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Suicide and Life-Threatening BEHAVIOR

ORIGINAL ARTICLE

Inferring sleep disturbance from text messages of suicide attempt survivors: A pilot study

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Abstract

Objective: Identifying digital markers of sleep disturbance—a known suicide risk factor—may aid in the detection of imminent suicide risk. This study examined sleep-related communication and texting patterns in personal text messages ($N = 86{,}705$) of suicide attempt survivors.

Method: Twenty-six participants provided dates of past suicide attempts and 2-week periods of positive mood, depressed mood, or suicidal ideation. Linguistic Inquiry Word Count was used to identify sleep-related texts via a custom dictionary. Mixed effect models were fitted 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, nightly count of texts sent from midnight to 5:00 AM, and sum of unique hour bins from midnight to 5:00 AM with outgoing texts.

Results: Analyses with a sleep dictionary that was manually revised to be more accurate (but not the original unedited dictionary) showed sleep-related communication was more likely during depressed mood episodes than positive mood episodes. Otherwise, there were no significant differences in sleep-related communication or objective texting patterns across episode type.

Conclusions: Although we did not detect differences in sleep-related communication tied to suicidal thoughts or behaviors, sleep-related communication may differ as a function of within-person mood level.

KEYWORDS

depression, insomnia, risk-assessment, smartphones, suicide

INTRODUCTION

Suicide is a leading cause of death in the United States (Hedegaard et al., 2020), yet the field of suicide prevention lacks 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*.

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., accelerometer 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 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- and individual-level trends and risk status markers. In line with these goals, the present study sought to examine whether naturalistic text messaging patterns indicating 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 more broadly have emerged as modifiable, independent risk factors for suicidal ideation, attempts, and death by suicide (Liu et al., 2020). Yet, most studies have examined sleep disturbance and STBs cross-sectionally, precluding identification of temporal 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 follow-up periods 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, poor sleep quality and short sleep duration predicted greater severity of next-day suicidal ideation in adults with a major depressive episode (Littlewood et al., 2019). Similar patterns have been found in younger adults with a suicide attempt history; 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).

There is thus some evidence that sleep problems can be considered prospective, near-term risk factors for suicidal ideation. 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 reporting has provided some clues. Based on third-party informant interviews with family and friends, adolescent (Goldstein et al., 2008) and adult (Kodaka et al., 2014) suicide decedents had higher rates of sleep disturbance prior to death than living control participants. These findings suggest that it is possible to discern *nomothetic* (i.e., group level) differences in associations between sleep disturbance and suicide-related outcomes. However, relying on third-party informants does not clarify whether and how sleep disturbance changes *idiographically* (i.e., within a given individual) in the short-term window leading up to an 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 (Fisher et al., 2018). The present study begins to address these gaps by inferring sleep disturbance directly from text messages of individuals who made (non-lethal) suicide attempt(s). Additionally, we partition suicide risk across a severity spectrum, to more finely differentiate the imminent period prior to an attempt from other 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 how people communicate with others about their sleep issues. For instance, individuals often share their personal insomnia coping strategies on Twitter (Jamison-Powell et al., 2012). However, no study 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. Nevertheless, such data could provide valuable insight, especially because private communication about sleep problems may well reflect more significant distress than communication shared on public forums.

In addition to studying message content, it can be beneficial to probe objective message patterns. Twitter users who self-identified as having sleep issues tweeted significantly more than a control group of Twitter users from hours of midnight – 6:00 AM, despite being less active on the platform in general (McIver et al., 2015). Additionally, 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 it is possible to infer different subgroups (e.g., insomnia vs. no insomnia) based on technology use patterns scraped from publicly available social media timestamps to predict intraindividual behavior change.

