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Detecting adolescent depression through passive monitoring of linguistic markers in smartphone communication

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Background: Cross sectional studies have identified linguistic correlates of major depressive disorder (MDD) in smartphone communication. However, it is unclear whether monitoring these linguistic characteristics can detect *when* an individual is experiencing MDD, which would facilitate timely intervention. **Methods:** Approximately 1.2 million messages typed into smartphone social communication apps (e.g. texting, social media) were passively collected from 90 adolescents with a range of depression severity over a 12-month period. Sentiment (i.e. positive vs. negative valence of text), proportions of first-person singular pronouns (e.g. 'I'), and proportions of absolutist words (e.g. 'all') were computed for each message and converted to weekly aggregates temporally aligned with weekly MDD statuses obtained from retrospective interviews. Idiographic, multilevel logistic regression models tested whether within-person deviations in these linguistic features were associated with the probability of concurrently meeting threshold for MDD. **Results:** Using more first-person singular pronouns in smartphone communication relative to one's own average was associated with higher odds of meeting threshold for MDD in the concurrent week (OR = 1.29; p = .007). Sentiment (OR = 1.07; p = .54) and use of absolutist words (OR = 0.99; p = .90) were not related to weekly MDD. **Conclusions:** Passively monitoring use of first-person singular pronouns in adolescents' smartphone communication may help detect MDD, providing novel opportunities for early intervention. **Keywords:** Adolescence; depression; e-health; language; longitudinal studies.

Introduction

Major depressive disorder (MDD) is the leading cause of global disability (Friedrich, 2017) and incidence rates increase markedly during adolescence (Avenevoli, Swendsen, He, Burstein, & Merikangas, 2015). Rates of adolescent depression have increased over the past several decades, doubling during the COVID-19 pandemic (Mojtabai, Olfson, & Han, 2016; Racine et al., 2021). Conversely, treatment-seeking rates have remained relatively low and most cases of MDD are not detected or treated until years after onset (Avenevoli et al., 2015; Richardson, Russo, Lozano, McCauley, & Katon, 2010; Wang et al., 2005). Novel approaches to identify adolescents with MDD and bridge them to clinical services are needed (Office of the Surgeon General, 2021).

Leveraging passively collected data from smartphones is a promising approach to detect adolescent MDD (de Angel et al., 2022). Smartphone use is ubiquitous among adolescents (Pew Research Center, 2022), and smartphones can acquire large amounts of ecologically valid data with minimal user effort, affording new insight into MDD symptoms or proximal risk factors. Accordingly, passive smartphone data could inform the development of tools to monitor indicators of MDD. Encouragingly, smartphone-derived variables (e.g. greater homestay from Global Positioning System [GPS] data) have been associated with MDD (Auerbach, Srinivasan, Kirshenbaum, Mann, & Shankman, 2022; de Angel et al., 2022; Shin & Bae, 2023). However, these studies primarily focused on mobility features, and identifying other predictive data streams may serve to improve detection.

Naturalistic smartphone communication (e.g. text messages, social media posts) may be especially relevant for detecting adolescent depression given the importance of social relationships and online communication (Pew Research Center, 2022). Although few studies have examined associations between smartphone communication content and depression in adolescents, depressed adults have been shown to use more negative sentiment (e.g. more negative words and fewer positive words) than healthy controls (Liu et al., 2022; Tølbøll, 2019). Also, first-person singular pronouns (e.g. *I*) are a linguistic indicator of self-focus (Brockmeyer et al., 2015), are involved in perseverative thinking (Brockmeyer

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et al., 2015; Pyszczynski & Greenberg, 1987), and are more frequently used by depressed individuals than healthy controls (Edwards & Holtzman, 2017; Eichstaedt et al., 2018; Liu et al., 2022; Tackman et al., 2019; Tølbøll, 2019). Finally, 'all-or-nothing' thinking is common in depressed individuals (Beck, 1987) and often reflected through absolutist words (e.g. *all*; Al-Mosaiwi & Johnstone, 2018; Bathina, ten Thij, Lorenzo-Luaces, Rutter, & Bollen, 2021), which are more frequent in the social media posts of depressed individuals versus healthy controls (Al-Mosaiwi & Johnstone, 2018; Bathina et al., 2021).

Most prior work linking linguistic features to depression has relied on cross sectional designs (Chancellor & De Choudhury, 2020; de Angel et al., 2022), which can help determine *who* is depressed at a particular time. However, detecting *when* someone is depressed requires testing within-person associations using longitudinal data. Uncoupling between-person versus within-person effects is essential because results from these analytic approaches may not align (Curran & Bauer, 2011). For example, people who exercise are at lower risk for a heart attack (i.e. a negative between-person association), but one's heart attack risk is higher when exercising than when not exercising (i.e. a positive within-person association; Curfman, 1993). The few studies examining within-person associations between linguistic features and depression suggest that more negative sentiment and first-person singular pronouns in digital communication may predict greater depressive symptoms in adults (Nook, Hull, Nock, & Somerville, 2022; Stamatis et al., 2022). No research in adolescents has studied within-person links between linguistic features and depression, and while several studies have investigated associations between adolescents' linguistic features and daily mood, findings have been mixed (Kross et al., 2019; Li et al., 2023; McNeilly et al., 2023). Taken together, elucidating within-person associations between smartphone communication and adolescent depression could inform dynamic risk prediction models and offer a novel opportunity for more timely intervention during a high-risk developmental period.

This study tested whether linguistic features extracted from smartphone communication related to interview-assessed weekly MDD over a year-long period among adolescents experiencing a range of depressive severity. Given prior research (Al-Mosaiwi & Johnstone, 2018; Bathina et al., 2021; Edwards & Holtzman, 2017; Liu et al., 2022; Nook et al., 2022; Stamatis et al., 2022; Tackman et al., 2019; Tølbøll, 2019), analyses focused on sentiment, first-person singular pronouns, and absolutist words. We hypothesized that adolescents would use more negative sentiment, first-person singular pronouns, and absolutist language in weeks during which they met threshold for MDD. To support future research, exploratory analyses extracted data-driven topics using latent dirichlet allocation (LDA; Blei, Ng, & Jordan, 2003) – a hierarchical Bayesian method to extract clusters of naturally co-occurring words (i.e. topics) – and tested whether LDA topics related to weekly MDD. LDA topics may afford unique insights into adolescents' smartphone communication, as they could contain communication types that are difficult to include in predefined dictionaries (e.g. misspellings, slang). Notably, preliminary research has shown that certain LDA-derived topics (e.g. loneliness) in digital communication related to depression (Eichstaedt et al., 2018; Li et al., 2023).

