Protocol

Identifying Person-Specific Drivers of Depression in Adolescents: Protocol for a Smartphone-Based Ecological Momentary Assessment and Passive Sensing Study

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Abstract

Background: Adolescence is marked by an increasing risk of depression and is an optimal window for prevention and early intervention. Personalizing interventions may be one way to maximize therapeutic benefit, especially given the marked heterogeneity in depressive presentations. However, empirical evidence that can guide personalized intervention for youth is lacking. Identifying person-specific symptom drivers during adolescence could improve outcomes by accounting for both developmental and individual differences.

Objective: This study leverages adolescents’ everyday smartphone use to investigate person-specific drivers of depression and validate smartphone-based mobile sensing data against established ambulatory methods. We describe the methods of this study and provide an update on its status. After data collection is completed, we will address three specific aims: (1) identify idiographic drivers of dynamic variability in depressive symptoms, (2) test the validity of mobile sensing against ecological momentary assessment (EMA) and actigraphy for identifying these drivers, and (3) explore adolescent baseline characteristics as predictors of these drivers.

Methods: A total of 50 adolescents with elevated symptoms of depression will participate in 28 days of (1) smartphone-based EMA assessing depressive symptoms, processes, affect, and sleep; (2) mobile sensing of mobility, physical activity, sleep, natural language use in typed interpersonal communication, screen-on time, and call frequency and duration using the Effortless Assessment of Risk States smartphone app; and (3) wrist actigraphy of physical activity and sleep. Adolescents and caregivers will complete developmental and clinical measures at baseline, as well as user feedback interviews at follow-up. Idiographic, within-subject networks of EMA symptoms will be modeled to identify each adolescent’s person-specific drivers of depression. Correlations among EMA, mobile sensor, and actigraph measures of sleep, physical, and social activity will be used to assess the validity of mobile sensing for identifying person-specific drivers. Data-driven analyses of mobile sensor variables predicting core depressive symptoms (self-reported mood and anhedonia) will also be used to assess the validity of mobile sensing for identifying drivers. Finally, between-subject baseline characteristics will be explored as predictors of person-specific drivers.

Results: As of October 2023, 84 families were screened as eligible, of whom 70% (n=59) provided informed consent and 46% (n=39) met all inclusion criteria after completing baseline assessment. Of the 39 included families, 85% (n=33) completed the 28-day smartphone and actigraph data collection period and follow-up study visit.

Conclusions: This study leverages depressed adolescents’ everyday smartphone use to identify person-specific drivers of adolescent depression and to assess the validity of mobile sensing for identifying these drivers. The findings are expected to offer novel insights into the structure and dynamics of depressive symptomatology during a sensitive period of development and to
inform future development of a scalable, low-burden smartphone-based tool that can guide personalized treatment decisions for depressed adolescents.

**International Registered Report Identifier (IRRID):** DERR1-10.2196/43931

*JMIR Res Protoc 2024;13:e43931* doi: 10.2196/43931

**KEYWORDS**
adolescents; depression; idiographic assessment; network modeling; treatment personalization; ecological momentary assessment; mobile sensing; digital phenotyping; actigraphy; smartphones

**Introduction**

**Background**

Adolescents experience escalating risk of developing clinical depression, with lifetime prevalence rates doubling from age 13 years (8%) to 18 years (15%) [1]. Depression impairs young people’s academic, social, and physical functioning [2]; often continues into adulthood [2]; and increases the risk of developing other disorders [2] and suicide attempts [3]. Puberty brings a host of changes, including significant developmental changes in the brain, physical growth spurts and sexual maturation, metabolic and circadian changes, along with an emerging identity, increasingly complex social contexts, and increased learning capacity [4]. These changes may contribute to the risk of developing depression but also signal an opportunity for high-impact intervention [5]. Mastering mood management skills during adolescence can alter the developmental course of depression, thereby improving long-term outcomes. Unfortunately, existing therapies fail to sufficiently capitalize on this developmental window. Meta-analyses revealed significantly smaller effects of psychotherapy for depressed adolescents than for adults [6] and for youth depression than for anxiety or conduct problems [7]. The efficacy of evidence-based psychotherapies such as cognitive behavioral therapy (CBT) may be limited by their fixed, linear delivery to all individuals. Personalizing intervention selection, sequencing, and combination may maximize therapeutic benefit [8], especially for a disorder as heterogeneous as depression. However, empirical support on how to do so is lacking.