The few studies that have leveraged objective digital communication on *private* data streams found that nighttime phone use and texting is common in general, particularly among adolescents and young adults (Rod et al., 2018; Troxel et al., 2015). The present study was well-poised to examine more detailed digital communication dynamics, including the *total* number of texts sent when individuals were expected to be sleeping, and *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

This 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 2-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 objective texting patterns as 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 primary research questions (see https://osf.io/9f3v2/). 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 more texts 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 and 5:00 AM (e.g., first unique hour bin: midnight – 1:00 AM and second unique hour bin: 1:00–2:00 AM). The present study is the first to our knowledge to examine 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) who experienced at least one past suicide attempt were recruited from the local community and the University of Virginia (UVA) participant pool. Participants were compensated with course credit or $40. Short message service (SMS) data were available for 26 participants,[1] so analyses are restricted to texts from those individuals (M_{age} = 20.8, SD_{age} = 2.6). Twenty-two participants self-identified as female (84.6%) and four as male (15.4%). Seventeen participants self-identified as White (65.4%), four as Asian (15.4%), two as Black (7.7%) and three as multiple or "other" (11.5%). Nineteen participants self-identified as heterosexual (73.1%), one as gay/lesbian (3.8%), four as bisexual (15.4%) and two as "other"/"declined to state" (7.7%). The full study CONSORT diagram and demographics are available at https://osf.io/kgq8h/ (Glenn et al., 2020).

Procedures

Pre-screening

The Institutional Review Board approved all study procedures. Individuals completed two surveys assessing study interest and prior periods of hopelessness (survey 1) and suicide attempt history/current suicidality (survey 2). Those who reported a past suicide attempt and not wanting to kill themselves at the time of screening could 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 and provided informed consent before completing a clinical interview with a masters-level clinical psychology graduate student. The interviewer elicited detailed information about previous 2-week episodes of (1) a suicide attempt episode (defined as the 2-week period leading up to an attempt), (2) periods of suicidal ideation (with no attempt) that lasted 2 weeks, (3) periods of depressed mood not characterized by suicidality that lasted 2 weeks, and (4) periods of positive mood that lasted 2 weeks. To help ensure that participants were accurately matching episodes to dates, participants were asked to identify the circumstances precipitating each episode (e.g., major life stressors) from a check-all-that-apply list. Participants could report on episodes occurring as far in the past as they remembered. About 85% of reported episodes took place in 2016 (the year data were collected) or 2015, whereas the remaining 15% took place two or more years prior to data collection. However, episodes were only included in analyses if participants had accompanying digital data corresponding to a given episode.

Participants downloaded text messages from their smartphones and/or other personal devices onto a study computer. Raw data were transferred and stored on a highly secure UVA server following the study session. No participants reported increased negative mood or desire to die from the beginning to the end of the study session. See Glenn et al. (2020) for additional details about study procedures.

Sleep dictionary creation

Linguistic Inquiry and Word Count (*LIWC*; Pennebaker et al., 2015) is a software that scores text data based on various linguistic features grouped into categories. For most variables, LIWC generates a score that reflects the percentage of words in a given text document that belong to each category. In addition to offering pre-defined categories, LIWC allows users to also create custom dictionaries to represent a user-defined category. Given there is no preexisting LIWC category assessing communication tied to sleep, we created a custom sleep dictionary for this study to examine whether sleep-related communication differed across episode types (see Table S1). 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** flagged variants including *napped* and *napping*). Five clinical psychologists with sleep expertise provided feedback on the list and suggested additional words and phrases. Many flagged texts were variations on the question, "Are you up?". Other texts were longer and more descriptive (e.g., "I haven't slept since Sunday and I'm panicking"; "I've been trying to fall asleep for an hour").

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 (Table 1), text messages containing words, phrases, and/or emojis related to sleep were identified and each text message was classified accordingly as sleep-related or non-sleep-related.

Note, after completing the first set of analyses which yielded fully null results, we manually reviewed the texts flagged as sleep-related. Upon inspection, it was clear that the original sleep dictionary overestimated the number of texts truly indicating sleep disturbance. To more closely capture sleep disturbance, author IEL went through and refined the sleep dictionary prior to re-running analyses. For transparency, information on the original sleep dictionary, how it was reduced, and results from analyses with the original dictionary is included in the supplement.