Methods

Participants

Adolescents ages 13–18-years-old were recruited from the community and mental health clinics in the New York City and Chicago areas from September 2020 to March 2022 as part of a larger, ongoing longitudinal study. Inclusion criteria for the larger study included: (a) Tanner Stage (Tanner & Davies, 1985) ≥ 3, (b) fluency in English, (c) Wechsler Abbreviated Scale of Intelligence-II (WASI-II; Wechsler, 2011) > 85, and (d) ownership of a personal iOS or Android smartphone. Exclusion criteria included: (a) current moderate or severe substance use disorder, and (b) lifetime history of oppositional defiant disorder, conduct disorder, or a bipolar, psychotic, or neurodevelopmental disorder. To capture a wide range of depressive symptom severity, the study recruited adolescents from three groups: current MDD, remitted MDD, and healthy controls with no lifetime psychiatric diagnoses. Participants who had completed at least one follow-up ($N = 101$) were considered for inclusion in this study. Eleven participants were excluded for having <3 weeks of temporally matched MDD and social communication data, as three is the minimum number of within-person observations recommended for longitudinal analyses (Singer & Willett, 2003). The analyzed sample therefore included 90 adolescents. Sample characteristics are summarized in Table 1. Included and excluded adolescents did not differ on sociodemographic or clinical characteristics (Table S1).

Ethical considerations

All study procedures were approved by the New York State Psychiatric Institute Institutional Review Board. Written informed assent and consent were obtained from participants aged 13–17 and legal guardians, whereas 18-year-old participants provided written consent. There are important ethical considerations associated with the collection of mobile sensing data. Passive smartphone data in this study were collected using the Effortless Assessment Research System (EARS) app (Lind et al., 2023; Lind, Byrne, Wicks, Smidt, & Allen, 2018), which was developed and maintained by Ksana Health. Participants received verbal and written information about EARS before providing consent or assent. EARS data are encrypted and stored on a cloud-based server. The authors downloaded and then unencrypted the data. Only the study team can access the data. Other parties involved in data collection and storage (e.g. Ksana Health) did not have access to the data. More detailed information about steps taken to protect participants' privacy can be found in Lind et al. (2018, 2023) and at https://ksanahealth.com/privacy-policy/. De-identified data from this study were submitted to the National Data Archive (NDA) in compliance with the National Institute of Mental Health's Data Sharing Policy. To protect participants' confidentiality, we did not submit 'raw' key input data to the

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Table 1 Demographic and clinical characteristics

Characteristics	No. (%) or *M* (*SD*)
Age	16.57 (1.43)
Sex (% female)	57 (63%)
Cisgender	82 (91%)
Race	
White	52 (58%)
Asian	15 (17%)
Black	10 (11%)
American Indian/Alaska Native	1 (1%)
Native Hawaiian/other Pacific Islander	1 (1%)
More than one race	11 (12%)
Hispanic	32 (36%)
Family Income	
<$24,999	3 (4%)
$25,000–$49,999	11 (14%)
$50,000–$74,999	8 (11%)
$75,000–$99,999	13 (17%)
≥$100,000	40 (53%)
MDD status	
Current	17 (19%)
Remitted	40 (44%)
Never (Healthy controls)	33 (37%)
Lifetime social anxiety disorder	25 (28%)
Lifetime generalized anxiety disorder	32 (36%)
Lifetime posttraumatic stress disorder	13 (14%)
Lifetime attention-deficit hyperactivity disorder	11 (12%)
Lifetime substance use disorder	3 (3%)
Currently taking psychiatric medication	25 (28%)
Weeks with depression rating and social communication data	26.31 (13.92)
Weeks with depression rating and mood data	23.80 (13.04)
Phone type	
iOS	78 (87%)
Android	12 (13%)
Weekly social communication aggregates	
Sentiment	0.08 (0.04)
% First-person singular pronouns	5.04 (0.94)
% Absolutist words	0.76 (0.23)
Word count	2,498.59 (2,688.50)
Message count	674.10 (634.71)

NDA as key input data can include potentially identifying information (e.g. names, social media handles and uncommon word strings). Instead, only daily aggregates of key input data (e.g. daily word count) were submitted to the NDA.

Procedures

At a baseline visit, participants completed the Kiddie Schedule for Affect Disorders and Schizophrenia (K-SADS-PL; Kaufman et al., 1997) to assess lifetime DSM-5 disorders and the two subtest form of the WASI-II to assess IQ. Next, participants downloaded the Effortless Assessment Research System (EARS) application (Lind et al., 2018, 2023) onto their personal smartphone to collect keyboard inputs over a 12-month follow-up period. They were instructed to keep the app running while using their phone naturalistically. Keyboard inputs across all apps were passively collected via a keyboard logger and continuously encrypted and uploaded to a secure cloud-based server.

At the 6- and 12-month follow-up assessments, participants completed the Adolescent Longitudinal Interval Follow-Up Evaluation (A-LIFE; Keller et al., 1987), a timeline follow-back interview assessing MDD severity for each week in the prior 6 months. All 90 participants completed the 6-month follow-up, and 46 (51%) additionally completed the 12-month follow-up. The other 44 (49%) had not yet reached their 12-month follow-up ($n = 41$) or did not respond when contacted for the 12-month follow-up ($n = 3$).

Measures

Clinical interviews. Participants completed the K-SADS-PL at baseline to assess lifetime disorders. At the 6- and 12-month follow-up assessments, participants completed the A-LIFE. Participants were reminded of MDD symptoms and severity reported at their previous assessment and identified change points in MDD severity since the previous assessment. Time anchors (e.g. birthdays, holidays) were used to improve recall. MDD symptoms were assessed for each period between change points, and psychiatric status ratings (PSRs) indexed MDD severity for each week since the prior assessment. PSRs ranged from 1 (*absent*) to 6 (*full-threshold MDD with extreme impairment/distress*), with PSRs ≥4 indicating full-threshold MDD (Table 2). The start and end date of each week assessed by the A-LIFE was recorded, allowing PSRs to be temporally aligned with social communication and daily mood data. PSRs have previously demonstrated good inter-rater reliability, test–retest reliability, and strong associations with concurrently assessed depressive symptoms (Porter et al., 2022; Warshaw, Dyck, Allsworth, Stout, & Keller, 2001).

Smartphone assessment. Daily mood ratings: Each day at approximately 12:00 pm, participants received a prompt, '*In general, how have you been feeling over the last day?*' Participants could respond any time before 11:59 PM that day. After that, the survey expired and could not be submitted. We made the survey available at a fixed time and allowed it to be completed anytime within this 12-h window to maximize completion. Ratings were made on a visual analog scale from 0 (*very negative*) to 100 (*very positive*). The response rate was 58.6%. Mood ratings were reverse-coded to match the A-LIFE PSR scale's direction. Thus, higher values indicated more negative mood.