One promising avenue for informing personalization is to identify symptoms that are influential in the onset and maintenance of dynamic variability in depressive symptoms (ie, short-term, temporal relationships among symptoms), that are modifiable through intervention, and that vary across individuals—referred to here as person-specific drivers of depression. Most evidence-based approaches to therapy, such as CBT, attempt to teach individuals coping skills that will allow them to moderate these dynamics in real time. As such, understanding these drivers can inform personalized intervention that focuses on the specific skills most relevant to an individual’s own affective dynamics. Extant theory suggests possible drivers, such as negative affect, rumination, avoidance, social isolation, and anhedonia. Empirical research with 3000+ adults with major depression has documented sadness, loss of energy, interest, and pleasure; concentration problems; sympathetic arousal; and panic as the most central (ie, strongly interconnected) among a network of depressive and nondepressive symptoms [9].

Moreover, in never-depressed adults, central depressive symptoms prospectively predicted the onset of depression [10]. Importantly, some central symptoms predicted subsequent changes in other symptoms among depressed or anxious adults, and marked heterogeneity was found in these temporally-ordered predictive relationships [11,12], with no 2 persons sharing the exact number or nature of predictive relationships. Similarly, a large internet-based CBT trial showed that >90% of depressed adults had unique patterns of treatment response, with certain symptoms impacted directly by treatment, which then influenced the reduction of other symptoms [13]. Modeling these person-specific patterns may uncover the mechanisms by which symptoms are maintained and resolved with treatment, providing powerful tools for personalizing treatment. Researchers have led efforts to select and sequence CBT modules to target person-specific drivers identified by idiographic models early in therapy [12,14], which is purportedly more efficacious and efficient due to the drivers’ downstream effect on other symptoms. An open trial [15] of personalized CBT returned effect sizes 1.5-2 times larger, achieved over a shorter duration, compared to a historical benchmark [16]. However, no published studies have examined person-specific drivers of depression among adolescents. To our knowledge, only group-level central internalizing symptoms have been studied among youth [17-19]. An idiographic approach is needed to obtain novel insights about symptom dynamics among depressed adolescents in order to inform interventions that account for both developmental and individual differences and that can shift the trajectory of depression onset, maintenance, and recurrence.

To model symptom dynamics, ecological momentary assessment (EMA) is often used [11,20]. Participants are prompted to provide subjective self-report of experiences and events through brief web-based or text surveys daily or repeatedly throughout the day. Whereas EMA involves active input from participants, passive assessment uses a mobile or wearable device to unobtrusively record participants’ behavior or physiology. Wrist-worn actigraphs are research-grade devices containing accelerometers and sometimes other sensors (eg, a light sensor) to estimate behavioral indices of sleep and physical activity [21], which relate to key symptoms of depression (ie, hypersomnia or insomnia, fatigue, and psychomotor retardation or agitation). Actigraphy has been validated against gold standard lab-based measures of sleep (ie, polysomnography [22]) and physical activity (ie, indirect calorimetry [23]). Smartphone-based EMA and wrist actigraphy have been successfully used with youth [24-26] and can be feasibly used to examine person-specific drivers with depressed adolescents.
Smartphone-based mobile sensing may offer advantages over established methods—especially for adolescents—but needs validation. Mobile sensing or digital phenotyping [27,28] minimizes response burden while leveraging adolescents’ near universal (95%) smartphone ownership [29] and usage to obtain objective, fine-grained data about their everyday behaviors. Systematic reviews [30,31] have documented promising evidence for using mobile sensor data (sometimes with EMA) to monitor mood by measuring behaviors related to depression, including sleep (through light sensors, accelerometers, and screen time), physical activity (through accelerometers), mobility (through GPS), and social activity (through call and text frequency or duration). Moreover, a national study of depressed adults showed that idiographic models of GPS-based mobility and other sensor data predicted daily mood at the individual level but not at the group level [32], suggesting the utility of such data for elucidating person-specific symptom dynamics. However, there are very few published studies using mobile sensing to collect data or monitor mood among depressed youth, and of these studies, participant samples tend to be small (range 11-37) [33-36], and large amounts of missing data that affect prediction modeling have been reported [33-37]. More validation studies—especially those with larger samples of depressed adolescents—are needed to demonstrate that mobile sensor data collected from depressed adolescents are correlated with, or predictive of, their EMA and actigraph data before mobile sensing can supplement or substitute these established methods.

