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# Unremitting Suicidality in Borderline Personality Disorder: A Single Case Study and Discussion of Technology in Clinical Care

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## CASE HISTORY AND TREATMENT

This report presents the case of a young woman, “Jane.” The case is followed by commentary from three experts in suicidal or self-destructive behavior and the use of technology in clinical care. Jane is a college-aged female with a diagnosis of borderline personality disorder (BPD) and a history of repetitive self-harm, including head banging and cutting, as well as chronic, unremitting suicidal ideation. Jane had been in an intensive residential program for many months, and during this time she was stepped up to inpatient psychiatric hospitalization multiple times due to concerns about safety. Jane had a history of multiple suicide attempts while in outpatient, residential, and inpatient settings. Most of these attempts occurred on hospital units using methods like self-strangulation with available objects, self-suffocation, and self-starvation.

Upon discharge from her last inpatient psychiatric admission, Jane was admitted to an intensive specialized residential program for adult women with borderline and other severe personality disorders. This unit integrates evidence-based treatments including dialectical behavior therapy (DBT),<sup>1</sup> mentalization based treatment (MBT),<sup>2</sup> and good psychiatric management (GPM).<sup>3</sup> The standard treatment protocol includes daily DBT diary cards, check-ins with the program’s 24-hour counselors,

and regular assessment of patient risk for behavioral dyscontrol, specifically self-harm and suicidal action.

Jane continued to have multiple episodes of cutting and head-banging. On standard assessment methods such as diary cards, Jane’s reported consistently high levels of suicidality, with very little variability. This resulted in hypervigilance among the staff, as it was difficult to discern when Jane’s level of immediate risk was spiking. The need to provide one-to-one attention to Jane was also causing burnout amongst the staff. After two months, Jane was again stepped up to inpatient care due to a lack of reduction in her level of suicidality, despite extensive coaching from interdisciplinary staff.

During hospitalization, the clinical team regrouped with two novel ways of assessing Jane’s risk for suicidal action. The first adjustment was for Jane to send daily emails to her primary therapist. This choice was driven by Hooley et al.’s finding that daily journaling improves deliberate self-injury, regardless of the topic of the journal entry.<sup>4</sup> The team also implemented daily ecological momentary assessment (EMA) prompts assessing momentary stress and enjoyment, and they purchased an over-the-counter wearable device to track Jane’s activity and sleep levels. In order to understand the data collected, the team gathered retrospective information from Jane about her subjective experiences during this phase of treatment.

Data was collected over a period of 44 days. The wearable device used was a Garmin Vivofit 4 smartwatch, and data regarding the patient’s activity and sleep were exported daily. Online surveys were sent to the patient three times a day at randomly generated times. The survey asked three questions: (1) What are you doing right now? (2) How enjoyable is it (1–5)? and (3) How stressful is it (1–5)?

In total, 133 EMA responses were recorded, with 99% compliance. Jane granted the first author and the research team access to her daily emails, her diary cards, and her medical chart. We conducted a literature review of narrative expressions of

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suicidality and constructs related to suicide risk and constructed a list of relevant terms. The term list included words and concepts related to (1) passive suicidal thinking, (2) active suicidal thinking and urges, (3) nonsuicidal self-injury urges, and 4) passive thoughts of nonsuicidal self-injury. (See Table 1 for a list of terms included.) Two research assistants read and manually coded each email's count of words/concepts from each category.

With the EMA data, we visualized the ratings of momentary stress and enjoyment levels, taking into account the patient's retrospective report of her experiences, as well as the highly structured daily schedule of the program. Her enjoyment stayed low throughout the EMA period, ranging only from 1–2 out of 5 (Mean = 1.13, SD = 0.34). Isolated spikes in enjoyment ratings typically occurred during solitary activities, consistent with her retrospective report that less stimulation was “comforting” and that she often lay in bed or watched television to “distract herself” from her distress. Other spikes in enjoyment were related to structured interactions

with the milieu. The patient's stress was more variable, ranging from 1–5 out of 5 (Mean = 2.57, SD = 0.83), though her ratings were consistently greater than or equal to 2 in the three weeks before she was again hospitalized. Spikes in stress tended to accompany regular treatment-related activities, which the patient retrospectively described as “overwhelming” due to both the required homework and the fact that she “was around other people” (Figure 1).