Social communication: Each keyboard input (i.e. each character typed into any app) was stamped with the date, time, and application being used. Keyboard inputs were transformed into messages using a custom script that identified logical divisions (e.g. long pauses, changes in app). The average message length was 5.33 words ($SD = 5.94$). Only messages from apps whose primary purpose was social communication (e.g. text messaging, social media) were included. We used each app's classification and description in the Apple App Store and/or Google Play Store to determine whether it was primarily for social communication (Li et al., 2023; McNeilly et al., 2023). The most used social communication apps were messaging (e.g.

Table 2 Description of A-LIFE psychiatric status ratings

Code	Description
1	No symptoms present
2	One or two symptoms present with minimal impairment/distress
3	Three or four symptoms present or moderate impairment/distress
4	Full threshold (i.e. meets DSM-5 criteria for MDD)
5	Full threshold with major impairment/distress
6	Full threshold with extreme impairment/distress

A-LIFE, Adolescent Longitudinal Interval Follow-Up Evaluation; MDD, Major depressive disorder.

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Messaging, Discord, and Kakao) and social media apps (e.g. Snapchat, Instagram; see Figure S1 for a list of all included apps). To improve text analysis accuracy, we removed URLs and mentions (e.g. @JohnSmith), extracted hashtag contents and separated them into words, and removed elongated tails (e.g. changed 'yayyyy' to 'yay'). All included messages were in English. Messages were converted to lowercase for all text analyses except sentiment to aid matching. All other information (e.g. punctuation, emojis/emoticons) was preserved.

Sentiment scores were calculated for each message using the Valence Aware Dictionary and sEntiment Reasoner (VADER; Hutto & Gilbert, 2014). VADER is especially sensitive to social media text and outperforms other sentiment analysis tools (e.g. Linguistic Inquiry and Word Count [LIWC]) at matching consensus human ratings (Hutto & Gilbert, 2014). For each message, a sentiment score was estimated by: (a) summing the valence score of each word in the VADER lexicon, (b) adjusting by sentence-level rules such as negations (e.g. 'not'), degree modifiers (e.g. 'very'), and punctuation, and (c) normalizing to be between −1 (*most negative*) and 1 (*most positive*). Subjective first-person singular pronouns (i.e. *I*) and related contractions (e.g. *I'm*; Table S2) were used as indicators of self-focused attention. We focused on subjective first-person singular pronouns because depression has been more strongly associated with subjective first-person singular pronouns than objective (e.g. *me*) or possessive (e.g. *my*) first-person singular pronouns (Rude, Gortner, & Pennebaker, 2004). Total first-person singular pronoun use (*I, me*, *myself*, *my*, and *mine*) was examined in sensitivity analyses. Absolutist words were identified using a 19-word dictionary (Al-Mosaiwi & Johnstone, 2018).

Last, exploratory data-driven topics were identified using LDA (see Appendix S1). LDA extracts topics based on word co-occurrence, much like factor analysis extracts factors from indicators. To determine the optimal number of topics (k), LDA models were fit in the text2vec R package (Selivanov, Bickel, & Wang, 2022) with k ranging from 10 to 200 in increments of 10. The optimal number of topics ($k = 40$) was selected using probabilistic topic coherence (Douven & Meijs, 2007), which measures the semantic similarity between words within each topic. To mitigate risk of type I error, analyses focused on the 13 topics that four judges perceived as interpretable and likely to covary with MDD (Appendix S2; Table S3).

Time-matching and aggregating data

To evaluate the validity of weekly A-LIFE MDD PSRs, we examined their association with self-reports of daily mood that were collected each day. To align mood assessments with the temporal resolution and dates of the weekly MDD PSRs, weekly mood aggregates were created by averaging the daily mood ratings within each week assessed by the PSRs. Participants on average had 23.80 weeks (SD = 13.04) of matched A-LIFE and weekly mood data.

Smartphone communication messages were similarly aligned with the A-LIFE PSRs. Specifically, average sentiment scores, percentages of first-person singular pronouns and absolutist words, and average LDA topic scores were time-anchored to the A-LIFE PSRs and aggregated by week. We excluded 366 person-weeks (i.e. weeks of data) with <60 words, which was the cut-off at which weekly aggregates stabilized (Figures S2–S4; McNeilly et al., 2023). This resulted in 26.31 weeks (SD = 13.92; range = 3–53) of matched A-LIFE and social communication data per person. Overall, there were 2,368 matched person-weeks containing 1,259,239 messages and 65,724,770 words.

Data analytic approach

Longitudinal logistic multilevel models estimated associations between social communication features and whether the MDD threshold was met (PSR ≥ 4) in the concurrent week. Features were uncorrelated (Table S4) and examined separately. Thus, each analysis included one communication feature. Supplementary analyses operationalizing PSRs using other thresholds or continuously are reported in Tables S5, S6 and Figure S5. If a social communication feature was concurrently associated with the MDD threshold, follow-up analyses tested whether MDD risk was prospectively predicted by the feature in a prior week while adjusting for MDD status in that prior week (i.e. Granger causality). A person-centered term (reflecting deviation from one's average) and a person-mean term (reflecting one's average across the follow-up period) was included for each social communication feature to simultaneously model within-person and between-person effects (Enders & Tofighi, 2007). Each model included a random participant-level intercept, fixed slopes, and covaried for the number of weeks since baseline to remove the potential confound of time (Bolger & Laurenceau, 2013). We considered a range of demographic (e.g. sex, age, and race), clinical (e.g. psychiatric medication status), and other (e.g. recruitment site, phone type, local COVID-19 cases, and weekly smartphone communication quantity) characteristics as potential covariates, and tested each characteristic's association with weekly MDD. MDD risk was significantly higher in females, those taking psychiatric medication, those enrolled at Columbia University (site), and in weeks during the school year (vs summer break). Thus, all models covaried for these four factors. Parameter estimates are reported as odds ratios (ORs) and were standardized at their relevant level (e.g. within-person). Analyses were conducted in R using the lme4 (Bates, Mächler, Bolker, & Walker, 2015) and parameters (Lüdecke, Ben-Shachar, Patil, & Makowski, 2020) packages.

Results

Participants' time courses of MDD severity as assessed by the A-LIFE are presented in Figure S6. The MDD threshold was met in 245 (10%) person-weeks and 30 (33%) participants met the MDD threshold for at least two consecutive weeks, suggesting they met criteria for MDD.

