide risk severity is associated with nighttime texting patterns – a largely unexplored, but potentially robust, indicator of sleep disturbance.

The Present Study

The present study is a secondary data analysis of a previously published study from our team, which found that changes in emotion language (e.g., anger, positive emotion) used in text-message communication were associated with within-person changes in suicide risk state (Glenn et al., 2020; Nobles et al., 2018). Here, we tested whether sleep disturbance –inferred from linguistic features and temporal patterns observed in text messages– differed as a function of within-person suicide risk level among young adults who made at least one prior, non-lethal suicide attempt. Participants provided dates of past suicide attempts, as well as two-week periods (i.e., “episodes”) of suicidal ideation, depressed mood, and positive mood. We examined whether text communication patterns were differentially associated with risk levels on a within-person basis, comparing each individual to their own personal baseline of risk severity. The linguistic content of text messages was analyzed given interest in communication about sleep-related difficulties. We also examined behavioral patterns associated with texting (e.g., how many texts were sent when individuals would likely be sleeping) as objective indicators of wakefulness, and by proxy, sleep disturbance. Though the presence of texts is an imperfect indicator of sleep disturbance given that sleep is not being measured directly, this approach provides a non-intrusive, scalable method to infer sleep patterns.

We pre-registered three hypotheses corresponding with our primary research questions (see https://osf.io/9f3v2/ for full preregistration). First, it was hypothesized that greater suicide risk severity (conceptualized along the continuum from positive mood, depressed mood, ideation, to attempt episodes) would be associated with a higher incidence of sleep-related text messages. Second, it was expected that greater suicide risk severity would be associated with a greater number of text messages sent during an expected sleep window of midnight – 5:00 AM. Third, it was hypothesized that greater suicide risk severity would be associated with individuals having sent texts across more unique hours between midnight – 5:00 AM (e.g., first unique hour bin: midnight – 1:00 AM, second unique hour bin: 1:00 AM – 2:00 AM, etc.). Given the potential theoretical utility of comparing episode type groupings (e.g., positive mood and depressed mood episodes versus ideation and attempt episodes), we preregistered a set of contrasts to test. Specifically, for each hypothesis, we compared: 1) each episode type to all other episode types; 2) the average of positive mood and depressed mood periods versus the average of ideation and attempt periods; and 3) the average of ideation and attempt periods versus positive mood periods and versus depressed mood periods. These contrasts were chosen given our theoretical interest in examining differences between “suicidal” (i.e., ideation and attempt episodes) and “non-suicidal” (i.e., positive mood and depressed mood) episodes, and in line with prior research with these data (Nobles et al., 2018).

Additionally, we examined whether a series of potential covariates (i.e., age, time of week, and season) were associated with texting behaviors for the second and third hypotheses. These contextual factors were chosen given their potential to affect nighttime texting patterns. For example, participants might have had more freedom to text people late at night during summer months, when school was not in session, compared with the school year. Though we did not outline any specific hypotheses tied to these potential covariates, we planned to add any significant covariates to the final models testing the association between episode type and texting behavior. To illustrate, if season were to be a significant predictor of the number of texts sent between midnight – 5:00 AM, then we would covary season when examining the association between episode type and number of sent texts between midnight – 5:00 AM. To our knowledge, the present study is the first to examine whether there are differences in sleep-related communication and objective texting behaviors indicative of sleep disturbance across various levels of within-person suicide risk severity.

Method

Participants

Participants (*N* = 33) were recruited from the local community and the University of Virginia (UVA) participant pool and experienced at least one past suicide attempt. Participants were compensated with up to 3 hours of course credit or $40 for participation in the study. Due to a software error, short message service (SMS) data was only available for 26 participants[2], and analyses are restricted to texts from those individuals. The 26 participants included in the

[2] Though 33 participants completed the full study procedure, including the study visit and clinical interview, text message data was only available for 26 participants. We thus report demographics, episode characteristics, and results for the 26 participants with available text data. See Glenn et al. (2020) for results from all 33 participants for other research questions.

analyses mostly identified as female (84.6%), White (65.4%), heterosexual (73.%), and students (96.2%). See Table 1 for full demographic characteristics of the sample included in the present study. Additional details about the screening process, including the full study CONSORT diagram and demographics for the full sample, are available in the supplement from Glenn et al. (2020) at https://osf.io/kgq8h/.

Procedures

Pre-screening. The UVA Institutional Review Board approved all study procedures. Individuals recruited from the UVA participant pool completed two surveys. The first survey asked whether they had ever had a period of sadness during which they felt hopeless and whether they wanted to be contacted about studies that would ask more questions about this period. The second survey, which was sent via e-mail to individuals who responded “yes” to both questions on the pre-screener, asked whether individuals had ever made a suicide attempt and whether they currently had thoughts about wanting to kill themselves. Participants who reported a past suicide attempt but reported not wanting to kill themselves at the time of screening could then complete a phone screen to determine their eligibility. Individuals were required to have had access to at least some personal communication data (e.g., text messages; e-mails) spanning back to the period of time before their attempt and to be at least 18 years old at the time of screening.

Clinical Interview and Digital Data Collection. Eligible participants attended an in-person study session where they first provided informed consent to all study procedures. During the in-person study session, participants completed a clinical interview with the experimenter, who was a masters-level graduate student in clinical psychology. The purpose of the clinical interview was to elicit detailed information about previous two-week episodes in which individuals experienced: 1) a suicide attempt episode (defined as the two-week period leading up to an attempt), 2) periods of suicidal ideation that lasted two weeks, 3) periods of depressed mood not characterized by suicidality that lasted two weeks, and 4) periods of positive mood that lasted two weeks. During the clinical interview, participants could report up to three instances of each type of episode (suicide attempt, suicide ideation with no attempt, depressed mood, and positive mood). To supplement the clinical interview, participants also completed several self-report questionnaires and provided demographic information.

Participants were also asked to download their text messages (as well as other private data streams that were not part of the present study) from their smartphones onto a study computer with the help of the experimenter. Participants could download SMS data from iPhones or Android devices as well as other devices that contained any personal data (see Glenn et al., 2020, for details about the various data streams obtained and the specific software used to download digital data from participant devices). Raw data were transferred and stored on a highly secure UVA server following the study session. All SMS data files were subsequently cleaned in Python prior to analyses.

Risk Assessment. Though asking about suicide is not thought to lead to distress or iatrogenic effects among individuals who are currently suicidal and/or have a history of suicidality (Coppersmith et al., 2020; Polihronis et al., 2020), participants were asked to respond to questions about their mood as well as their desire to die at the beginning and end of the lab session. Both scales ranged from 0-10, with higher values indicating more negative mood and desire to die, respectively. There was no significant change in mood rating from before the study (M = 6.33, SD = 1.38) to after the study (M = 6.12, SD = 1.17), $t(32) = 1.05$, $p = .304$, and there was a small, significant decrease in desire to die from before the study (M = 0.82, SD = 1.10) to after the study (M = 0.61, SD = 0.90), $t(32) = 2.23$, $p = .033$. No participants were deemed to be at high or imminent risk for suicide at their study visit.