Using a Hidden Markov Model, a computational model for identifying hidden discrete states in dynamic data,<sup>9</sup> we fit a two-state model with the R package *depmix4*.<sup>10</sup> The two-state model captured two underlying states: high versus low stress. The model (Figure 2) indicates that Jane tended to oscillate between these states relatively quickly at the beginning of data collection, but that over time, duration of the high stress states increased. We additionally used a vector autoregression model to evaluate contemporaneous (i.e., same assessment) and lag relationships (i.e., across assessments) between stress and enjoyment (Figure 3). We fit the model with the R package *graphicalVAR*.<sup>11</sup> As expected, there was a negative contemporaneous correlation between stress and enjoyment. There was no significant lagged relationship between the two variables, meaning stress at Time 1 did not predict enjoyment at Time 2. There was a positive significant autocorrelation for stress, but not for enjoyment. This finding indicates that if Jane was already feeling stressed, she was likely to continue feeling stressed, but if she was already feeling some enjoyment, she was not significantly more likely to continue feeling enjoyment.

Jane's diary card showed no variability in her daily ratings of suicidal ideation throughout her stay. However, her daily emails included detailed and explicit mentions of suicidality. A simple visualization of the data by day showed repeated ebbs and flows of suicidality over time, reflected in active suicidality, passive suicidality, aloneness, and hopelessness. The active suicidality seems to increase over time, with the peaks steadily increasing, even while separated by periods of low acuity. Interestingly, diary card ratings of suicidal urges during the same time period remained relatively stable at a high level, with little variation (Figure 4).

To understand how the emails reflect changing levels of suicidality over time, we ran a nonlinear growth curve model with the predictor variable as day at the RTP and the outcome variable as the number of references to active suicidality in the daily emails (Figure 5). The result indicates an increase over time, as well as a bump prior to Jane's hospitalization, which may represent some warning signs of Jane's increasing risk.

There was high variability in both hours of sleep (Mean = 8.29, SD = 1.19, Min. = 6, Max. = 11.3) and activity level (i.e., steps; Mean = 7,745.35, SD = 2,893.15, Min. = 1,519, Max. = 13,523). Linear models of each variable indicate an overall decrease in activity level, paired with an increase in hours of sleep (Figure 6).

On the daily level, we looked at correlations between the EMA and wearable data (Figure 7). To do this, we took the daily averages of the EMA data. Aside from the negative correlation between stress and enjoyment, we do not see significant relationships, suggesting that these two types of data provide unique

**Table 1**

**Email Coding Terms**

**Passive suicidal thinking** - Burnap et al. (2015),<sup>5</sup> O'Dea et al. (2017)<sup>6</sup>

- Sleep and never wake or sleep forever
- Disappear or don't want to exist
- Can't go on
- Not worth living/nothing matters

**Active suicidal thinking**

- Overdose
- Hurt/kill myself
- End it all/end my life
- *Description of suicidal urge*