Associations between weekly mood and weekly A-LIFE MDD

To validate the weekly A-LIFE MDD PSRs, we examined within-person associations between the weekly A-LIFE MDD threshold and temporally matched weekly averages of daily mood ratings. As expected, more negative mood relative to one's average was associated with significantly greater odds of meeting threshold for MDD that week (OR = 1.31; 95% CI = 1.10–1.56; p = .002).

Associations between social communication and weekly A-LIFE MDD

A higher percentage of subjective first-person singular pronouns relative to one's average was associated with significantly greater risk for meeting the weekly MDD threshold (OR = 1.29; 95% CI = 1.07–1.55; p = .007). Exploratory analyses examining the predictive performance of this model indicated that its sensitivity and specificity for predicting weekly MDD status was .51 and .99 respectively (area under the

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curve = .75; see Table S7). Neither sentiment (OR = 1.07; 95% CI = 0.87–1.31; p = .54) nor absolutist words (OR = 0.99; 95% CI = 0.80–1.21; p = .90) were significantly associated with concurrent MDD (Figure 1). Follow-up Granger causality analyses revealed that MDD risk for a given week was significantly predicted by subjective first-person singular pronouns 2, 3, and 6 weeks prior (ORs = 1.23–1.26; ps = .02–.05; Figure 2). Prospective effects of subjective first-person singular pronouns 1, 4, or 5 weeks prior were similar in magnitude, but not statistically significant (ORs = 1.20–1.24; ps = .06–.10).

In sensitivity analyses, the association between subjective first-person singular pronouns and concurrent MDD risk remained significant when predicting a concurrent major depressive episode (i.e. PSR≥4 for 2 or more consecutive weeks) instead of the MDD threshold (OR = 1.30; 95% CI = 1.08–1.56; p = .006), excluding participants whose PSRs were always above or below the MDD threshold (OR = 1.28; 95% CI = 1.07–1.53; p = .006), excluding healthy controls (OR = 1.21; 95% CI = 1.01–1.44; p = .04), or additionally controlling for MDD diagnosis at the baseline visit (OR = 1.29; 95% CI = 1.07–1.55; p = .007). This association also remained significant when examining all first-person singular pronouns (*I*, *me*, *myself*, *my*, and *mine*) instead of only subjective first-person singular pronouns (OR = 1.27; 95% CI = 1.04–1.54; p = .02).

Exploratory analyses. Exploratory analyses of 13 LDA topics identified two topics that were significantly associated with the weekly MDD threshold at uncorrected $p < .05$ (Figure 3). Greater *feelings* (OR = 1.19; 95% CI = 1.01–1.41; p = .04) and less *judgment* (OR = 0.76; 95% CI = 0.61–0.94; p = .01) were associated with concurrent MDD. Neither association survived Benjamini–Hochberg correction. Supplementary analyses of all LDA topics are presented in Table S8.

Discussion

Most cases of MDD remain undetected for at least a year after onset (Avenevoli et al., 2015; Richardson et al., 2010; Wang et al., 2005), delaying treatment. Passive data collected naturalistically from smartphones have promise for helping to detect MDD earlier. Cross sectional research has shown that adults with MDD use more negative sentiment, first-person singular pronouns, and absolutist language

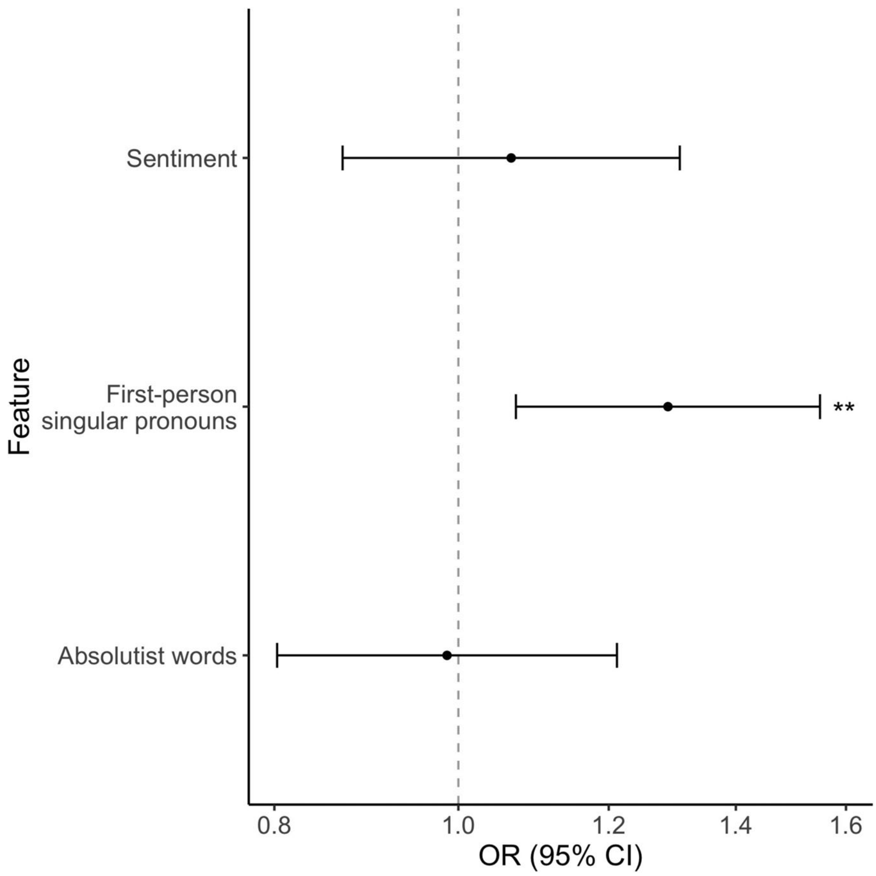

Figure 1 Within-person associations between smartphone communication features and MDD risk in the concurrent week. Error bars represent 95% confidence intervals. MDD, Major depressive disorder; OR, Odds ratio. **$p < .01$; *$p < .05$.