Sleep Dictionary Creation. Linguistic Inquiry and Word Count software (“LIWC”; Pennebaker et al., 2015) was used to examine whether sleep-related communication differed across episode types. LIWC efficiently reads and scores unstructured text data based on various linguistic features. For most variables, LIWC generates a score that reflects the percentage of words in a given text segment that belong to each category. For example, a text that says "I'm so sorry" will receive separate scores of 33.33 (33.33%) on both the "I" (for "*I'm*") and "negative emotion" (for "*sorry*") categories. Given there is no preexisting LIWC dictionary assessing communication tied to sleep, a custom sleep dictionary was created for this study (Jacobucci et al., 2021). We first developed a list of relevant words, phrases, and emojis related to sleep, including word-stems that could pick up on variations in text (e.g., the word-stem *nap** could also flag variants such as *naps*, *napped*, and *napping* in the texts). This is in contrast with prior research that used more stringent inclusion criteria for examined messages (e.g., Jamison-Powell et al., 2012, only analyzed Tweets containing the word "insomnia"). While we recognized that our comprehensive list of sleep words could lead to lower precision, we initially believed that the more inclusive sleep word list could better "flag" any communication indicative of sleep disturbance. Then, five clinical psychologists with expertise in sleep and suicide risk provided feedback on the list and suggested additional words and phrases. Sleep-related emojis were first coded into plain text (e.g., the bed emoji was recoded into the text phrase, 'BEDEMOJI') and then scored as a sleep word in the LIWC analyses. See Table 2 for the final version of the comprehensive sleep dictionary.

Measures of Sleep Communication and Phone Use

Hypothesis 1: Incidence of sleep-related text messages across episode type. The aim of hypothesis 1 was to examine differences in the likelihood of communicating about sleep across episode types. Using the custom sleep-word dictionary (see Table 2), text messages containing words, phrases, and/or emojis related to sleep were identified and each text message was classified accordingly as either a "sleep-text" or "non-sleep-text." This approach allowed for the detection of *any* sleep-related semantic content in each text, which is likely a more meaningful indicator of sleep disturbance than the *count* of sleep-related words in each text. For example, texting "I can't sleep" (1 sleep word) is likely just as indicative of sleep disturbance as a wordier text.

Hypothesis 2: Number of nightly texts sent during expected sleep window. The second hypothesis tested differences in the count of outgoing text messages sent from midnight-5:00 AM across episode type. Outgoing text messages sent from midnight – 5:00 AM would indicate wakefulness, with more messages possibly indicating a greater degree of stimulation and/or social engagement (i.e., a conversation). Analyses were limited to texts sent from midnight – 5:00 AM, based on typical adolescent sleep patterns (e.g., Crowley et al., 2007). Though we anticipated that some participants in our sample would have typically gone to bed before midnight during the period when the text data was recorded (i.e., many participants were still in high school during reported episodes and may have gone to bed earlier than they would have as college students), we believe that our choice of a more conservative expected sleep window would lead to higher model sensitivity and accuracy. The number of texts sent from midnight – 5:00 AM during each night within a specified, two-week episode was calculated at the individual level. Nights without any outgoing text messages from midnight – 5:00 AM were coded as "0."

Hypothesis 3: Number of unique nightly hour bins with sent texts. The third hypothesis tested differences in the total number of unique hours "bins" in which a text was sent between the hours of midnight and 5:00 AM. This could yield a nuanced picture of text-message activity and wakefulness throughout the five-hour expected sleep window. This is in contrast with hypothesis 2, in which an individual could have sent dozens of text messages, but all between the hours of midnight – 1:00 AM. For this analysis, each unique nightly hour was assigned a binary (i.e., 1 or 0) score to indicate whether any text was sent. Then, sum scores of unique hours with an outgoing text were calculated for each night. Possible values ranged from 0-5, with higher values reflecting more text activity spread out across the duration of the expected sleep window. Text messages were assigned a score of "1" if they were sent from midnight – 1:00 AM, "2" if they were sent from 1:01 AM – 2:00 AM, "3" if they were sent from 2:01 AM – 3:00 AM, "4" if they were sent from 3:01 AM – 4:00 AM, and "5" if they were sent from 4:00 AM – 5:00 AM. These scores were used to define the ordinal outcome variable for the model, reflecting the number of unique nightly hour bins with a sent text.

Data Analytic Plan

Analyses were conducted using R version 4.0.2. For each hypothesis, a multilevel modeling approach was used, which allowed for examination of differences in sleep indicators across episode type while accounting for individual participant and episode-level factors. Multilevel modeling enabled the inclusion of an uneven number of messages and episodes across participants. Each episode was assigned a unique episode identifier (e.g., Participant 5's first reported depressed mood episode was labeled as "P05DE1," to distinguish it from other depressed mood episodes reported by Participant 5, as well as first depressed mood episodes reported by other participants). Models were fitted using the lme4 (Bates et al., 2014) and ordinal (Christensen, 2015) R packages and odds ratios and confidence intervals for logistic regression models were calculated using sjStats (Lüdecke, 2019). For all analyses, we used a subset of the original corpus of > 1,000,000 collected text messages that only included outgoing (versus incoming) text messages, as well as messages that fell under a prespecified episode type (versus episodes that fell under "unidentified" dates), which resulted in a total of 86,705[3] text messages available for analyses. We included random intercepts for participant and for unique participant episode, but not random slopes, given that the models were not able to converge with the inclusion of random slopes.

Hypothesis 1: Incidence of sleep-related text messages across episode type. Generalized linear mixed models (GLMMs) were conducted using the lme4 package with episode type as the within-subject fixed effect and text type (i.e., sleep text vs. non-sleep-text) as the outcome. Models were specified with a logit link function given the outcome variable was binomially distributed. Random intercepts for participant and unique participant episode were

[3] Because the present study only used outgoing text messages (versus incoming text messages), there is a lower text count than that reported in Glenn et al. (2020).

specified in the model to account for the levels of participant nesting. Risk severity was defined accordingly based on each contrast tested (e.g., when attempt and ideation episodes were compared to positive mood and depressed mood episodes, it was hypothesized that more sleep-texts would be sent during attempt/ideation episodes).

Hypothesis 2: Number of nightly texts sent during expected sleep window. Negative binomial models were used because the count variable was over dispersed (M_{count} = 3.61, Var_{count} = 143.20) and zero inflated (reflecting that there were several nights with no outgoing texts). As in hypothesis 1, random intercepts for participant and unique participant episode were specified. In line with our preregistration, we also tested whether certain demographic and seasonal contexts were independently associated with the count of text messages sent from midnight – 5:00 AM. Significant predictors would then be included as covariates in the final models. First, the effect of season was tested given that adolescent sleep schedules are often markedly different in the summer, compared to when school is in session (Crowley et al., 2006). Season was binarized into “summer” (which encompassed all texts sent during the months of June, July, or August) and “non-summer” (which encompassed texts sent during all other months). Second, the effect of time of week (i.e., weekday versus weekend) was tested, since adolescent sleep patterns often differ on the weekends. Texts were classified as “weekend” if they were sent between midnight and 5:00 AM on either Saturday or Sunday. Finally, participant age during each sent text was calculated and tested as a predictor of text count, given that adolescent bedtimes tend to become later as individuals become older (Crowley et al., 2007).