**NSSI urges**

- *Description of an explicit urge to self-harm*

**NSSI-related thoughts**

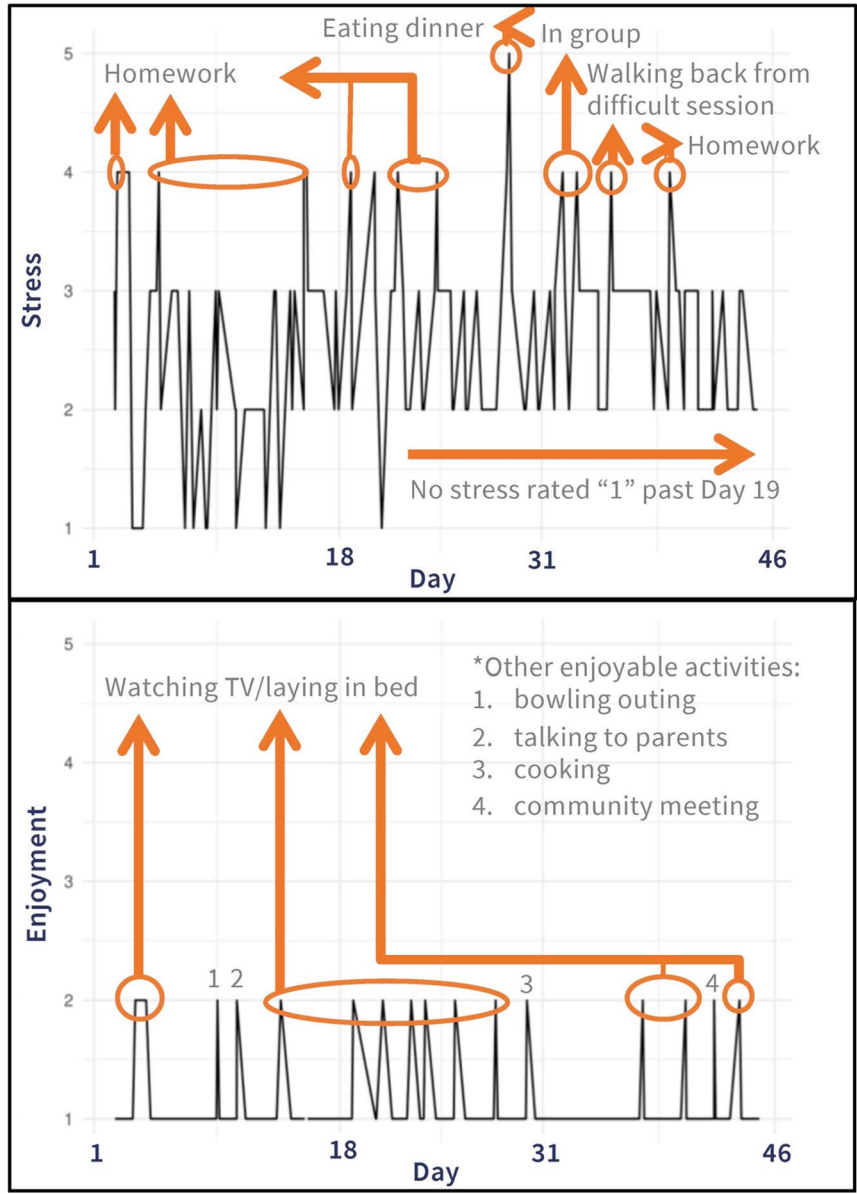
- *Descriptions of thoughts regarding self-harm, with no indication of a specific urge*

**Joiner's Interpersonal Theory of Suicide** - Joiner et al. (2002)<sup>7</sup>

- Feeling like a burden
- Thwarted belongingness - *coded as descriptions of incidents in which the patient tries to connect with a group and reports it to be unsuccessful*
- Hopelessness - *coded as the literal word “hopeless-” or an expressed feeling that things will “never” get better*

**Uncategorized** - O'Dea et al. (2017),<sup>6</sup> Van de Nest et al. (2018)<sup>8</sup>

- Death/die/dying
- Suicide/suicidal
- Aloneness
- A general “other” category - *used rarely, when content clearly referenced self-harm or suicidality but did not fit any other phrase or idea in this list*