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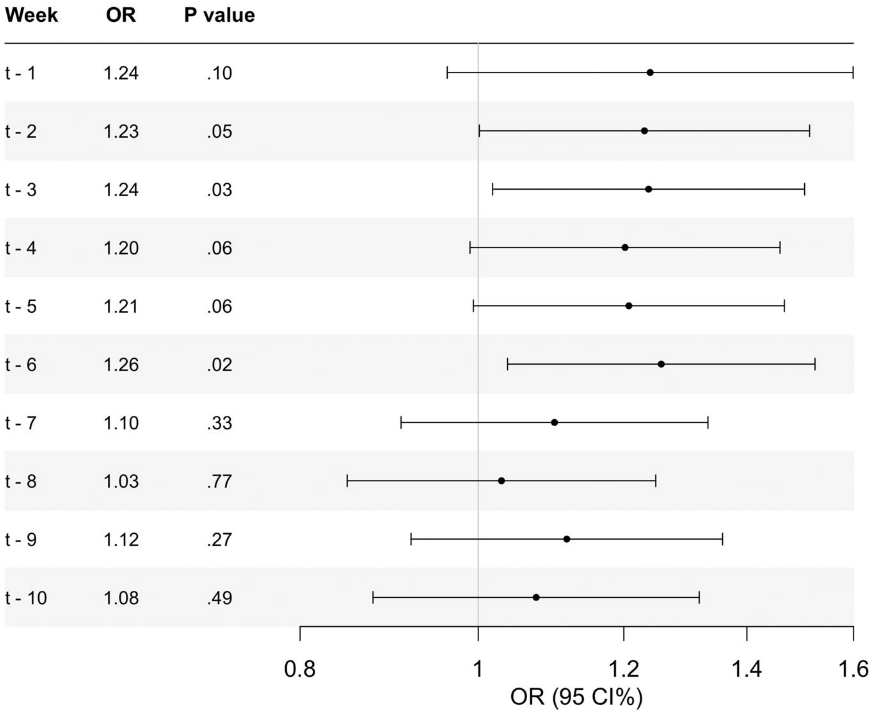

Figure 2 Within-person effects of subjective first-person singular pronouns in a prior week (week $t-1$, week $t-2$, etc.) on MDD risk this week (week t) at various lags. Each model adjusted for MDD status in that prior week (week $t-1$, week $t-2$, etc.). Error bars represent 95% confidence intervals. MDD, Major depressive disorder; OR, Odds ratio. **$p < .01$; *$p < .05$.

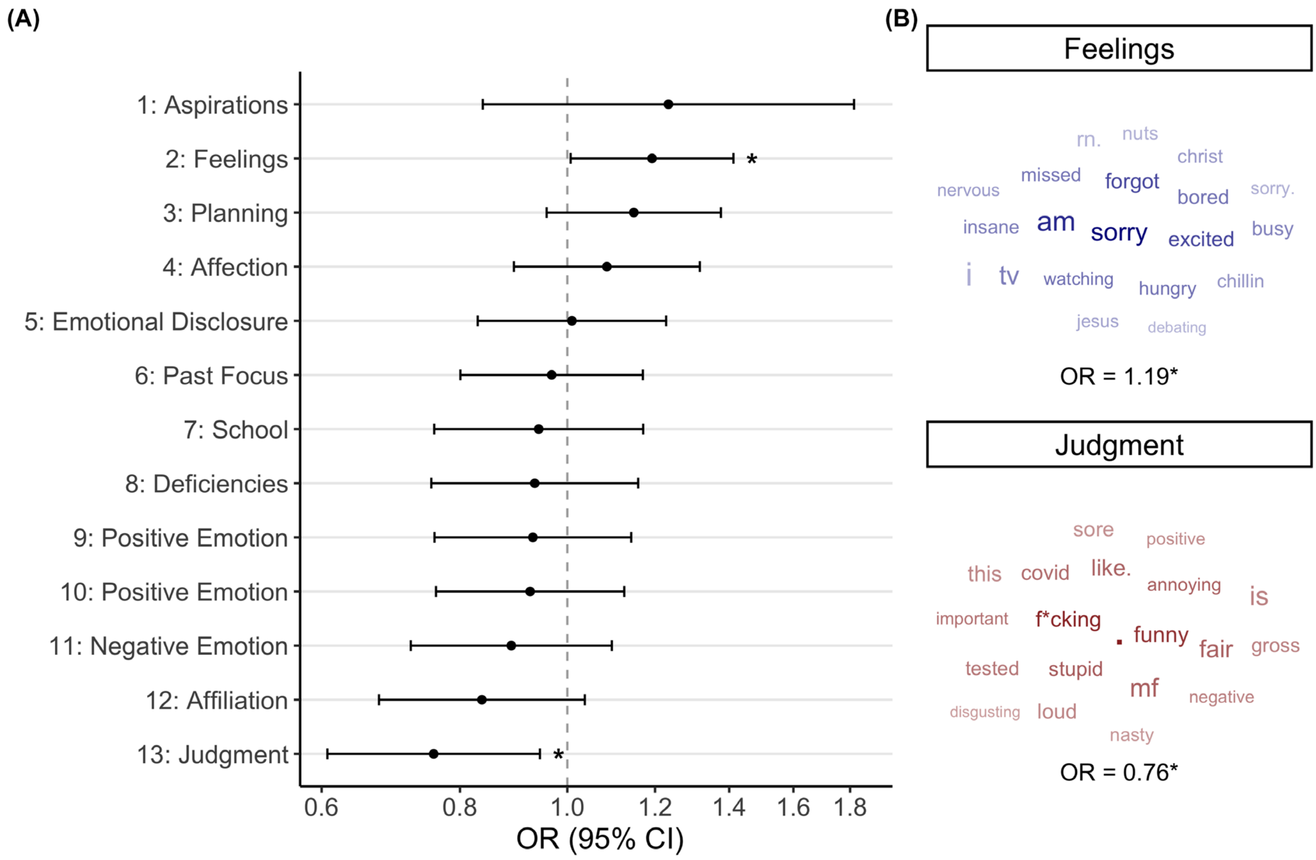

Figure 3 (A) Within-person associations between LDA topics and concurrent MDD risk. (B) Word clouds containing the 20 most relevant terms for the two significant topics in panel A. In panel A, error bars represent 95% confidence intervals and asterisks indicate unadjusted $p < .05$. In panel B, blue text indicates the topic was associated with increased MDD risk and red text indicates the topic was associated with decreased MDD risk. Words with larger and darker font have stronger relevance. LDA, Latent dirichlet allocation; MDD, Major depressive disorder; OR, Odds ratio. *$p < .05$

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in their digital communication (Al-Mosaiwi & Johnstone, 2018; Edwards & Holtzman, 2017; Eichstaedt et al., 2018; Liu et al., 2022; Tackman et al., 2019). However, these studies cannot detect *when* someone is experiencing MDD (and when they are not). To this end, this study examined within-person associations between these linguistic features and weekly MDD risk over a yearlong period. Results indicated that using more first-person singular pronouns was associated with greater MDD risk in the concurrent week; however, sentiment and absolutist language were not related to concurrent MDD risk. These findings suggest that passively monitoring adolescents' use of first-person singular pronouns in smartphone communication may improve early detection of MDD.