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 to 5:00 AM would indicate likely wakefulness, with more messages possibly indicating more social engagement. Analyses were limited to texts sent from midnight to 5:00 AM, based on typical adolescent sleep patterns (Crowley et al., 2007). The number of texts sent from midnight to 5:00 AM during each night within a specified, 2-week episode was calculated at the individual level. Nights without any outgoing text messages from midnight to 5:00 AM were coded as "0."

TABLE 1 Reduced LIWC custom sleep dictionary

Root words	Multi-word phrases
Insomnia	In bed
Snor*	Passed out
Doz*	Pass out
Ambien	Can't sleep
Lunesta	Can't sleep
Asleep	Not sleep*
Wiped	Couldn't sleep
Nightmare	Couldn't sleep
Nyquil	Didn't sleep
Melatonin	Didn't 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.

Hypothesis 3: Number of unique nightly hour bins with sent texts

The third hypothesis tested differences in the total number of unique hour "bins" in which a text was sent between the hours of midnight – 5:00 AM. This could yield a nuanced picture of text-message activity and wakefulness throughout the 5-h expected sleep window by indicating how long participants were awake throughout the night (irrespective of *how many* texts were sent). Text messages were coded as "1" if they were sent from midnight to 1:00 AM, "2" if they were sent from 1:01 AM to 2:00 AM, "3" if they were sent from 2:01 AM to 3:00 AM, "4" if they were sent from 3:01 AM to 4:00 AM, and "5" if they were sent from 4:00 AM to 5:00 AM. Then, sum scores of unique hours with an outgoing text were calculated for each night. Possible values ranged from 0 to 5, with higher values reflecting more text activity spread out across the expected sleep window. 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 identifier. Models were fitted using the lme4 (Bates et al., 2015) and ordinal packages (Christensen, 2019), and odds ratios and confidence intervals were calculated using sjStats (Lüdecke, 2021). We 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 left 86,705[2] text messages to analyze. 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.

Analysis for Hypothesis 1: Incidence of sleep-related text messages across episode type

Generalized linear mixed models 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 for the binomial outcome variable. 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).

Analysis for 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. In line with our preregistration, we also tested whether demographic and seasonal contexts were independently associated with the count of texts sent from midnight to 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 different in the summer, when school is not in session (Crowley et al., 2006). Season was divided into "summer" (i.e., June–August) and "non-summer" (all other months). Second, the effect of time of week (i.e., weekday versus weekend) was tested, because adolescent sleep patterns often differ on the weekends. "Weekend" texts were sent between midnight and 5:00 AM on either Saturday or Sunday. Finally, participant age during episode was tested as a predictor of text count, given that adolescent bedtimes tend to become later as individuals become older (Crowley et al., 2007).

Analysis for Hypothesis 3: Number of unique nightly hour bins with sent texts

Multilevel ordinal models were fitted to test differences in the total number of unique hours with a sent text between midnight and 5:00 AM. Episode type was the predictor, and total number of unique hours with a sent text was the outcome. 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.

RESULTS

Description of episodes

Participants reported a total of 66 attempt episodes, 68 ideation episodes, 78 depressed mood episodes, and 81 positive mood episodes. SMS data were not available for all reported episodes, as some episodes took place several years prior to the study. There were SMS data available for a total of 21 attempt episodes across 15 unique participants (M_{age} = 20.0, SD_{age} = 2.5), 32 ideation episodes across 20 unique participants (M_{age} = 19.6, SD_{age} = 2.2), 40 depressed mood episodes across 22 unique participants (M_{age} = 19.8, SD_{age} = 2.3), and 41 positive mood episodes across 24 unique participants (M_{age} = 20.1, SD_{age} = 2.2).

Incidence of sleep-related text messages across episode type with the revised sleep dictionary (Hypothesis 1)

Descriptive text characteristics

Of the 86,705 text messages included in analyses, 0.71% contained a sleep-related word, phrase, or emoji. Participants sent between 1 and 50 sleep-related texts, with a between-subjects mean of 24.72 sleep texts (SD = 19.81). Roughly 18% of sleep-related texts were sent between midnight and 5:00 AM.