Hypothesis 3: Number of unique nightly hour bins with sent texts. Multilevel ordinal models were conducted using the ordinal package (Christensen, 2015) to test differences in the total number of unique hours in which a text was sent between midnight and 5:00 AM. Episode type was the predictor and total number of unique hours in which a text was sent was the outcome variable. As with Hypothesis 2, season, weekend, and age were all tested as independent predictors of the total number of nightly hours with a sent text. Random intercepts were included for participant and participant-episode.

Results

Description of Episodes

Participants reported a total of 66 attempt episodes, 68 ideation episodes, 78 depressed mood episodes, and 81 positive mood episodes. There was not SMS data available for all reported episodes. Some episodes took place several years prior to the study, and participants did not have texts from those dates. There was SMS data available for a total of 21 attempt episodes across 15 unique participants, 32 ideation episodes across 20 unique participants, 40 depressed mood episodes across 22 unique participants, and 41 positive mood episodes across 24 unique participants.

Incidence of Sleep-Related Text Messages Across Episode Type (Hypothesis 1)

Descriptive Text Characteristics. Of the 86,705 text messages included in analyses, 2.71% contained a sleep related word, phrase, or emoji. Participants sent between 2 and 316 sleep-related texts, with a between-subjects mean of 90.23 sleep-texts (SD = 79.47) sent across 26 different participants. Across all participants, sleep-related texts (n = 2,356) were longer [$M_{word\ count}$ = 18.25, SD = 30.55] than non-sleep-related texts (n = 84,349; $M_{word\ count}$ = 8.16, SD = 10.18]).

Effect of Episode Type. Contrary to hypotheses, there were no significant differences in the likelihood of communicating about sleep across episode types. See Table 3 for full results.

Number of Nightly Texts sent During Expected Sleep Window (Hypothesis 2)

Descriptive Text Characteristics. Twenty-five out of the 26 participants had outgoing texts sent from midnight and 5:00 AM (see Figures 1 and 2 for a between- and within-subjects visual of texts sent during this time frame, respectively). Of the 2,012 separate nights that were analyzed (inclusive of all participants), 70.3% nights had no outgoing messages, 6.4% had one outgoing message, and 23.2% had more than one outgoing message. A total of 7,546 texts sent between midnight and 5:00 AM across 601 unique participant nights were included in analyses. For nights with any outgoing texts, the count of texts from midnight – 5:00 AM ranged from 1 to 165 (M_{count} = 12.6, SD_{count} = 19.6). Furthermore, 9.4% of texts were sent in the summer; 19.8% were sent in the fall; 28.5% were sent in the winter; and 42.3% were sent in the spring. 31.8% of texts were sent on weekend nights and 68.2% were sent on weeknights.

Effect of Season. Season (i.e., summer vs. all other seasons) was tested as an independent predictor of text count. On average, significantly more text messages were sent from midnight – 5:00 AM during non-summer months, relative to summer months (b = .84, SE = .31, z = 2.71, p = .007).

Effect of Time of Week. The effect of weekend vs. not weekend was tested as a predictor of text count per night, independent from season. On average, significantly more text messages were sent from midnight – 5:00 AM on weekend nights, relative to non-weekend nights (b = .31 SE = .14, z = 2.15, p = .032).

Effect of Age. Finally, age was tested as a predictor of text count, independent from season and time of week. The model with age as a predictor would not converge, and age was not included as a covariate in the final model. Of note, only 6.7% of texts included in analyses (across all participants) were sent when participants were younger than 18, and 86.6% of texts were sent when participants were 18-21 years old. While age likely influences bedtime and nighttime phone use, there was not sufficient variation in age during episode types to detect those differences in the present study.

Effect of Episode Type. The final models tested episode type as a predictor of text count while controlling for both season and time of week. In these models, season and time of week remained significant predictors of text count. Contrary to hypotheses, there were no significant differences in text message count between midnight and 5:00 AM across episode types. See Table 4 for full results.

Number of Unique Nightly Hour Bins with Sent Texts (Hypothesis 3)

Descriptive Text Characteristics. A total of 7,546 texts sent between midnight and 5:00 AM across 601 unique participant nights were included in analyses. 61.9% of texts were sent during the first bin (i.e., from midnight – 1:00 AM), 21.8% of texts were sent during the second bin (from 1:00 AM- 2:00 AM), 11.0% of texts were sent during the third bin (from 2:00 AM – 3:00 AM), 4.2% of texts were sent during the fourth bin (from 3:00 AM – 4:00 AM), and 1.2% of texts were sent during the fifth bin (from 4:00 AM – 5:00 AM). See Figure 3 for a between-subjects visual.

Effect of Season. As in hypothesis 2, season was a significant predictor of the number of unique nightly hour bins (b = -.72, SE = .31, z = -2.31, p = .021). Participants were more likely to send texts across 2 or more hour bins in non-summer months, relative to summer months. In contrast, participants were more likely to send texts across just one hour bin in summer months, relative to non-summer months.

Effect of Time of Week. As in hypothesis 2, the effect of weekend vs. not weekend was a significant predictor of the number of unique nightly hour bins (b =.47, SE = .18, z = 2.56, p = .01). Participants were more likely to send texts across multiple hour bins on weekend nights, relative to non-weekend nights. In contrast, participants were more likely to send texts across just one hour bin on non-weekend nights, relative to weekend nights.

Effect of Age. As in hypothesis 2, when age was tested as a predictor of the number of unique nightly hour bins, the model could not converge. Thus, age was not included as a covariate in the final model.

Effect of Episode Type. The final models tested episode type as a predictor of the number of unique nightly hour bins while controlling for both season and time of week. In these models, season and time of week remained significant predictors of the number of unique nightly hour bins. Contrary to hypotheses, however, there were no significant differences in the number of unique nightly hour bins between midnight and 5:00 AM across episode types. See Table 5 for full results.