The finding that increased first-person singular pronouns was related to higher weekly MDD risk suggests that previously documented within-person associations in adults (Nook et al., 2022; Stamatis et al., 2022) generalize to adolescents. This result is also consistent with evidence that adolescents use more first-person pronouns on days characterized by unusually negative mood (McNeilly et al., 2023). Granger causality analyses suggested that adolescents may increase their use of subjective first-person singular pronouns in the weeks prior to the onset of MDD, suggesting that monitoring this linguistic feature may help identify periods of imminent risk for MDD and provide opportunities for preventative intervention. Effects were only significant at certain lags, however, and this issue requires further research.

Sentiment and absolutist words were unassociated with weekly MDD risk. Prior studies linking these features to depression have primarily estimated cross sectional, between-person associations in adults (Chancellor & De Choudhury, 2020; de Angel et al., 2022). This study provides initial evidence that these associations may not generalize to within-person effects in adolescents, which is consistent with preliminary evidence that adolescents' sentiment may not covary with daily mood (Kross et al., 2019; McNeilly et al., 2023). Thus, sentiment and absolutist language may be more useful for determining *who* is depressed than *when* someone is depressed.

Exploratory analyses of data-driven LDA topics revealed that a language topic reflecting *feelings* was associated with increased risk for concurrent MDD, extending cross sectional research linking feelings-related words to depression (Li et al., 2023; Liu et al., 2022; Stamatis et al., 2022; Tølbøll, 2019). Additionally, less *judgment* – a topic primarily reflecting positive and negative appraisals (e.g. *funny*, *stupid*) – was associated with greater MDD risk. The direction of this effect was somewhat unexpected given evidence of more negative appraisals in MDD (Gollan, Pane, McCloskey, & Coccaro, 2008), but could be due to a confounder (e.g. behavioral withdrawal) contributing to fewer judgments and higher MDD risk. This topic also contained some COVID-19-related words (e.g. *covid*, *tested*), so this finding might alternatively reflect an association between COVID-19-related stress and MDD. These associations should be interpreted cautiously pending replication in future topic-driven research.

It is worth noting that the effect sizes in this study were relatively small, which is typical of within-person associations (Li et al., 2023; McNeilly et al., 2023; Nook et al., 2022; Stamatis et al., 2022). Relatedly, subjective first-person singular pronoun use had poor sensitivity when predicting weekly MDD status, likely because the MDD threshold was not met in most weeks during the follow-up period. These issues reflect broader challenges involved in detecting when depressive episodes (or other infrequent events) occur, and detection tools may benefit from incorporating numerous features, which may improve prediction sensitivity. Using larger samples and/or longer follow-up intervals may also help address this issue (Barnett, Torous, Reeder, Baker, & Onnela, 2020).

Study strengths included the examination of within-person effects, the relatively long follow-up period, the clinical sample, and the excellent construct validity of the A-LIFE PSRs, which is unusual for studies relating digital communication to psychopathology (Chancellor & De Choudhury, 2020). Due to these strengths, these findings have direct implications for developing clinical tools that monitor dynamic indicators to detect depressive episodes. Not all adolescents are comfortable with mobile sensing data being collected to inform their clinical care (Orr et al., 2023). These analyses only included adolescents who opted into the mobile sensing part of the study, who are not representative of all adolescents, but likely resemble the subset of adolescents who would use a mobile sensing tool to monitor and detect depression. Of note, adolescents' use of certain linguistic features changes over time. Although many changes in depression-related language occur over relatively long timescales (Bollen et al., 2021), these changes may limit the generalizability of linguistic associations over time. Models incorporating linguistic features may therefore need to be monitored and updated to reflect changes in adolescents' language.

There are also several notable limitations. First, although the A-LIFE PSRs demonstrated convergent validity through associations with concurrent mood ratings and previously have been strongly correlated with concurrent self-reported depressive symptoms (Porter et al., 2022), they may have been influenced by recall inaccuracies or biases. Second, we examined select linguistic features, and considering additional linguistic features (e.g. use of words related to affiliation or differentiation; Li et al., 2023; Stamatis et al., 2022) and/or multiple

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data streams may improve detection. Third, the temporal dynamics of keyboard inputs were not examined in this study, but may be associated with depressive symptoms (Zulueta et al., 2018) and are a promising direction for future research. Fourth, we aggregated messages across all social communication apps to minimize missingness due to an insufficient number of weekly messages, but communication styles may differ across apps. Fifth, daily mood surveys were delivered at a fixed time (noon) and available for the rest of the day in an effort to increase completion by increasing predictability and flexibility. However, this could have introduced biases (e.g. if mood varied systematically by time-of-day and participants completed the item around the same time each day). Sixth, findings may not be depression-specific. For example, first-person singular pronouns are also associated with anxiety disorders, eating disorders, schizophrenia, and suicidal thoughts and behaviors in adults (Lyons, Aksayli, & Brewer, 2018; Nook et al., 2022; Stamatis et al., 2022). Clarifying which passive features covary with which psychopathologies could allow interventions to be better tailored to the problem(s) being experienced (Nahum-Shani et al., 2018). The potential for mobile sensing tools to passively monitor or detect depression has received much attention (de Angel et al., 2022) because detecting a recent onset or imminent risk provides opportunities for early or just-in-time intervention. For example, an adolescent whose depression remits after psychotherapy could utilize a mobile sensing tool to offer an appropriate intervention (e.g. a smartphone notification recommending that they resume psychotherapy or schedule a booster session) when increased risk for recurrence is detected. Similarly, prediction models based on daily assessments and shorter timescales could generate intervention opportunities by detecting or predicting short-term fluctuations in depression-related phenomena (e.g. negative mood).

Conclusion

Increased use of first-person singular pronouns in smartphone communication is a promising candidate for long-term passive monitoring of adolescent depression, which could help detect depressive episodes and facilitate early intervention.

Supporting information

Additional supporting information may be found online in the Supporting Information section at the end of the article:

Appendix S1. Identifying data-driven topics using latent Dirichlet allocation.

Appendix S2. Identifying a subset of LDA topics for primary analysis.

Table S1. Comparisons of adolescents included versus excluded from the study.

Table S2. Subjective first-person singular pronouns and related acronyms and abbreviations.

Table S3. Summaries of LDA topics.

Table S4. Spearman correlations between weekly social communication features.

Table S5. Within-person effects of social communication features on weekly A-LIFE MDD severity thresholds.

Table S6. Within-person effects of social communication features on continuous weekly A-LIFE MDD severity scores.

Table S7. The confusion matrix for the model using subjective first-person singular pronouns to predict weekly MDD status.

Table S8. Within-person associations between LDA topics and concurrent weekly MDD.

Figure S1. Social communication apps used by participants during the follow-up period.

Figure S2. The distribution of average weekly sentiment relative to weekly word count.

Figure S3. The distribution of the weekly percentage of subjective first-person singular pronouns relative to weekly word count.