Baseline predictors of person-specific drivers could distinguish subgroups with different treatment targets. Identifying between-subject characteristics that predict within-person drivers could facilitate efficient assessment and treatment decisions. For example, a study examining a network of positive and negative emotions, stress, and physical activity found that high arousal positive affect (eg, enthusiastic) was the strongest driver (ie, reduced stress and negative affect) among nonanhedonic individuals, whereas low arousal positive affect (eg, relaxed) was the strongest driver among anhedonic individuals [38]. These findings suggest different optimal intervention targets for the 2 subgroups of depressed adults. Exploring baseline markers that predict person-specific drivers and within-person symptom dynamics is an initial step toward the development of strategies to tailor interventions to optimize outcomes.

Objectives

This study will leverage adolescents’ everyday smartphone use for the purpose of evaluating the contributions of these data to understanding person-specific drivers of depression and to further validate smartphone-based mobile sensing data against established ambulatory methods such as EMA and actigraphy. We plan to address three specific aims in this study after data collection is complete. Aim 1: model idiographic, within-subject networks of EMA symptoms to identify person-specific symptom dynamics. We hypothesize that most (≥50%) adolescents will have person-specific drivers: (1a) symptoms strongly associated with, or (1b) prospectively predict change in other symptoms in an idiographic network, and (1c) differ markedly across adolescents. Aim 2: (2a) compute correlations among EMA, mobile sensor, and wrist-worn actigraph measures of sleep, physical, and social activity; and (2b) conduct data-driven analyses of core depressive symptoms (ie, self-reported mood and anhedonia) to assess the validity of mobile sensing for identifying person-specific drivers. Aim 3: explore between-subject baseline characteristics as predictors of these person-specific drivers. For this protocol report, the objectives are to describe the methods of this study and provide an update on the status of this study.

Methods

Participants and Recruitment

A total of 50 adolescents who are (1) aged between 12 and 18 years, (2) have one parent or legal guardian willing to participate, (3) report elevated levels of depressive symptoms (a score of ≥16 on the Center for Epidemiologic Studies Depression (CES-D) [39]), and (4) own a smartphone will be included in the study. The targeted age range covers the period when depression rates start to climb until they peak, and when the sex difference in prevalence widens [40]. Thus improved, personalized treatment is likely to be most impactful at these ages. Adolescents of these ages are also likely to own a smartphone—mobile sensing research assumes typical phone use, and research found that adults often did not carry study phones with them or use them as they would use personal phones [31]. Exclusion criteria include the following: (1) if receiving pharmacotherapy or psychotherapy for depression, the type or dose of therapy or dosage of medication has not been stable for at least the past 4 weeks; (2) current psychotropic medication taken as needed that could influence mood and related symptoms; (3) acute suicidality (ie, past-month method, plan, intent, access, perceived ability and probability of carrying out attempt); (4) past-year suicide attempt or serious nonsuicidal self-injury (NSSI), or history of suicide attempt over a year ago and not currently receiving mental health services; (5) history of mania or psychosis; (6) adolescent is not fluent in English; and (7) parent or legal guardian is fluent in neither English nor Spanish. Before December 2022, adolescents who reported any history of suicide attempt were excluded, and before February 2022, adolescents who reported any history of serious NSSI were also excluded, and the cutoff score was ≥20 on the CES-D to be included in the study. However, we broadened the inclusion criteria to address challenges with recruitment.

To account for expected attrition of 15%, 59 participants will be recruited from multiple sources, which include a university youth mental health clinic and local middle and high schools within south Florida in the United States, as well as social media posts, advertisements, and community referrals. Interested families are contacted to complete a brief phone screen where they will be assessed for eligibility. Adolescents are screened with the CES-D, which has been validated extensively with adolescents aged between 12 and 18 years [41], including those of Hispanic ethnicity [42], expected to comprise roughly 70% of our sample. The CES-D can discriminate severity at lower levels of depression [43], and 40%-50% of adolescents are likely to meet our cutoff score of ≥16 [44], making this an appropriate measure to select a sample of adolescents with elevated symptoms of depression.
Ethical Considerations and Informed Consent

Study procedures were approved by the Florida International University Institutional Review Board in April 2020 (IRB-20-0257) and renewed annually thereafter. Due to the sensitive nature and large amount of data collected by the smartphone app from a vulnerable youth population, informed consent is required from both legal guardians (if applicable) of adolescents under the age of 18 years to participate in the study. Adolescents aged 18 years (ie, legal adults in the United States), as well as caregivers, provide informed consent for themselves to participate.