Rationale for Analyses with Revised Sleep Dictionary and Reduced Sleep Window

After completing the preregistered analyses, we decided to conduct additional analyses that could potentially provide insight into the non-significant effects for episode type. For Hypothesis 1, we manually reviewed the words that had been flagged as sleep-related by LIWC. Upon visual inspection, it was clear that the sleep dictionary overestimated the number of texts that were truly indicative of sleep disturbance. This was partially because the dictionary was defined too broadly. For example, a text that simply read “good night!” was flagged, though it is a common phrase and not indicative of sleep disturbance. Also, some of the words and phrases included in the initial dictionary inadvertently captured something other than sleep disturbance. Word stems such as *nap** and *zz** were frequently subsumed within words like *snapchat* and *pizza* and erroneously flagged as sleep-related. To more closely capture sleep disturbance, author IEL went through and refined the sleep dictionary once prior to re-running analyses. Specifically, word stems and phrases such as *nap**, *zz**, and *good night*, as well as sleep-related emojis, were removed. The *sleep** word stem was also removed and replaced with multiword phrases that more closely indicate sleep disturbance (e.g., *couldn’t sleep; didn’t sleep; need sleep*). Analyses were then re-conducted with this reduced sleep dictionary (see Table 6). Results are described below and in Table 7.

Regarding Hypotheses 2 and 3, it is possible that there were not significant main effects for episode type because the expected sleep window of midnight – 5:00 AM was too broad. More than half of texts fell into the first hour bin (ranging from midnight – 1:00 AM) and about one-fifth of texts fell into the second hour bin (ranging from 1:00 AM – 2:00 AM). This suggests that participants tended to be awake past midnight, which is typical for college students (Rod et al., 2018). Thus, we re-ran analyses for Hypotheses 2 and 3 with a narrower sleep window of 1:00 AM – 5:00 AM. Results are described below and in Table 8.

Results from Analyses with Revised Sleep Dictionary and Reduced Sleep Window

Incidence of Sleep-Related Text Messages Across Episode Type (Hypothesis 1)

Descriptive Text Characteristics. Of the 86,705 text messages included in analyses, 0.71% contained a sleep related word, phrase, or emoji (based on the new sleep dictionary). Participants sent between 1 and 50 sleep-related texts, with a between-subjects mean of 24.72 sleep-texts (SD = 19.81) sent across 25 unique participants. Across all participants, sleep-related texts (n = 618) were longer [$M_{word\ count}$ = 17.89, SD = 24.80] than non-sleep-related texts (n = 86,087; $M_{word\ count}$ = 8.37, SD = 11.17]).

Effect of Episode Type. Contrary to findings from the first set of analyses, the likelihood of a text being sleep-related was significantly greater during depressed mood episodes, compared with positive mood episodes. No other tested episode type contrasts were significant. See Table 7 for full results.

Number of Nightly Texts sent During Expected Sleep Window (Hypothesis 2)

Descriptive Text Characteristics. Twenty-four out of the 26 participants had outgoing texts sent between 1:00 and 5:00 AM. A total of 3,949 texts sent between 1:00 and 5:00 AM across 360 unique participant nights were included in analyses. For nights with any outgoing texts, the count of texts sent between 1:00 – 5:00 AM ranged from 1 to 113 (M_{count} = 10.97, SD_{count} = 16.55). Furthermore, 15.6% of texts were sent in the summer; 17.0% were sent in the fall; 28.8% were sent in the winter; and 38.5% were sent in the spring. 37.7% of texts were sent on weekend nights and 62.3% were sent on weeknights.

Effect of Season. Season (i.e., summer vs. all other seasons) was tested as an independent predictor of text count. The model with season as a predictor of text count would not converge.

Effect of Time of Week. The effect of weekend vs. not weekend was tested as a predictor of text count per night, independent from season. The model with time of week as a predictor of text count would not converge.

Effect of Age. Finally, age was tested as a predictor of text count, independent from season and time of week. As with the prior analyses, the model with age as a predictor of text count would not converge.

Effect of Episode Type. The final models tested episode type as a predictor of text count while controlling for both season and time of week, in line with the first set of analyses. The model with season, time of week, and episode type as predictors of text count would not converge.

Number of Unique Nightly Hour Bins with Sent Texts (Hypothesis 3)

Descriptive Text Characteristics. A total of 3,949 texts sent between 1:00 and 5:00 AM across 360 unique participant nights were included in analyses. 73.3% of texts were sent from 1:00 AM- 2:00 AM, 14.2% of texts were sent from 2:00 AM – 3:00 AM, 6.7% of texts were sent from 3:00 AM – 4:00 AM, and 5.8% of texts were sent from 4:00 AM – 5:00 AM.

Effect of Season. As in the first set of analyses, season was a significant predictor of the number of unique nightly hour bins (b = -.81, SE = .38, z = -2.17, p = .030). Participants were more likely to send texts across 2 or more hour bins in non-summer months, relative to summer months. In contrast, participants were more likely to send texts across just one hour bin in summer months, relative to non-summer months.

Effect of Time of Week. As in the first set of analyses, the effect of weekend vs. not weekend was a significant predictor of the number of unique nightly hour bins (b =.61, SE = .25, z = 2.48, p = .013). Participants were more likely to send texts across multiple hour bins on weekend nights, relative to non-weekend nights. In contrast, participants were more likely to send texts across just one hour bin on non-weekend nights, relative to weekend nights.

Effect of Age. As in the first set of analyses, when age was tested as a predictor of the number of unique nightly hour bins, the model could not converge. Thus, age was not included as a covariate in the final model.

Effect of Episode Type. The final models tested episode type as a predictor of the number of unique nightly hour bins while controlling for both season and time of week, in line with the first set of analyses. As in the initial analyses, season and time of week remained significant predictors of the number of unique nightly hour bins. However, there were no significant differences in the number of unique nightly hour bins between 1:00 and 5:00 AM across episode types. See Table 8 for full results.

Discussion

Overview of Results

The present study examined whether sleep-related communication and objective texting patterns differed as a function of within-person suicide risk severity. Results showed that individuals were more likely to communicate about sleep during depressed mood episodes, relative to positive mood episodes. This effect was only observed when analyses were conducted using the reduced sleep dictionary. The remaining hypotheses were not supported, such that there were no other discernable differences in sleep-related communication, the number of sent texts during expected sleep windows, or the number of unique hours during expected sleep windows with a sent text, based on episode type. However, both season and time of week emerged as significant predictors of the number of texts and the number of unique hours with a sent text during expected sleep windows. Specifically, more texting activity was observed on weekend nights, relative to non-weekend nights, and during non-summer months, versus summer months. This proof-of-concept pilot study lays the ground for future research that leverages objective digital communication data to detect suicide risk and other hard-to-track behaviors.

Regarding the first research question, there were initially no significant differences in the likelihood of communicating about sleep across episode types. After revising the sleep dictionary, however, there was a significant effect in the hypothesized direction: on average, participants communicated about sleep more in depressed mood episodes, relative to positive mood episodes. When people are feeling depressed, they may be more likely to struggle with sleep and convey that they are struggling to others. This aligns with prior research that found that disclosing one's sleep struggles to others is a common method of coping with sleep problems (Jamison-Powell et al., 2012). Insomnia in particular can affect several aspects of a person's life, and the impairment it causes can be isolating (Kyle et al., 2010). Sharing that burden with others (e.g., via writing) may serve to ease the load (Pennebaker & Seagal, 1999).