Figure S4. The distribution of the weekly percentage of absolutist words relative to weekly word count.

Figure S5. Within-person associations between weekly mood and A-LIFE MDD severity defined using binary thresholds (panel A) or continuously (panel B).

Figure S6. The time course of weekly A-LIFE MDD severity scores by participant.

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Key points

- Smartphone communication (e.g. text messages, social media posts) is a promising passive data stream for long-term monitoring of adolescents' mental health.
- Previous research indicates that linguistic characteristics in smartphone communication (e.g. text messages, social media posts) can identify *who* is experiencing Major Depressive Disorder (MDD) at a particular time.
- We tested whether monitoring these linguistic characteristics can identify *when* someone is experiencing MDD.
- Increased use of first-person singular pronouns (e.g. 'I') relative to one's own average was associated with greater risk for MDD in the concurrent week.
- Passively monitoring linguistic characteristics in adolescents' smartphone communication may help detect depressive episodes as they emerge, facilitating earlier intervention.

References

Al-Mosaiwi, M., & Johnstone, T. (2018). In an absolute state: Elevated use of absolutist words is a marker specific to anxiety, depression, and suicidal ideation. *Clinical Psychological Science*, *6*, 529–542.

Auerbach, R.P., Srinivasan, A., Kirshenbaum, J.S., Mann, J.J., & Shankman, S.A. (2022). Geolocation features differentiate healthy from remitted depressed adults. *Journal of Psychopathology and Clinical Science*, *131*, 341–349.

Avenevoli, S., Swendsen, J., He, J.P., Burstein, M., & Merikangas, K.R. (2015). Major depression in the national comorbidity survey–adolescent supplement: Prevalence, correlates, and treatment. *Journal of the American Academy of Child and Adolescent Psychiatry*, *54*, 37–44.e2.

Barnett, I., Torous, J., Reeder, H.T., Baker, J., & Onnela, J.-P. (2020). Determining sample size and length of follow-up for smartphone-based digital phenotyping studies. *Journal of the American Medical Informatics Association*, *27*, 1844–1849.

Bates, D., Mächler, M., Bolker, B.M., & Walker, S.C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, *67*, 1–48.

Bathina, K.C., ten Thij, M., Lorenzo-Luaces, L., Rutter, L.A., & Bollen, J. (2021). Individuals with depression express more distorted thinking on social media. *Nature Human Behaviour*, *5*, Article 4.

Beck, A.T. (1987). Cognitive models of depression. *Journal of Cognitive Psychotherapy*, *1*, 5–37.

Blei, D.M., Ng, A.Y., & Jordan, M.I. (2003). Latent Dirichlet allocation. *The Journal of Machine Learning Research*, *3*, 993–1022.

Bolger, N., & Laurenceau, J.-P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. New York, NY: Guilford Press.

Bollen, J., ten Thij, M., Breithaupt, F., Barron, A.T.J., Rutter, L.A., Lorenzo-Luaces, L., & Scheffer, M. (2021). Historical language records reveal a surge of cognitive distortions in recent decades. *Proceedings of the National Academy of Sciences*, *118*, e2102061118.

Brockmeyer, T., Zimmermann, J., Kulessa, D., Hautzinger, M., Bents, H., Friederich, H.-C., ... & Backenstrass, M. (2015). Me, myself, and I: Self-referent word use as an indicator of self-focused attention in relation to depression and anxiety. *Frontiers in Psychology*, *6*, 1564.

Chancellor, S., & De Choudhury, M. (2020). Methods in predictive techniques for mental health status on social media: A critical review. *npj Digital Medicine*, *3*, Article 1.

Curfman, G.D. (1993). Is exercise beneficial – Or hazardous – To your heart? *New England Journal of Medicine*, *329*, 1730–1731.

Curran, P.J., & Bauer, D.J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology*, *62*, 583–619.

de Angel, V., Lewis, S., White, K., Oetzmann, C., Leightley, D., Oprea, E., ... & Hotopf, M. (2022). Digital health tools for the passive monitoring of depression: A systematic review of methods. *npj Digital Medicine*, *5*, Article 1.

Douven, I., & Meijs, W. (2007). Measuring coherence. *Synthese*, *156*, 405–425.

Edwards, T., & Holtzman, N.S. (2017). A meta-analysis of correlations between depression and first person singular pronoun use. *Journal of Research in Personality*, *68*, 63–68.

Eichstaedt, J.C., Smith, R.J., Merchant, R.M., Ungar, L.H., Crutchley, P., Preoţiuc-Pietro, D., ... & Schwartz, H.A. (2018). Facebook language predicts depression in medical records. *Proceedings of the National Academy of Sciences of the United States of America*, *115*, 11203–11208.

Enders, C.K., & Tofighi, D. (2007). Centering predictor variables in cross-sectional multilevel models: A new look at an old issue. *Psychological Methods*, *12*, 121–138.

Friedrich, M.J. (2017). Depression is the leading cause of disability around the world. *JAMA*, *317*, 1517.

Gollan, J.K., Pane, H.T., McCloskey, M.S., & Coccaro, E.F. (2008). Identifying differences in biased affective information processing in major depression. *Psychiatry Research*, *159*, 18–24.

Hutto, C., & Gilbert, E. (2014). VADER: A parsimonious rule-based model for sentiment analysis of social media text. *Proceedings of the International AAAI Conference on Web and Social Media*, *8*, Article 1.

Kaufman, J., Birmaher, B., Brent, D., Rao, U., Flynn, C., Moreci, P., ... & Ryan, N. (1997). Schedule for affective disorders and schizophrenia for school-age children-present and lifetime version (K-SADS-PL): Initial reliability and validity data. *Journal of the American Academy of Child and Adolescent Psychiatry*, *36*, 980–988.

Keller, M.B., Lavori, P.W., Friedman, B., Nielsen, E., Endicott, J., McDonald-Scott, P., & Andreasen, N.C. (1987). The longitudinal interval follow-up evaluation. A comprehensive method for assessing outcome in prospective longitudinal studies. *Archives of General Psychiatry*, *44*, 540–548.

Kross, E., Verduyn, P., Boyer, M., Drake, B., Gainsburg, I., Vickers, B., ... & Jonides, J. (2019). Does counting emotion words on online social networks provide a window into People's subjective experience of emotion? A case study on Facebook. *Emotion*, *19*, 97–107.