Safety Planning and Daily Safety Surveys

All families who consent to participate in the study are given brief psychoeducation about depression. Given the increased risk of adolescents with depression having thoughts of suicide [45], adolescents also complete a suicide risk assessment and safety plan [46] with a member of the research team during baseline assessment. The adolescent’s assessment and safety plan are then reviewed with the participating caregiver, who is engaged to provide additional information and feedback and encouraged to support the adolescent in following the safety plan whenever needed, and a copy of the safety plan is provided to the family. Adolescents with elevated risk are excluded from the study and connected to crisis support services as appropriate. In addition, all adolescent participants complete a daily safety survey as part of our EMA procedures. Adolescents are asked whether they have experienced abuse or suicidal ideation since the last survey. Endorsement of abuse will prompt an automated reminder to call 911 or contact a trusted adult, as well as a call from the research team to the youth within 24 hours. Endorsement of suicidal ideation will prompt an automated reminder to use the safety plan or call 911, as well as a call from the research team to the caregiver within 24 hours. Families are instructed not to use the safety survey or other mobile data collected as a way to seek help in an emergency, as it is not feasible for data to be reviewed frequently throughout the day. The adolescent and parent participating in the study then complete a brief quiz to demonstrate that they understand risk procedures in the event that the adolescent reports suicidal ideation or abuse on their daily surveys. All research team members who interact with families receive training and ongoing supervision by the principal investigator, a licensed clinical psychologist, in risk and mandated reporting procedures. In addition, research team members are instructed to contact the principal investigator or an on-call licensed mental health clinician at the university mental health clinic shortly after receiving any report of suicidality or possible abuse from adolescents to ensure that appropriate steps are taken to ensure the safety of the adolescents.

Data Collection

All assessments take place remotely [47]. The wrist-worn actigraph is mailed to participants in advance of the baseline assessment. During the baseline assessment, caregivers and adolescents who meet all inclusion criteria complete a series of questionnaires measuring demographics, depressive symptoms, and depressogenic processes (Table 1). Adolescents are guided to install the Effortless Assessment of Risk States (EARS) mobile app [27,48] on their smartphones, and, for the next 28 days, the app collects EMA and mobile sensor data, and adolescents wear the actigraph device. EARS was developed for both iPhones and Android phones, is updated to maintain compatibility with newer operating systems, and uses rigorous data security features. During the 28-day smartphone and actigraph period, the app presents feedback to adolescents about their survey completion and bonuses earned and uses gamification features (eg, graphics and trophies) to reinforce adherence. Smartphone data will be continuously uploaded to a cloud server and monitored; those who uninstall the app or miss consecutive surveys will be called or texted and offered assistance. Families receive up to US $191 for study completion, including bonuses for completion of all surveys per day and 80%-90% overall adherence to EMA and actigraph procedures. At follow-up, families complete measures and a user feedback interview (Table 1). EARS is then uninstalled, and the actigraph is mailed back to the research team.
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<td>Adolescent Medication, Therapy, and Services assesses mental health service use</td>
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<td>Adolescent depressogenic processes and Research Domain Criteria constructs</td>
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<td>Rumination Response Scale [58] measures negative perseverative cognitions</td>
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<td>Automatic Thoughts Questionnaire [59] measures negative automatic cognitions</td>
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<td>Responses to Stress Questionnaire [61] measures coping and involuntary stress responses. Adolescents select the version of the questionnaire that corresponds to the stressor that is most applicable to them. Adolescents can select from peer stress, maternal depression, paternal depression, family stress, academic problems, COVID-19, or financial problems</td>
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<td>Multidimensional Scale of Perceived Social Support [62,63] measures affiliation with friends, family, and significant other</td>
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<td>Snaith-Hamilton Pleasure Scale [65] measures anhedonia</td>
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<td>Feedback interview about ecological momentary assessment, mobile sensing, and actigraphy. Rate how enjoyable, easy to use, disruptive, acceptable; privacy concerns and changes in phone use during the study; describe likes or dislikes, suggested improvements, and health-related apps currently used</td>
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<td>Adolescent and caregiver</td>
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*Measures not given to adolescents and caregivers.