Moreover, there were not significant differences in the number of sent texts across episode type. It is likely that we were underpowered to detect effects, given the small sample size, coupled with the paucity of episodes with consecutive nights of outgoing text messages. These factors may also explain the non-convergence issues encountered with Hypothesis 2, particularly given the specification of multiple random effects in each model. Nevertheless, both season and time of week were significant predictors of the number of sent texts. Participants sent more texts on weekend nights, relative to weeknights, and during non-summer months, relative to all other months. It is unsurprising that participants sent more texts on weekends than on weekend nights, given adolescents and young adults are more likely to be awake and using their phones later on weekends (Lund et al., 2010). Less intuitive, though, is the finding that more texts were sent during non-summer months than summer months. If most texts had been sent when participants were in high school and had more restrictive bedtimes, there might have been more night-time texting activity in summer months (Crowley et al., 2006). However, 86.6% of texts were sent while participants were between 18 and 21 years old, and presumably, already in college. College students might stay up later during the academic year compared to summers, because summers likely involve a lighter amount of socializing and schoolwork for college students, allowing them to go to bed earlier. It is also likely that college students simply have more social contacts with whom they can text during the school year, compared with summer months.

Finally, there were no significant differences in the number of unique nightly hour bins with sent texts across episode types. There may not have been a sufficient distribution of texts across hour bins to observe a significant effect for episode type. As with the second hypothesis, there was more texting activity across unique hour bins on weekend nights than weeknights, and during non-summer months than summer months. Again, participants were likely staying up later and sending more texts throughout the night on weekends and during the school year, versus on weeknights and during summer months, when college is not in session.

Limitations and Future Directions

The study has a number of limitations that must be addressed. First, the sample was small and relatively homogeneous with respect to race, gender, ethnicity, and sexual orientation. Given that suicide risk is particularly pronounced among LGBTQ+ people (Hatchel et al., 2019), and LGBTQ+ people of color (Sutter & Perrin, 2016), research that recruits individuals from these communities and centers their experiences is sorely needed. Additionally, given that smartphone ownership was a prerequisite for study participation, we may have failed to recruit participants from lower socioeconomic classes, which poses another limitation. To expand upon this pilot study, future research should recruit participants with a more diverse array of racial, ethnic, and gender identities, socioeconomic backgrounds, and sexual orientations. In line with much of the extant research in this area, an expansion of this study could also make use of data collected from free platforms (e.g., social media sites) instead of relying on data from private devices.

Additionally, though we managed to collect over one million text messages from participants' devices, the number of texts that fell during circumscribed, two-week episodes – and thus could be used for analyses– was significantly smaller. Our dataset was further truncated by the choice we made to only include outgoing text messages, instead of both outgoing and incoming text messages (*c.f.* Glenn et al., 2020). However, we believe that using outgoing texts only allowed for a closer approximation of potential sleep disturbance. The inclusion of incoming texts could have generated several false positives (e.g., if a participant often *receives* texts in the middle of the night). Research with a larger corpus of text messages during more specified episode types may yield valuable information about episode-level differences in objective texting behaviors.

Finally, though it is beyond the scope of this study, it would be useful to examine common themes that emerged in texts flagged by the sleep dictionary, as a further validation check. Revising the sleep dictionary likely allowed for closer approximation of sleep disturbance, but it was still not perfect. Though precautions were taken to ensure that the sleep dictionary would pick up on slightly different variants of common sleep-related phrases (e.g., we included both “I’m gonna crash” and “I’m going to crash”), LIWC could not flag words and phrases that were otherwise misspelled. It is also possible that certain slang words associated with sleep disturbance were left out.

Conclusions

This proof-of-concept pilot study represents a first step towards identifying objective indicators of sleep disturbance that can be inferred non-intrusively via personal communication channels. There was some indication that individuals with a suicide attempt history were more likely to communicate about sleep when they were experiencing two-week periods of depressed mood, relative to two-week periods of positive mood. That this difference emerged only following the refinement of the sleep dictionary underscores the importance of thoroughly validating tools used to identify potential markers of mood-state fluctuation in text-based documents (e.g., clinical notes or electronic health records). Including the wrong key words or phrases could yield false positives or lead an algorithm to miss an important indicator of mood deterioration. The present study was also able to detect systematic differences in texting behaviors based on broad environmental factors (i.e., time of week and time of year). These objective findings complement and bolster much of the literature on self-reported smartphone use patterns in young adults (e.g., that young adults tend to use their smartphones later on the weekends, relative to weekdays). Though additional research is needed, the method used here could potentially be scaled up and applied in larger, public channels to infer mood-state fluctuation, including among individuals at-risk for suicide.

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Table 1

Demographic Characteristics for N = 26 Participants

Gender	
Female	22
Male	4
Nonbinary	0
Age	
Mean	20.8
SD	2.6
Ethnicity	
Hispanic	3
Non-Hispanic	23
Race	
White	17
Asian	4
Black	2
Multiple/Other	3
Sexuality	
Heterosexual/Straight	19
Gay/Lesbian/Homosexual	1
Bisexual	4
Other/Decline to state	2
Citizenship	
U.S. Citizen or Permanent Resident	25
Non-U.S. Citizen or Permanent Resident	1
Professional Status	
Student	25
Employed full-time	2
Employed part-time	4
Highest Level of Education Completed	
High-school/GED	5
Some college	17
Associates degree	2
Bachelor’s degree	1
Master’s degree	1

Table 2

Comprehensive LIWC Custom Sleep Dictionary

Root words	Multi-word phrases	Emojis
Sleep*	Passed out	💤
Insomnia	Pass out	😴
Exhausted	Can’t sleep	🛌
Tired	Cant sleep	🛏️
Drowsy	Still up	🥱
Bed*	Still awake	⏰
Nap*	I am wrecked	
Awake	I’m wrecked	
Snor*	Im wrecked	
Snooz*	Wiped out	
Doz*	Go to bed	
Ambien	U up	
Lunesta	Im gonna knock	
Asleep	Im going to knock	
Wiped	I’m gonna knock	
Nightmare	I’m going to knock	
Shut-eye	Im gonna crash	
Shuteye	Im going to crash	
Nyquil	I’m gonna crash	
Dead-tired	I’m going to crash	
Melatonin	Get some zz*	
Trazodone	Lay down	
Slumped	Drift off	
Rest*	Lights out	
Goodnight	Turn in	
Slumber	Hit the hay	
Dream*	Hit the sack	
Drained	Bedbugs bite	
Zombie	Catch a wink	
Fitful	Nodding off	
Collapse	Nod off	
Blackout	I have to be up in	
Wired	Sleep tight	
Fried	Up all night	
Daze	Running on fumes	
Lethargy	Strung out	
Coma	Forty winks	
Hibernate	Wake up	
Catnap	Woke up	
Siesta		
Groggy		
Zz*		

Note. Words tagged with an asterisk are word-stems that detect all word variants containing that stem. LIWC is not case sensitive.