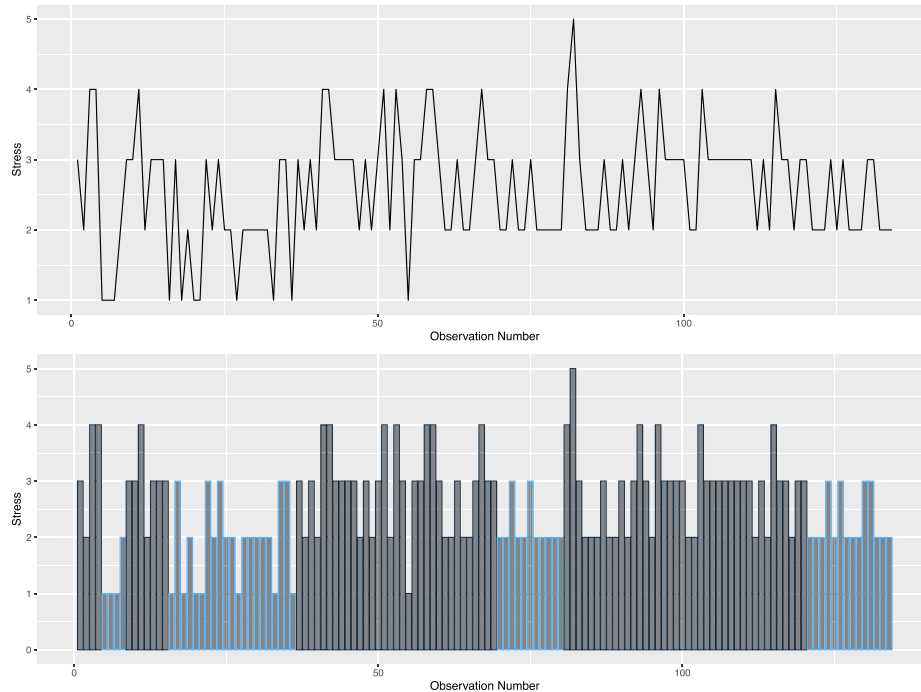


**Figure 1.** Stress and Enjoyment Ratings in Context of Patient Experience. Visual representation of EMA data on momentary stress and enjoyment levels. Enjoyment is low throughout, never exceeding 2 out of 5 ( $M = 1.13$ ,  $SD = 0.34$ ). Isolated spikes in enjoyment ratings mostly occurred during solitary activities. Stress ratings show greater variability, ranging from 1–5 out of 5 ( $M = 2.57$ ,  $SD = 0.83$ ). After day 19, stress was consistently rated 2 or higher.

information. Lastly, interested in correlations across EMA and the emails, we took a daily average of their stress ratings, and we found no significant relationship between the momentary stress and the active suicidal thinking reported in the emails (Figure 8). This suggests that these sources of data are providing unique information and the importance of understanding both momentary stress and a global, daily experience of suicidal thinking.

While there were no instances of self-harm or suicide attempts during data collection, Jane needed to be stepped up to inpatient treatment a second time, during which time clinical consultation was obtained regarding the effectiveness of residential care and treatment alternatives; the patient was ultimately discharged.

Jane, like most people with BPD, especially at intensive care levels, reported a history of suicidal behavior.<sup>12,13</sup> Despite the fatality of the disorder, with up to 10% completing suicide,<sup>14</sup> predicting when and which individuals are at greatest risk for lethal attempts remains elusive.<sup>15</sup> Severity of symptoms and risk of completed suicide in BPD vary within and between individuals. In Jane’s case, like many, reactive suicidal threats (i.e., verbal expressions of suicidal thoughts or nonlethal gestures without intent to die) can be a communication of distress in close relationships, in contrast to suicidal ideation with significant hopelessness and despair, which is thought to occur when the individual is alone and disconnected.<sup>16–18</sup> When suicidal communications of distress



**Figure 2.** Stress States Over Time. The top graph shows the patient's raw stress rating at each observation. The bottom graph is a representation of a Hidden Markov model of two proposed underlying states: high versus low stress. In the beginning of data collection, the patient oscillated relatively quickly between states. Over time the duration of high stress states increased.

are met with increased care and attention, the social response that emerges may be behaviorally reinforcing of some forms of self-destructive behavior.<sup>1</sup>

Identifying accurate suicide risk level is especially important to avoid this iatrogenic effect for those with BPD, but clinicians' ability to identify acute suicide risk in chronically suicidal patients is hindered by limitations of retrospective self-report measures, which prove imprecise and unreliable.<sup>19–21</sup> To address these limitations, an emerging body of literature focuses on EMA as a fine-grained, accurate assessment of momentary suicidal ideation and behavior, which may be interpreted as indicators of immediate risk. Suicide risk can change rapidly.<sup>22</sup> Research focusing on individuals diagnosed with BPD suggests that the relationship between momentary levels of negative affect and the intensity of suicidality is stronger in individuals with BPD than in those without BPD.<sup>23</sup>

With further research and development, EMA data may support suicide prevention through Just-In-Time Adaptive Interventions (JITAs), which can tailor the level of intervention based on the severity of the patient's EMA response.<sup>24</sup> A recent systematic review indicated that many existing EMA interventions lack empirical support for their feasibility and efficacy, but some interventions have yielded promising results such as significant reductions in suicidal ideation, emotional instability, and self-reported self-injury.<sup>25</sup> Additional measurement tools that may augment self-report EMA include wearable devices that record physiological data such as heart rate variability and skin conductance, as well as activity level, sleep, and other measurable behaviors. These data (all collected via wearable

sensors) were among the most important features in a model predicting severity of depressive symptoms.<sup>26</sup> Actigraphy monitoring demonstrates that rest-activity pattern disturbance (i.e., disturbed sleep) significantly predicts BPD symptom severity, and could reliably distinguish participants with BPD from participants with bipolar disorder and healthy controls.<sup>27</sup> The use of objective behavioral and physiological data may be especially useful in populations or settings where repeated self-report measures are unreliable or not feasible, such as with geriatric patients with dementia.<sup>28,29</sup>

Due to the clinical acuity of the patient, the analyses presented in the current article could not be conducted in real time. This approach also relies on the compliance and consent of the patient, and is more feasible in a residential or other supervised setting. Despite these limitations, this approach may be used as a template for future applications of monitoring chronic suicidality in residential or inpatient settings.