**EMA**

Symptom surveys are administered 5 times a day on weekdays and 6 times a day on weekends, over 28 consecutive days. Prompts are delivered randomly within 2-hour blocks in the morning (9 AM-11 AM), around noon (11 AM-1 PM), early afternoon (1 PM-3 PM), late afternoon (3 PM-5 PM), and evening (5 PM-7 PM), with a late evening (7 PM-9 PM) block on weekends. Each block includes a 0.5-hour buffer to separate adjacent surveys. A similar sampling schedule has been used successfully (>80% compliance) with adolescents [24]. Adolescents rate on a 0-100 visual analogue scale 21 items adapted from previous studies [11,12,25]: depressive symptoms ("felt down or depressed," "felt hopeless," "felt irritable or
gyroscope, and the other model does not, whereas the GTX9 Link model has a liquid-crystal display and a

designed to give comparable results. The primary differences in participants' natural environments, and were

actigraphy using this model. Both models use a triaxial accelerometer and ActiGraph's proprietary filtering algorithm

80.2% for the 21 adolescents who completed 28 days of

Since then, 24 adolescents have used or are using the GT9X

drawing unwanted attention. A total of 15 adolescents wore the

However, feedback interviews from early in the study revealed a strong preference for a less conspicuous device to avoid
drawing unwanted attention. A total of 15 adolescents wore the wGT3X-BT model, with an average wear time of only 74.3%

Mobile Sensing

We selected 12 sensor variables to be analyzed based on

Actigraphy

Adolescents wear on their nondominant wrist a research-grade

actigraph, a wearable wrist monitor used to capture and record

continuous, high resolution physical activity and sleep and wake

information. The wGT3X-BT device (ActiGraph) is widely

used in research studies and has been validated against indirect calorimetry and polysomnography [22,23]. It also features a

light sensor; thus, this model was initially used with participants.

However, feedback interviews from early in the study revealed a strong preference for a less conspicuous device to avoid
drawing unwanted attention. A total of 15 adolescents wore the wGT3X-BT model, with an average wear time of only 74.3%

for the 13 adolescents who completed 28 days of actigraphy. We selected 12 sensor variables to be analyzed based on

previous literature [30,32,35,37]. These include raw data on battery status, calls (frequency\times duration), as well as extracted features on mobility (percentage of time spent at home and distance traveled from GPS), physical activity intensity from accelerometer, sleep duration and efficiency (from ambient light and accelerometer), and natural language use in social communication (from all text typed into email, text, and social media apps, captured by a keyboard logger). Specifically, we will assess word count and word sentience through the Linguistic Inquiry and Word Count [66] Positive Emotion and Negative Emotion dictionaries, and the use of first-person pronouns (eg, “I”) and absolutist words (eg, “never”) associated with mental health [67-69], in English and Spanish.

Data Analysis

Sample Size

The numbers of observations (n=148) and participants (n=50)

were estimated based on previous research using similar idiographic models [4,6]. Given the mean response rate (78%) in

smartphone EMA with youth [71], 115/148 observations per

adolescent are expected; thus, up to 23 EMA items can be

included in an idiographic model with ≥5 observations per item.