Table 3

Estimates for likelihood of a text being sleep related or not across episode types (Hypothesis 1)

Predictor		*B* (Log Odds)	Odds Ratio [95% CI]	*SE*	*z*	*p*	Random Effect Variance for Participant (SD)	Random Effect Variance for Unique Episode (SD)	$R^2M(R^2C)$
Episode Type (Intercept)							.13 (.36)	.11(.33)	.00 (.07)
Reference Level									
Positive	Depressed	−.01	.99 [.79, 1.23]	.11	−.11	.910			
	Ideation	.05	1.05 [.84, 1.31]	.11	.40	.688			
	Attempt	.02	1.02 [.78, 1.33]	.14	.14	.890			
Attempt	Depressed	−.03	.97 [.73, 1.28]	.14	−.22	.825			
	Ideation	.03	1.03 [.78, 1.36]	.14	.19	.849			
	Positive	−.02	.98 [.75, 1.28]	.14	−.14	.890			
Attempt and Ideation	Depressed and Positive	−.04	.96 [.81, 1.14]	.09	−.49	.625			
Positive	Depressed, Ideation, and Attempt	.03	1.03 [.88, 1.21]	.08	.41	.681			

Note. R^2M = marginal R^2. R^2M indicates the amount of variance in the model accounted for by the fixed effects. R^2C = conditional R^2. R^2C indicates the amount of variance in the model accounted for by random effects.
Depressed = Depressed Mood. Positive = Positive Mood.

Table 4

Estimates for count of outgoing sleep texts between midnight – 5:00 AM across episode types (Hypothesis 2)

Predictor		*B*	*SE*	*z*	*p*	Random Effect Variance for Participant (SD)	Random Effect Variance for Unique Episode (SD)	$R^2M(R^2C)$
Episode Type (Intercept)						2.90 (1.70)	1.45 (1.20)	.03 (.70)
Reference Level								
Positive	Depressed	−.33	.33	−1.02	.310			
	Ideation	.21	.35	.61	.542			
	Attempt	.35	.42	.83	.406			
	Weekend (vs. weekday)	**.34**	**.14**	**2.40**	**.016**			
	Summer (vs. all other seasons)	**−.88**	**.31**	**−2.89**	**.004**			
Attempt	Depressed	−.68	.42	−1.62	.105			
	Ideation	−.14	.43	−.31	.754			
	Positive	−.35	.42	−.83	.406			
	Weekend (vs. weekday)	**.34**	**.14**	**2.40**	**.016**			
	Summer (vs. all other seasons)	**−.88**	**.31**	**−2.89**	**.004**			
Attempt and Ideation	Depressed and Positive	−.42	.27	−1.59	.112			
	Weekend (vs. weekday)	**.34**	**.14**	**2.36**	**.018**			
	Summer (vs. all other seasons)	**−.92**	**.31**	**−2.99**	**.003**			
Positive	Depressed, Ideation and Attempt	.27	.25	1.10	.273			
	Weekend (vs. weekday)	**.34**	**.14**	**2.35**	**.019**			
	Summer (vs. all other seasons)	**−.92**	**.31**	**−2.99**	**.003**			

Note. R^2M = marginal R^2. R^2M indicates the amount of variance in the model accounted for by the fixed effects. R^2C = conditional R^2. R^2C indicates the amount of variance in the model accounted for by random effects.
Depressed = Depressed Mood. Positive = Positive Mood.

Table 5

Estimates for sum of total unique hour bins with outgoing texts between midnight – 5:00 AM across episode types (Hypothesis 3)

Predictor		*B*	*SE*	*z*	*p*	Random Effect Variance for Participant (SD)	Random Effect Variance for Unique Episode (SD)	$R^2M(R^2C)$
Episode Type								.04 (.23)
(Intercept)						.55 (.74)	.26 (.51)	
Reference Level								
Positive	Depressed	−.24	.27	−.87	.383			
	Ideation	−.45	.30	−1.49	.136			
	Attempt	.10	.37	.28	.779			
	Weekend (vs. weekday)	**.50**	**.19**	**2.69**	**.007**			
	Summer (vs. all other seasons)	**−.74**	**.31**	**−2.37**	**.018**			
Attempt	Depressed	−.34	.37	−.93	.353			
	Ideation	−.56	.39	−1.42	.155			
	Positive	−.10	.37	−.28	.779			
	Weekend (vs. weekday)	**.50**	**.19**	**2.69**	**.007**			
	Summer (vs. all other seasons)	**−.74**	**.31**	**−2.37**	**.018**			
Attempt and Ideation	Depressed and Positive	−.13	.23	−.57	.571			
	Weekend (vs. weekday)	**.48**	**.18**	**2.59**	**.010**			
	Summer (vs. all other seasons)	**−.75**	**.32**	**−2.38**	**.017**			
Positive	Depressed, Ideation and Attempt	−.18	.21	−.84	.399			
	Weekend (vs. weekday)	**.48**	**.18**	**2.59**	**.010**			
	Summer (vs. all other seasons)	**−.75**	**.31**	**−2.50**	**.017**			

Note. R^2M = marginal R^2. R^2M indicates the amount of variance in the model accounted for by the fixed effects. R^2C = conditional R^2. R^2C indicates the amount of variance in the model accounted for by random effects.
Depressed = Depressed Mood. Positive = Positive Mood.

Table 6

Reduced LIWC Custom Sleep Dictionary

Root words	Multi-word phrases
Insomnia	In bed
Snor*	Passed out
Doz*	Pass out
Ambien	Can’t sleep
Lunesta	Cant sleep
Asleep	Not sleep*
Wiped	Couldn’t sleep
Nightmare	Couldnt sleep
Nyquil	Didn’t sleep
Melatonin	Didnt sleep
Trazodone	Try to sleep
Slumber	Wanna sleep
Dream*	Want to sleep
Collapse	Get some sleep
Blackout	Need sleep
Groggy	Haven’t slept
	Still up
	Still awake
	Wiped out
	Go to bed
	U awake
	You awake
	Up late
	Lay down
	Hit the hay
	Nodding off
	Nod off
	I have to be up
	Up all night
	Woke up

Note. Words tagged with an asterisk are word-stems that detect all word variants containing that STEM. LIWC is not case-sensitive.

Table 7

Estimates for likelihood of a text being sleep related or not across episode types, with reduced sleep dictionary (Hypothesis 1)

Predictor		*B* (Log Odds)	Odds Ratio [95% CI]	*SE*	*z*	*p*	Random Effect Variance for Participant (SD)	Random Effect Variance for Unique Episode (SD)	$R^2M(R^2C)$
Episode Type (Intercept)							.05 (.23)	.18(.42)	.01 (.07)
Reference Level									
Positive	**Depressed**	**.39**	**1.47 [1.06, 2.04]**	**.17**	**2.32**	**.020**			
	Ideation	.19	1.21 [.85, 1.71]	.18	1.05	.292			
	Attempt	.38	1.46 [.98, 2.18]	.20	1.88	.060			
Attempt	Depressed	.00	1.00 [.68, 1.48]	.20	.02	.985			
	Ideation	−.19	.82 [.55, 1.23]	.21	−.95	.344			
	Positive	−.38	.68 [.46, 1.02]	.20	−1.88	.060			
Attempt and Ideation	Depressed and Positive	.06	1.06 [.81, 1.38]	.14	.44	.664			
Positive	Depressed, Ideation, and Attempt	−.16	.85 [.67, 1.10]	.13	-1.23	.217			

Note. R^2M = marginal R^2. R^2M indicates the amount of variance in the model accounted for by the fixed effects. R^2C = conditional R^2. R^2C indicates the amount of variance in the model accounted for by random effects.
Depressed = Depressed Mood. Positive = Positive Mood.