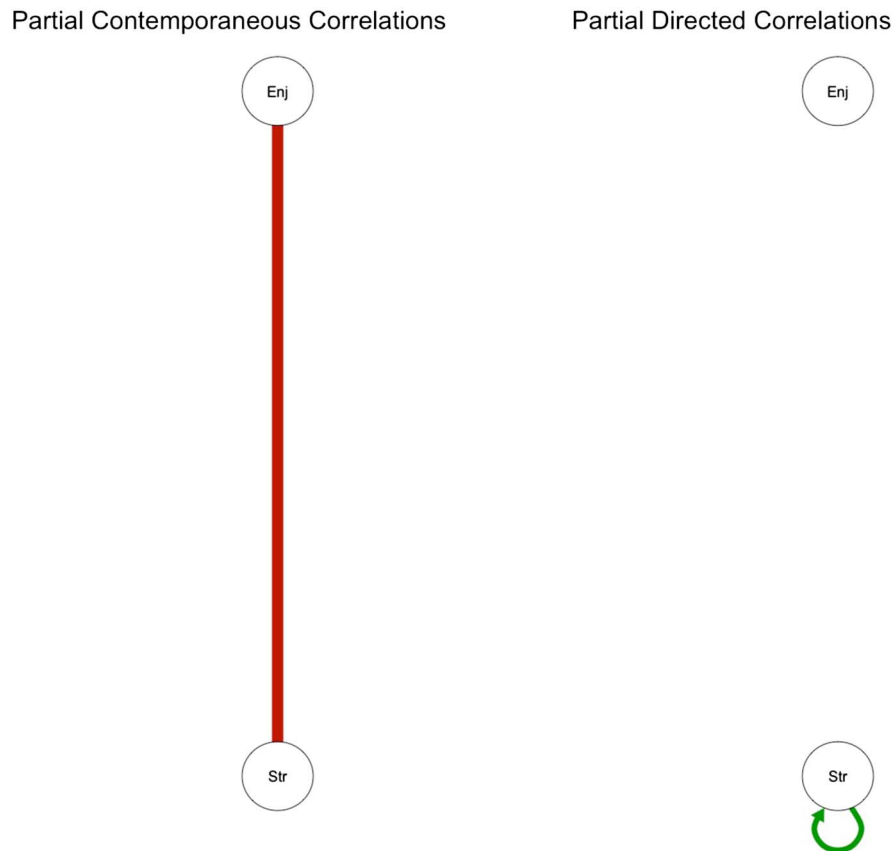
## QUESTIONS TO THE CONSULTANTS

- What is the value of EMA in the care of suicidal patients, above and beyond traditional self-report?
- What challenges need to be overcome before EMA and wearable devices can be used routinely in clinical care?

## COMMENTARY

### Mark J Goldblatt, MD

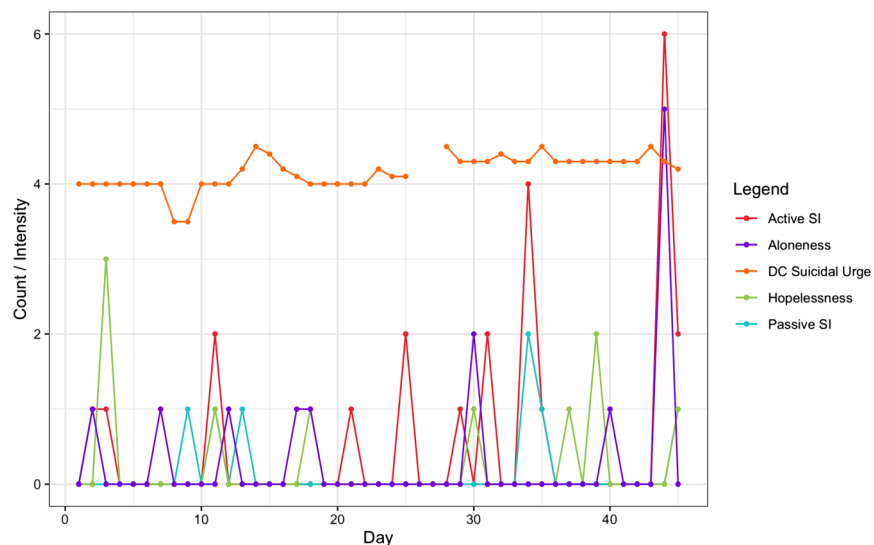
The treatment of suicidal patients with BPD is often complicated by the difficulty in distinguishing between serious suicide intent,