Aim 1 Analyses: Idiographic Dynamic Models of EMA

Data to Identify Person-Specific Drivers

EMA will yield a multivariate time series for each adolescent to be submitted to network analysis [11,12]. The graphical vector autoregressive (VAR) model will be used to identify contemporaneous and lag-1 directed effects. The graphical VAR function in R [72] models the autocorrelations and cross-predictions in a lag-1 VAR model as directed paths in the temporal portion of the network model, and the residual correlations as associations in the contemporaneous network. Regularization is applied through the least absolute shrinkage and selection operator (LASSO) algorithm, and model selection is performed by the extended Bayesian information criterion [73]. Hypotheses are supported if ≥50% adolescents (1) have contemporaneous networks in which ≥1 item has greater strength centrality at a given time t, (2) temporal networks in which ≥1 item has greater outstrength (ie, time t values that strongly predict other items at time t+1), and (3) if items with the greatest centrality and outstrength vary across adolescents. Because idiographic networks are a new area, there is no established threshold for identifying drivers and distinguishing significant differences among adjacent-ranked items for the same adolescent, other than selecting items with a CI that does not include zero. We will thus explore and consider using novel methods that may facilitate the identification of drivers. For example, a recently developed approach that ranks the items by their controllability (ie, how efficient it is to intervene on each item, taking into account downstream changes in the symptom network [74]) might be helpful for addressing this aim if it can be extended from group analyses to idiographic analyses. In addition, results may not generalize beyond the items in the measure used to generate the network, prompting recommendations to avoid multiple items measuring the same construct and to examine latent variables before estimating networks [75]. Person-specific dynamic factor analysis is another approach to identifying person-specific drivers by examining latent variables of symptoms that predict other latent variables of symptoms over time [76].

Aim 2 Analyses: Validation of Mobile Sensing to Identify Person-Specific Drivers

First, we will sample mobile sensor and actigraph data collected during the 15-minute intervals just before and just after each EMA response. (2a) Because of our idiographic focus and previous research showing high between-subject heterogeneity
First, we will investigate whether there is evidence for identifying person-specific drivers of depression in adolescents. We have provided a status update on data collection for this ongoing study. Of the 59 adolescents targeted for recruitment, two-thirds (n=39) have started the study, and half have completed all phases of the study (n=33). After data collection is complete, we plan to address the 3 specific aims of this study. First, we will investigate whether there is evidence for person-specific drivers of depression among this sample of adolescents. That is, we will identify symptoms that strongly predict change in other symptoms for each adolescent and examine whether these driver symptoms differ across adolescents. Second, we will validate mobile sensor data against EMA and actigraph measures. We will assess whether smartphone-measured sleep, physical activity, and social interaction variables correlate with conceptually similar actigraph-measured variables and EMA responses, and whether mobile sensor data can predict EMA responses about the key depressive symptoms of low mood and anhedonia within each adolescent. Third, we will explore whether baseline adolescent characteristics can predict which symptoms are drivers for which adolescents.
Empirical findings suggesting that person-specific drivers of adolescent depression exist would offer a plausible explanation for individual differences in clinical presentation and treatment response in this population. These findings would also support the need for a personalized approach to assessment and intervention, where treatments or their component modules are selected and sequenced to target each adolescent’s specific drivers [14,15]. Indeed, emerging research suggests that depressed youth display heterogeneous responses to individual CBT modules [83,84]. Moreover, the particular symptoms identified as drivers in our adolescent sample could be compared to those identified in adult samples. Differences in driver symptoms between adolescents and adults may provide clues as to why depressed adolescents do not benefit as much from psychotherapy as do adults [6], thereby informing the generation of hypotheses about developmental considerations in the treatment of adolescent depression for future testing.

Our efforts to validate mobile sensor data for predicting depressive symptoms in adolescents will add to the small but growing literature on this topic [33-36]. Recent studies have demonstrated promising results in predicting depressive symptom scores [33,35] and diagnosis [36] using smartphone and wearable sensor data. One study [34] found good prediction of elevated anger and anxiety but more modest prediction of sadness from mobile sensor data—a finding that is particularly relevant to this study’s focus on assessing and predicting the severity of individual depressive symptoms. Accurately predicting individual symptom severity with mobile sensor data obtained with minimal user effort can make the assessment of person-specific drivers more feasible to use with adolescents in clinical practice.

If adolescent characteristics measured at baseline are found to predict each adolescent’s driver symptoms reasonably well, then a preliminary assessment of drivers could be made early in the evaluation, shortening the lag time from intake to the initiation of treatment. The month-long smartphone tracking phase may be used to confirm the preliminary assessment results or perhaps even be skipped entirely. Although identifying drivers focuses on intrapersonal symptom dynamics, examining between-subject characteristics that predict those drivers could shed light on interpersonal differences in psychopathology and begin to illuminate subgroups of adolescents with different optimal treatment targets. A future direction is to use the data generated by this study to inform the development and testing of a scalable, low-burden smartphone-based tool and treatment algorithm to select and sequence therapy modules targeting person-specific drivers in depressed adolescents with potential public health impact.