Table 8

Estimates for sum of total unique hour bins with outgoing texts between 1:00 – 5:00 AM across episode types (Hypothesis 3)

Predictor		*B*	*SE*	*z*	*p*	Random Effect Variance for Participant (SD)	Random Effect Variance for Unique Episode (SD)	$R^2M(R^2C)$
Episode Type (Intercept)						.44 (.66)	.03 (.17)	.06 (.17)
Reference Level								
Positive	Depressed	−.01	.31	−.03	.977			
	Ideation	.36	.35	1.03	.304			
	Attempt	−.35	.43	−.81	.420			
	Weekend (vs. weekday)	**.62**	**.25**	**2.53**	**.012**			
	Summer (vs. all other seasons)	**−.87**	**.39**	**−2.23**	**.026**			
Attempt	Depressed	.34	.43	.79	.432			
	Ideation	.71	.46	1.55	.122			
	Positive	.35	.43	.81	.420			
	Weekend (vs. weekday)	**.62**	**.25**	**2.53**	**.012**			
	Summer (vs. all other seasons)	**−.87**	**.39**	**−2.23**	**.026**			
Attempt and Ideation	Depressed and Positive	.11	.27	.40	.686			
	Weekend (vs. weekday)	**.59**	**.25**	**2.42**	**.016**			
	Summer (vs. all other seasons)	**−.83**	**.39**	**−2.13**	**.033**			
Positive	Depressed, Ideation and Attempt	−.02	.27	−.08	.937			
	Weekend (vs. weekday)	**.59**	**.25**	**2.41**	**.016**			
	Summer (vs. all other seasons)	**−.81**	**.39**	**−2.80**	**.038**			

Note. R^2M = marginal R^2. R^2M indicates variance in the model accounted for by the fixed effects. R^2C = conditional R^2. R^2C indicates the amount of variance in the model accounted for by random effects.
Depressed = Depressed Mood. Positive = Positive Mood.

Figure 1

Count of outgoing texts from midnight – 5:00 AM across episode type (for all participants)