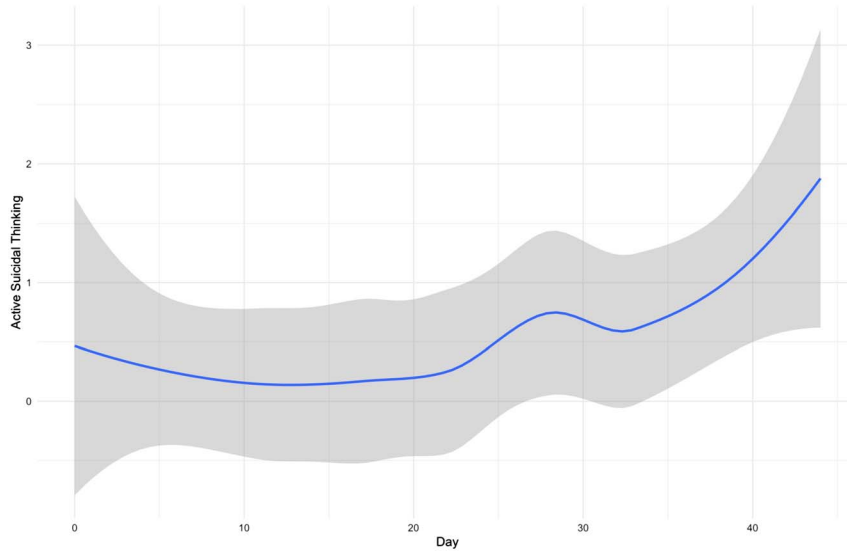
**Figure 3.** Vector Auto Regression Models of Stress and Enjoyment. Visual representation of a vector autoregression model evaluating contemporaneous and lag relationships between stress and enjoyment. There was a negative contemporaneous correlation between stress and enjoyment as shown on the left. Stress at Time 1 did not predict enjoyment at Time 2, as indicated by the lack of significant lagged relationship between the two variables.

probably related to a sense of disconnection and aloneness, and self-harming behaviors, which can be non-life-threatening communication of distress. Such a distinction may not always

be clearly apparent to the patient. The inability to recognize and respond to internal cues may exacerbate the need for violent self-attack.



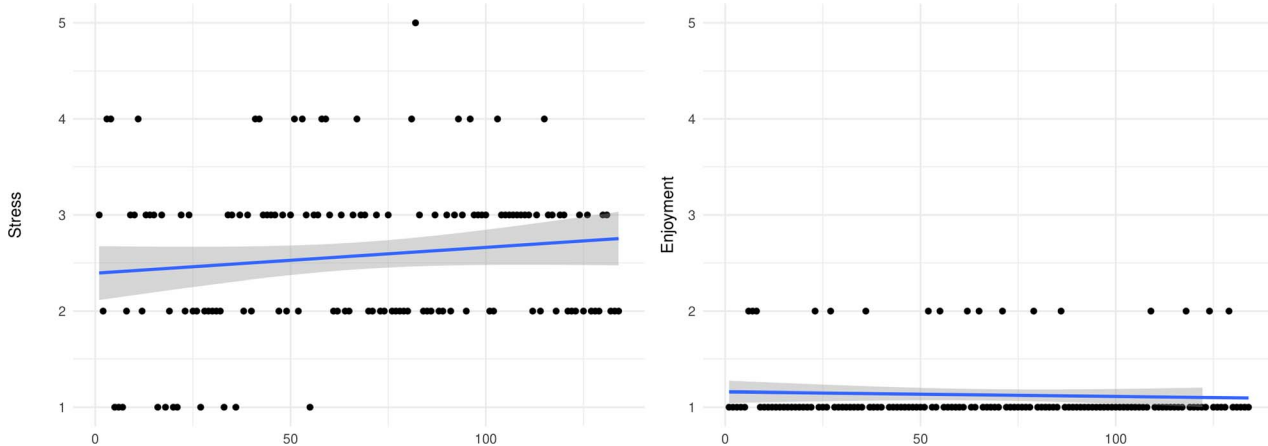
**Figure 4.** Suicidality in Daily Emails and Diary Cards. Graph of daily data on active suicidality, passive suicidality, aloneness, hopelessness, and diary card ratings of suicidal urges over 45 days. Peaks of active suicidality increase over time, even while separated by periods of low acuity. Diary card ratings of suicidal urges remain stably high with little variation.