Effect of episode type

Using the revised dictionary, 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 2.

Number of nightly texts sent during expected sleep window (Hypothesis 2)

Descriptive text characteristics

Twenty-five out of the 26 participants had sent texts between midnight and 5:00 AM (see Figures S1 and S2). Of the 2012 separate nights analyzed (across all participants), 70.3% nights had no outgoing texts, 6.4% had one outgoing text, and 23.2% had more than one outgoing text. 7546 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 to 5:00 AM ranged from 1 to 165 (M_{count} = 12.6, SD_{count} = 19.6).

Effect of season

Season was tested as an independent predictor of text count. On average, significantly more text messages were sent from midnight to 5:00 AM during non-summer months, relative to summer months (b = 0.84, SE = 0.31, z = 2.71, p = 0.007).

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 to 5:00 AM on weekend nights, relative to non-weekend nights (b = 0.31 SE = 0.14, z = 2.15, p = 0.032).

Effect of age

Finally, age was tested as a predictor of text count, independent from season and time of week. The model with

TABLE 2 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)						0.05 (0.23)	0.18 (0.42)	0.01 (0.07)
Reference level								
Positive								
Depressed	**0.39**	**1.47 [1.06, 2.04]**	**0.17**	**2.32**	**0.020**			
Ideation	0.19	1.21 [0.85, 1.71]	0.18	1.05	0.292			
Attempt	0.38	1.46 [0.98, 2.18]	0.20	1.88	0.060			
Attempt								
Depressed	0.00	1.00 [0.68, 1.48]	0.20	0.02	0.985			
Ideation	−0.19	0.82 [0.55, 1.23]	0.21	−0.95	0.344			
Positive	−0.38	0.68 [0.46, 1.02]	0.20	−1.88	0.060			
Attempt and ideation								
Depressed and positive	0.06	1.06 [0.81, 1.38]	0.14	0.44	0.664			
Positive								
Depressed, ideation, and attempt	−0.16	0.85 [0.67, 1.10]	0.13	−1.23	0.217			

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.

age as a predictor would not converge, and 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 text count 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 3.

Number of unique nightly hour bins with sent texts (Hypothesis 3)

Descriptive text characteristics

A total of 7546 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 to 1:00 AM), 21.8% of texts were sent during the second bin (from 1:00 AM to 2:00 AM), 11.0% of texts were sent during the third bin (from 2:00 AM to 3:00 AM), 4.2% of texts were sent during the fourth bin (from 3:00 AM to 4:00 AM), and 1.2% of texts were sent during the fifth bin (from 4:00 AM to 5:00 AM). See Figure S3.

Effect of season

As in Hypothesis 2, season was a significant predictor of the number of unique nightly hour bins ($b = -0.72$, $\mathrm{SE} = 0.31$, $z = -2.31$, $p = 0.021$). Participants were more likely to send texts across two or more hour bins in non-summer months, relative to summer months. In contrast, participants were more likely to send texts across just 1 h 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 ($b = 0.47$, $\mathrm{SE} = 0.18$, $z = 2.56$, $p = 0.01$). 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 1 h 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 4.

Rationale for analyses with reduced sleep window

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 (midnight – 1:00 AM) and about one-fifth of texts fell into the second hour bin (1:00–2:00 AM). This suggests that participants tended to be awake past midnight, which is typical for college students (Rod et al., 2018). Thus, we reran analyses for Hypotheses 2 and 3 with a narrower sleep window of 1:00–5:00 AM.

RESULTS FROM ANALYSES WITH REDUCED SLEEP WINDOW

Number of nightly texts sent during expected sleep window (Hypothesis 2)

Descriptive text characteristics

Twenty-four out of the 26 participants had sent texts between 1:00 and 5:00 AM. A total of 3949 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 and 5:00 AM ranged from 1 to 113 ($M_{\mathrm{count}} = 10.97$, $\mathrm{SD}_{\mathrm{count}} = 16.55$).