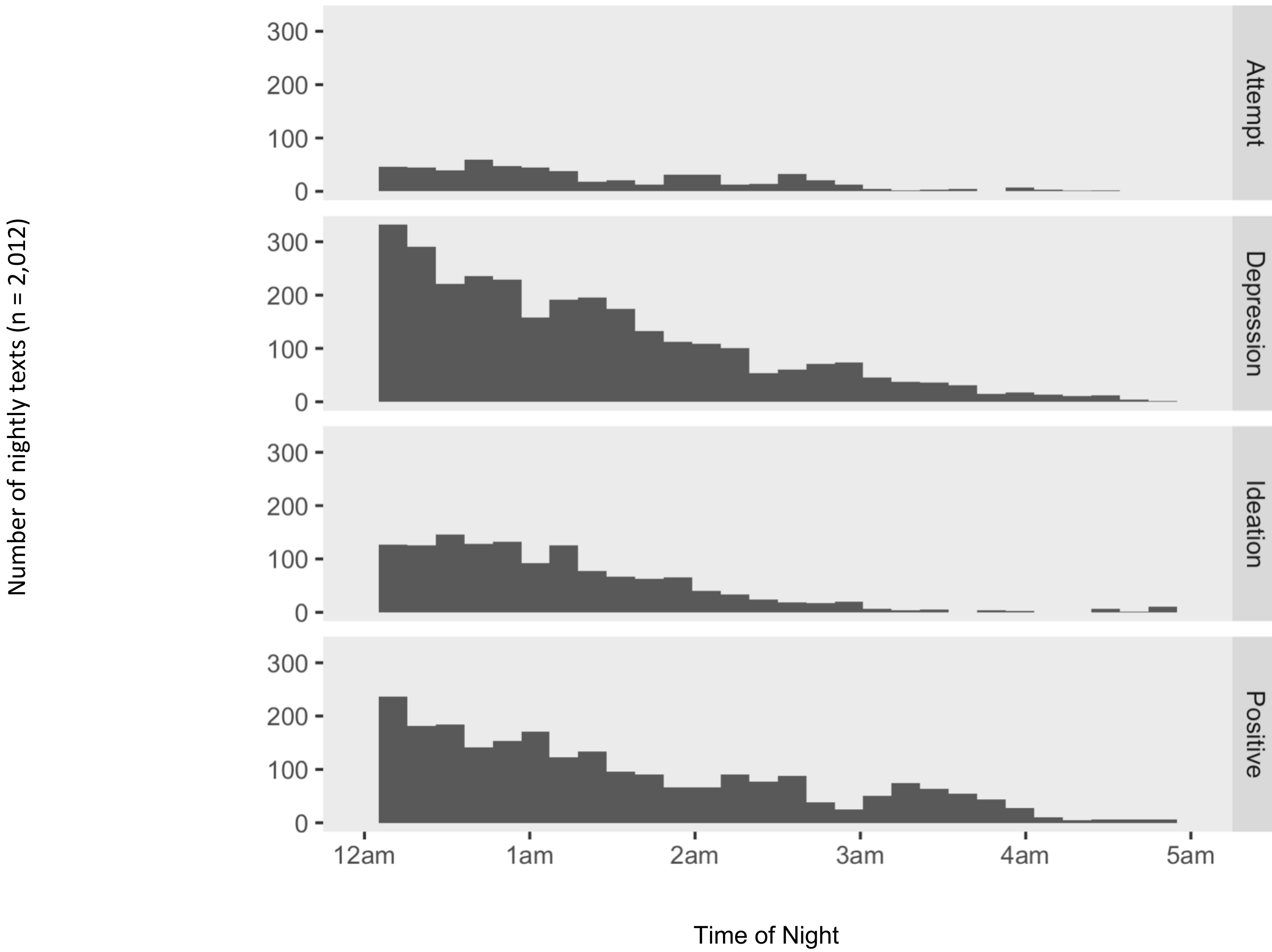


Figure 2

Count of outgoing texts from midnight – 5:00 AM across individual participants

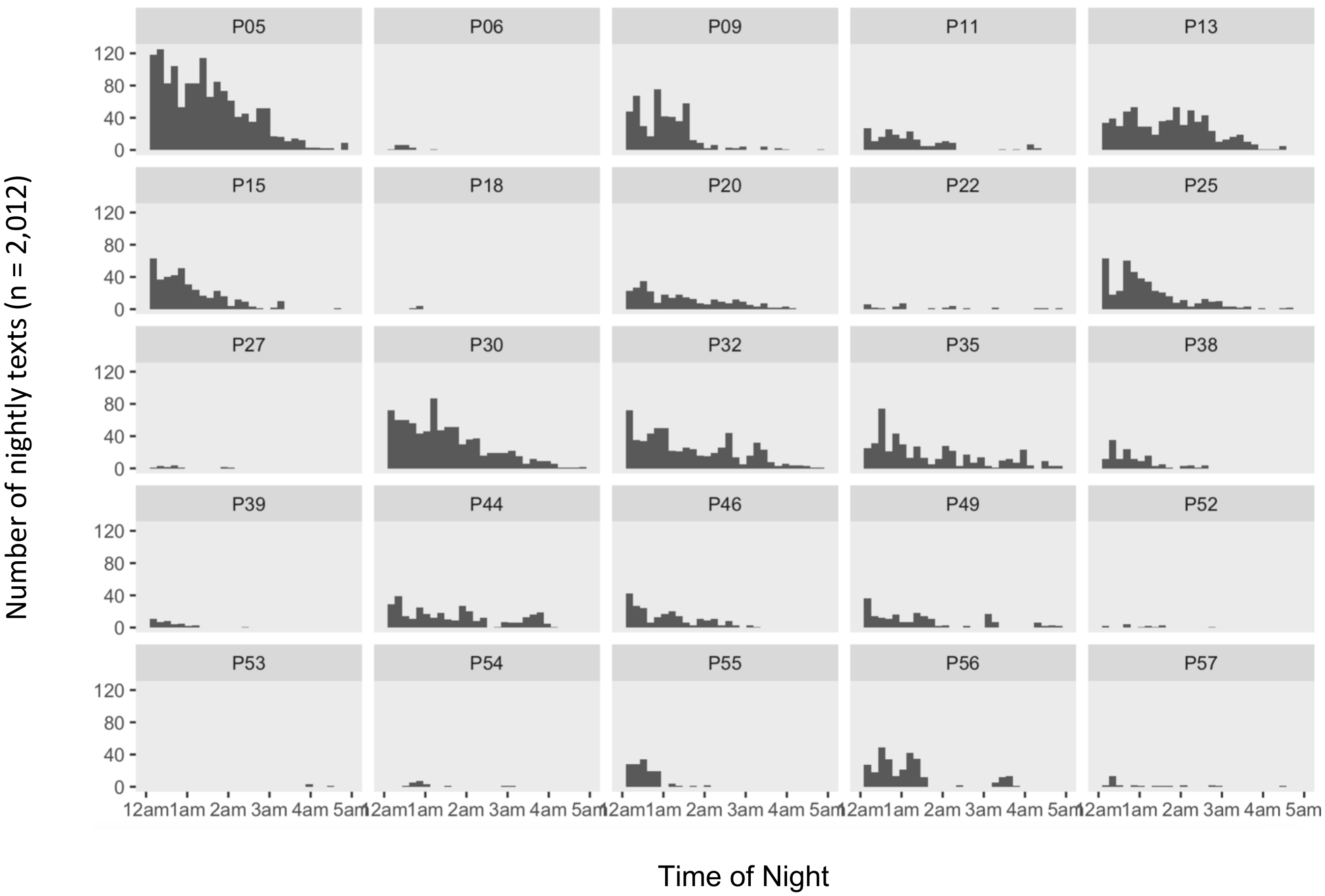
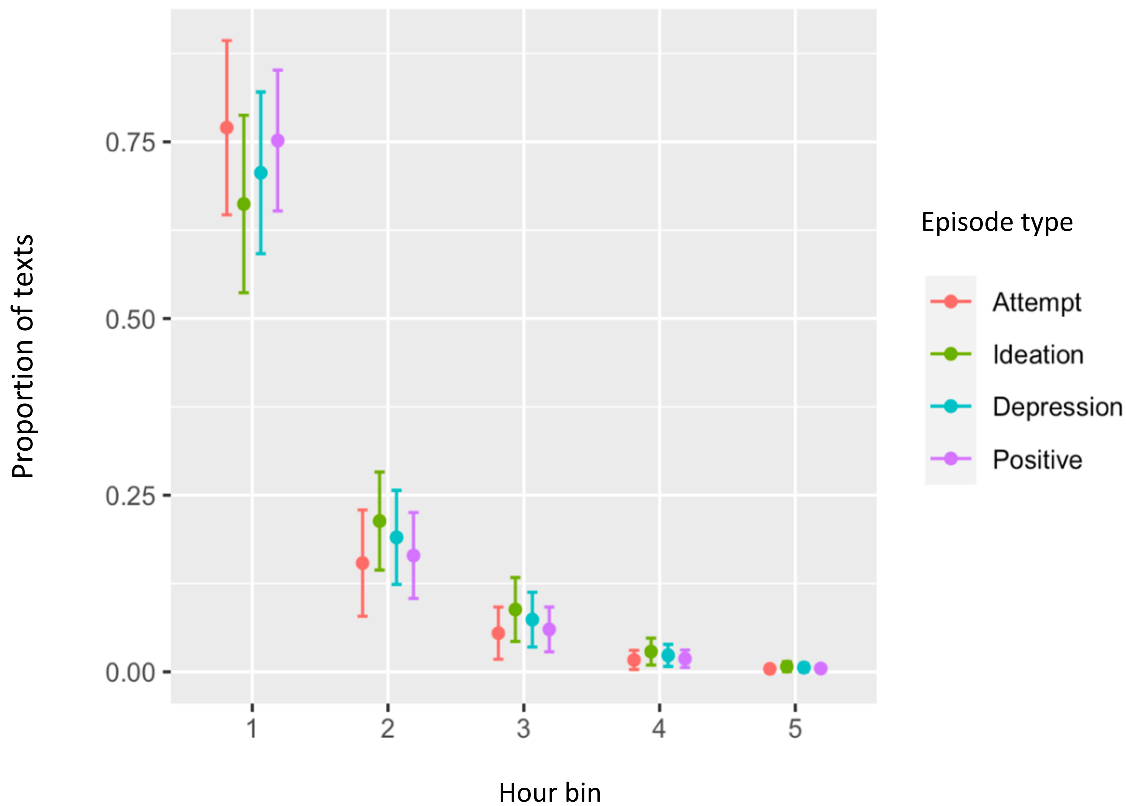


Figure 3.

Observed sums of unique nightly hour bins with outgoing texts from midnight – 5:00 AM across episode type (for all participants combined)



Note. Hour bin “1” = 12:00 – 1:00 AM; “2” = 1:00 – 2:00 AM; “3” = 2:00 – 3:00 AM; “4” = 3:00 – 4:00 AM; “5” = 4:00 – 5:00 AM