**Limitations**

This study is recruiting participants from the community who generally have mild depressive symptoms and low risk of suicide and self-harm. We focused on this population due to practical reasons relating to recruitment and our capacity for responding to emergent crises. However, adolescents with severe depressive symptoms and higher risk of suicide and self-harm may be in greatest need of effective treatment. In order to inform personalized treatment for the adolescents who may benefit the most from it, further research on person-specific drivers of depression needs to be conducted with this population.

In addition, this study cannot establish whether identified drivers cause changes in other depressive symptoms, only whether they are associated with changes in depressive symptoms. It is thus possible that a third variable is causing changes in both driver and nondriver depressive symptoms. Moreover, contemporaneous networks cannot determine the direction of association between central symptoms and other symptoms; changes in other symptoms may in fact precede changes in central symptoms, or the association may be bidirectional. A related concern is that the temporal networks’ ability to capture directional change is constrained by the EMA sampling intervals of 2 hours—directional change that occurs during a shorter or much longer time frame will not be detected.

Furthermore, data were collected during the COVID-19 pandemic, a time when adolescents had to deal with multiple stressors, including fears about themselves or their loved ones being infected, losses (eg, of life, job, or relationships) experienced by themselves or family members, disruptions to schooling and social activities, and isolation at home due to safe distancing measures [85]. Studies have documented increased depressive symptoms and loneliness, as well as poorer academic functioning among adolescents during the pandemic, with notable heterogeneity in pandemic impact attributed to differential access to resources and preexisting vulnerabilities [86]. To assess how the pandemic may influence the associations between adolescents’ behavior assessed by mobile sensors and their depressive symptoms, we have included several measures of pandemic impact on adolescents and their parents.

**Conclusions**

As one of very few studies examining depressive symptom networks among adolescents, this study is expected to offer novel insights into the structure and dynamics of depressive symptomatology during a sensitive period of development. A better understanding of what drives depression during this high-risk, high-impact window of development could lead to assessments and interventions that better address developmental and individual differences, ultimately producing greater benefit over the life course. Finally, this study is expected to contribute to the growing literature supporting a shift from standardized to personalized assessment and treatment of adolescent depression.

**Acknowledgments**

This protocol was submitted to the National Institute of Mental Health of the US National Institutes of Health and awarded an R21 Exploratory/Developmental Research Grant Award (R21MH126394). Changes made to the protocol in response to reviewer feedback or to address challenges with study implementation (eg, recruitment) after submission to the National Institute of Mental Health.
Health have been incorporated in this manuscript. The authors would like to thank all families who have participated in this study, Miami Dade County Public Schools for their help with recruitment, and members of the Mechanisms Underlying Treatment Technologies Lab who have assisted with recruitment, phone screens, assessments, and data monitoring, especially Lindsey Cunningham, Jenny Guo, Laurent Garchitorena Gomez, Lia Gimeno, Seline Coloma, and Maria Abella Garcia.

Data Availability
The data sets generated during this study are available from the National Institute of Mental Health Data Archive at the National Institutes of Health. The National Institute of Mental Health Data Archive is a collaborative informatics system created by the National Institutes of Health to provide a national resource to support and accelerate research in mental health. Data set identifier is 10.15154/88w5-4029. This manuscript reflects the views of the authors and may not reflect the opinions or views of the National Institutes of Health.

Authors’ Contributions
MYN is the principal investigator of this funded study; AJF, JWP, and DLM are coinvestigators who contributed to the study design and ongoing implementation of the study; NBA is a consultant providing expertise on smartphone data collection methods; and JAF is a graduate research assistant serving as the study coordinator.

Conflicts of Interest
NBA is the cofounder and CEO of, and has an equity interest in, Ksaana Health, the company that developed and maintains the EARS platform used in this study. JWP receives royalties from New Harbinger Publications and the American Psychological Association. All other authors declare no conflicts of interest.

References


Abbreviations

- CBT: cognitive behavioral therapy
- CES-D: Center for Epidemiologic Studies Depression Scale
- EARS: Effortless Assessment of Risk States
- EMA: ecological momentary assessment
- LASSO: least absolute shrinkage and selection operator
- NSSI: nonsuicidal self-injury
- VAR: vector autoregressive