TABLE 3 Estimates for count of outgoing sleep texts between midnight and 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)	0.03 (0.70)
Reference level							
Positive							
Depressed	−0.33	0.33	−1.02	0.310			
Ideation	0.21	0.35	0.61	0.542			
Attempt	0.35	0.42	0.83	0.406			
Weekend (vs. weekday)	**0.34**	**0.14**	**2.40**	**0.016**			
Summer (vs. all other seasons)	**−0.88**	**0.31**	**−2.89**	**0.004**			
Attempt							
Depressed	−0.68	0.42	−1.62	0.105			
Ideation	−0.14	0.43	−0.31	0.754			
Positive	−0.35	0.42	−0.83	0.406			
Weekend (vs. weekday)	**0.34**	**0.14**	**2.40**	**0.016**			
Summer (vs. all other seasons)	**−0.88**	**0.31**	**−2.89**	**0.004**			
Attempt and ideation							
Depressed and Positive	−0.42	0.27	−1.59	0.112			
Weekend (vs. weekday)	**0.34**	**0.14**	**2.36**	**0.018**			
Summer (vs. all other seasons)	**−0.92**	**0.31**	**−2.99**	**0.003**			
Positive							
Depressed, ideation and attempt	0.27	0.25	1.10	0.273			
Weekend (vs. weekday)	**0.34**	**0.14**	**2.35**	**0.019**			
Summer (vs. all other seasons)	**−0.92**	**0.31**	**−2.99**	**0.003**			

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.

Bolded results are significant at the $p < .05$ level.

TABLE 4 Estimates for sum of total unique hour bins with outgoing texts between midnight and 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)					0.55 (0.74)	0.26 (0.51)	0.04 (0.23)
Reference level							
Positive							
Depressed	−0.24	0.27	−0.87	0.383			
Ideation	−0.45	0.30	−1.49	0.136			
Attempt	0.10	0.37	0.28	0.779			
Weekend (vs. weekday)	**0.50**	**0.19**	**2.69**	**0.007**			
Summer (vs. all other seasons)	**−0.74**	**0.31**	**−2.37**	**0.018**			
Attempt							
Depressed	−0.34	0.37	−0.93	0.353			
Ideation	−0.56	0.39	−1.42	0.155			
Positive	−0.10	0.37	−0.28	0.779			
Weekend (vs. weekday)	**0.50**	**0.19**	**2.69**	**0.007**			
Summer (vs. all other seasons)	**−0.74**	**0.31**	**−2.37**	**0.018**			
Attempt and ideation							
Depressed and Positive	−0.13	0.23	−0.57	0.571			
Weekend (vs. weekday)	**0.48**	**0.18**	**2.59**	**0.010**			
Summer (vs. all other seasons)	**−0.75**	**0.32**	**−2.38**	**0.017**			
Positive							
Depressed, Ideation and Attempt	−0.18	0.21	−0.84	0.399			
Weekend (vs. weekday)	**0.48**	**0.18**	**2.59**	**0.010**			
Summer (vs. all other seasons)	**−0.75**	**0.31**	**−2.50**	**0.017**			

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.

Bolded results are significant at the $p < .05$ level.

Effects of season, week, and age

The models with season, week or age as a predictor of text count would not converge.

Number of unique nightly hour bins with sent texts (Hypothesis 3)

Descriptive text characteristics

A total of 3949 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 to 2:00 AM, 14.2% of texts were sent from 2:00 to 3:00 AM, 6.7% of texts were sent from 3:00 to 4:00 AM, and 5.8% of texts were sent from 4:00 to 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 ($b = -0.81$, $SE = 0.38$, $z = -2.17$, $p = 0.030$). 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 1 h 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 ($b = 0.61$, $SE = 0.25$, $z = 2.48$, $p = 0.013$). 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 1 h 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 5.

DISCUSSION

The present study examined whether sleep-related communication and texting patterns differed as a function of within-person suicide risk severity. 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. There were no other discernable differences in sleep-related communication or objective texting patterns based on episode type. 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 study lays the ground for future research that leverages digital communication data to detect suicide risk and other hard-to-track behaviors.