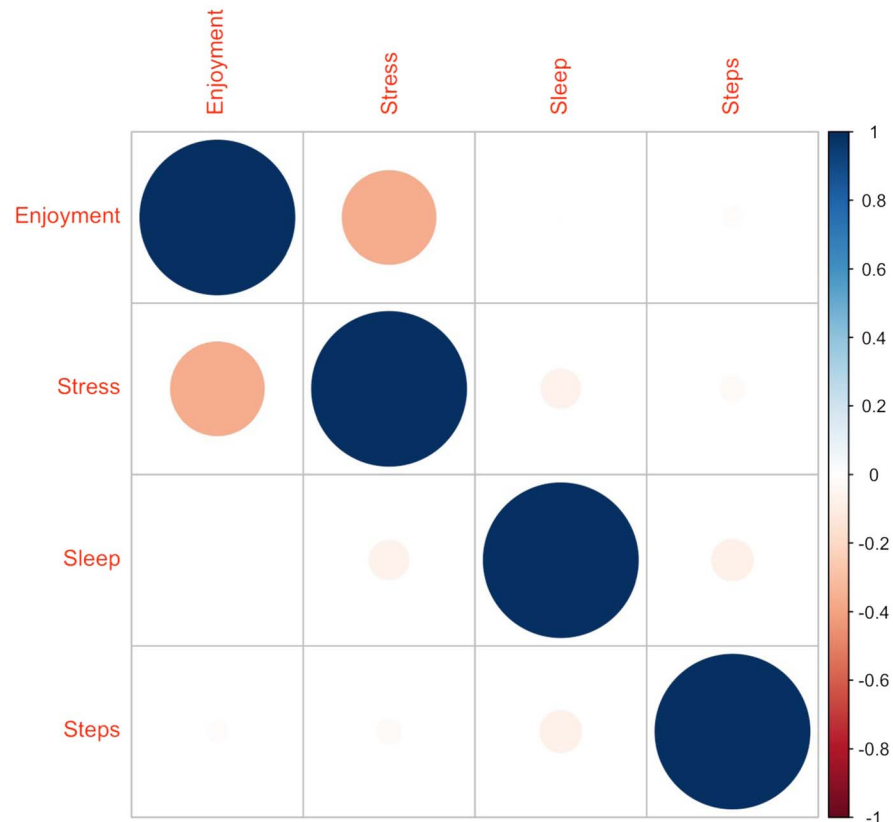
**Figure 5.** Nonlinear Growth Curve Model of Active Suicidality. Graph of nonlinear growth curve model of number of references to active suicidality in emails by day. Active suicidality by this measure increases over time, with an uptick prior to hospitalization.

Validation from an external source (the therapist) produces an intrapsychic reaction that may delay self-destructive action.<sup>30</sup> The appropriate therapeutic response decreases distress, allows the patient to feel contained, promotes self-awareness and models future responses that enable self-containment. The hope is that over time, this function is internalized, and the patient is able to recognize these indications of internal distress and react to self-soothe without self-destructive regression. EMA enables some patients to become aware of bodily expressions of their distress and may then function as indicators of approaching suicide risk. Data obtained through such methods adds to growing awareness that informs the therapist, and ultimately the patient, about severity of desperation that may be linked to suicidal intent. Used in this manner EMA can augment suicide prevention by supporting the patient through episodes of time-limited despair.