Li, L.Y., Trivedi, E., Helgren, F., Allison, G.O., Zhang, E., Buchanan, S.N., ... & Shankman, S.A. (2023). Capturing mood dynamics through adolescent smartphone social

© 2023 Association for Child and Adolescent Mental Health.

communication. *Journal of Psychopathology and Clinical Science*, *132*, 1072–1084.
Lind, M.N., Byrne, M.L., Wicks, G., Smidt, A.M., & Allen, N.B. (2018). The effortless assessment of risk states (EARS) tool: An interpersonal approach to mobile sensing. *JMIR Mental Health*, *5*, e10334.
Lind, M.N., Kahn, L.E., Crowley, R., Reed, W., Wicks, G., & Allen, N.B. (2023). Reintroducing the effortless assessment research system (EARS). *JMIR Mental Health*, *10*, e38920.
Liu, T., Meyerhoff, J., Eichstaedt, J.C., Karr, C.J., Kaiser, S.M., Kording, K.P., … & Ungar, L.H. (2022). The relationship between text message sentiment and self-reported depression. *Journal of Affective Disorders*, *302*, 7–14.
Lüdecke, D., Ben-Shachar, M.S., Patil, I., & Makowski, D. (2020). Extracting, computing and exploring the parameters of statistical models using R. *Journal of Open Source Software*, *5*, 2445.
Lyons, M., Aksayli, N.D., & Brewer, G. (2018). Mental distress and language use: Linguistic analysis of discussion forum posts. *Computers in Human Behavior*, *87*, 207–211.
McNeilly, E.A., Mills, K., Kahn, L., Crowley, R., Pfeifer, J., & Allen, N. (2023). Adolescent social communication through smartphones: Linguistic features of internalizing symptoms and daily mood. *Clinical Psychological Science*, *11*, 1090–1107.
Mojtabai, R., Olfson, M., & Han, B. (2016). National Trends in the prevalence and treatment of depression in adolescents and young adults. *Pediatrics*, *138*, e20161878.
Nahum-Shani, I., Smith, S.N., Spring, B.J., Collins, L.M., Witkiewitz, K., Tewari, A., & Murphy, S.A. (2018). Just-in-time adaptive interventions (JITAIs) in Mobile health: Key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine*, *52*, 446–462.
Nook, E.C., Hull, T.D., Nock, M.K., & Somerville, L.H. (2022). Linguistic measures of psychological distance track symptom levels and treatment outcomes in a large set of psychotherapy transcripts. *Proceedings of the National Academy of Sciences of the United States of America*, *119*, e2114737119.
Office of the Surgeon General. (2021). *Protecting youth mental health: The U.S. surgeon General's advisory*. Washington, DC: US Department of Health and Human Services.
Orr, M., MacLeod, L., Bagnell, A., McGrath, P., Wozney, L., & Meier, S. (2023). The comfort of adolescent patients and their parents with mobile sensing and digital phenotyping. *Computers in Human Behavior*, *140*, 107603.
Pew Research Center. (2022). *Teens, social media and technology*. Washington, DC: Pew Research Center. Available from: https://www.pewresearch.org/internet/2022/08/10/teens-social-media-and-technology-2022/
Porter, R.J., Moot, W., Inder, M.L., Crowe, M.T., Douglas, K.M., Carter, J.D., & Frampton, C. (2022). Validation of the longitudinal interval follow-up evaluation for the long-term measurement of mood symptoms in bipolar disorder. *Brain Sciences*, *12*, 1717.
Pyszczynski, T., & Greenberg, J. (1987). Self-regulatory perseveration and the depressive self-focusing style: A self-awareness theory of reactive depression. *Psychological Bulletin*, *102*, 122–138.
Racine, N., McArthur, B.A., Cooke, J.E., Eirich, R., Zhu, J., & Madigan, S. (2021). Global prevalence of depressive and anxiety symptoms in children and adolescents during COVID-19: A meta-analysis. *JAMA Pediatrics*, *175*, 1142–1150.
Richardson, L.P., Russo, J.E., Lozano, P., McCauley, E., & Katon, W. (2010). Factors associated with detection and receipt of treatment for adolescents with depression and anxiety disorders. *Academic Pediatrics*, *10*, 36–40.
Rude, S., Gortner, E.-M., & Pennebaker, J. (2004). Language use of depressed and depression-vulnerable college students. *Cognition and Emotion*, *18*, 1121–1133.
Selivanov, D., Bickel, M., & Wang, Q. (2022). *text2vec: Modern text mining framework for R*. [Computer software]. Available from: https://CRAN.R-project.org/package=text2vec
Shin, J., & Bae, S.M. (2023). A systematic review of location data for depression prediction. *International Journal of Environmental Research and Public Health*, *20*, Article 11.
Singer, J.D., & Willett, J.B. (2003). *Applied longitudinal data analysis: Modeling change and event occurrence*. New York, NY: Oxford University Press.
Stamatis, C.A., Meyerhoff, J., Liu, T., Sherman, G., Wang, H., Liu, T., … & Mohr, D.C. (2022). Prospective associations of text-message-based sentiment with symptoms of depression, generalized anxiety, and social anxiety. *Depression and Anxiety*, *39*, 794–804.
Tackman, A.M., Sbarra, D.A., Carey, A.L., Donnellan, M.B., Horn, A.B., Holtzman, N.S., … & Mehl, M.R. (2019). Depression, negative emotionality, and self-referential language: A multi-lab, multi-measure, and multi-language-task research synthesis. *Journal of Personality and Social Psychology*, *116*, 817–834.
Tanner, J.M., & Davies, P.S.W. (1985). Clinical longitudinal standards for height and height velocity for North American children. *The Journal of Pediatrics*, *107*, 317–329.
Tølbøll, K.B. (2019). Linguistic features in depression: A meta-analysis. *Journal of Language Works – Sprogvidenskabeligt Studentertidsskrift*, *4*, Article 2.
Wang, P.S., Berglund, P., Olfson, M., Pincus, H.A., Wells, K.B., & Kessler, R.C. (2005). Failure and delay in initial treatment contact after first onset of mental disorders in the National Comorbidity Survey Replication. *Archives of General Psychiatry*, *62*, 603–613.
Warshaw, M.G., Dyck, I., Allsworth, J., Stout, R.L., & Keller, M.B. (2001). Maintaining reliability in a long-term psychiatric study: An ongoing inter-rater reliability monitoring program using the longitudinal interval follow-up evaluation. *Journal of Psychiatric Research*, *35*, 297–305.
Wechsler, D. (2011). Wechsler abbreviated scale of intelligence. In *PsycTESTS dataset* (2nd edn). Upper Saddle River, NJ: Pearson.
Zulueta, J., Piscitello, A., Rasic, M., Easter, R., Babu, P., Langenecker, S.A., … & Leow, A. (2018). Predicting mood disturbance severity with Mobile phone keystroke metadata: A BiAffect digital phenotyping study. *Journal of Medical Internet Research*, *20*, e9775.

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