Regarding the first research question, with the revised dictionary, participants communicated about sleep more in depressed mood episodes on average, 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).

Unexpectedly, there were not significant differences in the number or spread of sent texts across episode type. This suggests these texting patterns are not reliable indicators of increasing suicide risk, though it may be that we were underpowered to detect effects, given the small sample size and paucity of episodes with consecutive nights of outgoing texts. These factors may also explain the non-convergence issues encountered with Hypothesis 2, particularly given the specification of multiple random effects. Nevertheless, both season and time of week were significant predictors of the number and spread of sent texts. Participants sent more texts on weekend nights, relative

TABLE 5 Estimates for sum of total unique hour bins with outgoing texts between 1:00 and 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)					0.44 (0.66)	0.03 (0.17)	0.06 (0.17)
Reference level							
Positive							
Depressed	−0.01	0.31	−0.03	0.977			
Ideation	0.36	0.35	1.03	0.304			
Attempt	−0.35	0.43	−0.81	0.420			
Weekend (vs. weekday)	**0.62**	**0.25**	**2.53**	**0.012**			
Summer (vs. all other seasons)	**−0.87**	**0.39**	**−2.23**	**0.026**			
Attempt							
Depressed	0.34	0.43	0.79	0.432			
Ideation	0.71	0.46	1.55	0.122			
Positive	0.35	0.43	0.81	0.420			
Weekend (vs. weekday)	**0.62**	**0.25**	**2.53**	**0.012**			
Summer (vs. all other seasons)	**−0.87**	**0.39**	**−2.23**	**0.026**			
Attempt and ideation							
Depressed and positive	0.11	0.27	0.40	0.686			
Weekend (vs. weekday)	**0.59**	**0.25**	**2.42**	**0.016**			
Summer (vs. all other seasons)	**−0.83**	**0.39**	**−2.13**	**0.033**			
Positive							
Depressed, ideation and attempt	−0.02	0.27	−0.08	0.937			
Weekend (vs. weekday)	**0.59**	**0.25**	**2.41**	**0.016**			
Summer (vs. all other seasons)	**−0.81**	**0.39**	**−2.80**	**0.038**			

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.

Bolded results are significant at the $p < .05$ level.

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). Furthermore, it is also likely that college students have more social contacts with whom they can text during the school year, compared to summer months.

Though it was beyond the scope of the present study, future research may benefit from examining the content of texts sent during expected sleep windows. Some content from the texts sent between midnight and 5:00 AM in the days leading up to participants' suicide attempts touched on themes and mental states associated with suicide risk. For example, two texts sent the day before one participant's attempt read, "I just wanna sleep forever but I can't" and "I feel like no matter how much I change my surroundings my core is never gonna change and that's always gonna be my problem". However, the content across the thousands of messages has not been systematically coded in this way, so we do not know to what extent this was unusual or reflects a pattern.

Limitations

The study also had a number of limitations, including our reliance on text messages as the sole proxy for wakefulness. Adding wearable sensors could have provided additional insight into participants' sleep patterns. Further, revising the sleep dictionary likely allowed for more precise detection of sleep disturbance, but it was still not perfect (e.g., LIWC could not flag misspelled words and phrases). Finally, the sample was small and relatively homogeneous with respect to race, gender, and sexual orientation. Given that suicide risk is pronounced among LGBTQ+ people (Hatchel et al., 2019) and, in particular, LGBTQ+ people of color (Sutter & Perrin, 2016), more research with these communities is sorely needed.

CONCLUSIONS

This proof-of-concept study represents a first step toward 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 2-week periods of depressed mood, relative to 2-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. 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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CONFLICT OF INTEREST

None.

DATA AVAILABILITY STATEMENT

In line with the University of Virginia Institutional Review Board's guidance, the data used for analyses in this paper cannot be shared publicly due to their highly sensitive nature and the vulnerable study population. Please contact the corresponding author with any questions or concerns related to the data or analyses.

ETHICAL APPROVAL

This study received an institutional review board (IRB) ethics approval before data collection began.

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ENDNOTES

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

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

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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