A key benefit of using this technology in the residential setting is the opportunity for staff who have a longitudinal relationship with the patient to work with the granular data in a more meaningful way. Patients with chronic suicidal distress are very difficult to treat as they appear resistant to the best efforts of the treatment team, often leading to therapeutic burnout or countertransference despair. In the case reported here, severe suicidal distress and self-destructive behavior continued despite inpatient and residential treatment programs. Unremitting suicidality that is unresponsive to the usual interventions emboldened the new treatment team to pursue an innovative therapeutic approach. Although the outcome in this particular case appears mixed (the patient did not self-harm or attempt suicide during this time period, but did require re-hospitalization), the treatment team’s novel approach suggests they were actively trying to communicate to the patient that



**Figure 6.** Linear Trends in Stress and Enjoyment. Ratings of stress (left graph) and enjoyment (right graph) over 133 observations. Stress level shows high variability throughout each day while enjoyment level stays stably low, between 1 and 2, throughout.



**Figure 7.** Correlations between Stress, Enjoyment, Sleep, and Activity. Visual representation of correlations between EMA and wearable data using daily averages of EMA data. The only significant relationship is a negative correlation between stress and enjoyment.

they had not given up and believed her distress could be alleviated. The team held out this hope and were willing to go to extraordinary lengths to help the patient recognize their commitment to helping her. The residential treatment setting enabled the clinical team to monitor and encourage the patient's compliance in maintaining multiple streams of data collection, which would be more difficult in an outpatient or less well-resourced clinical setting. The meta-communication was that people cared about her and wanted to help, even though previous attempts had been unsuccessful. This addressed two crucial suicide preventing functions, i.e., the importance of feeling connected to people or things<sup>31</sup> and the role of hope associated with suicide.<sup>32,33</sup>

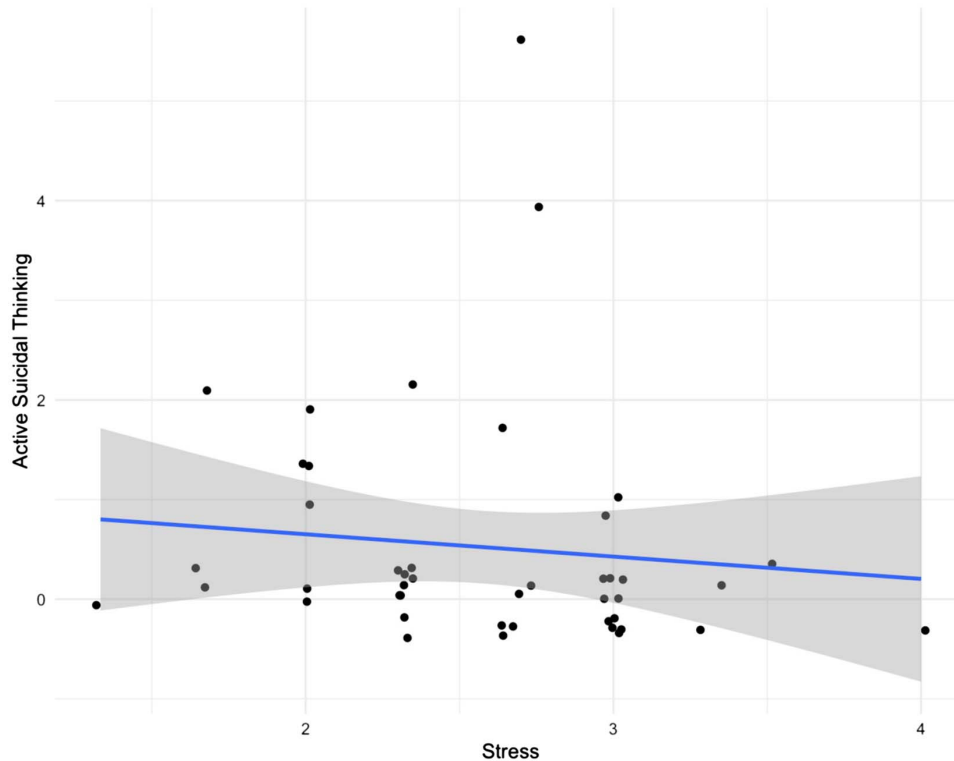
The clinical tracking of subjective distress through objective data holds the promise that the underlying metabolic pathology can be identified and addressed. Clinical interaction with concerned staff members who are empathically interested in the patient's well-being has previously been assumed to be essential. However, in this age of remote treatments and digital interventions, perhaps we are coming to realize that different is not inferior, but better suited to nontypical patients. Self-assessment utilizing digital tools can enable patients to recognize and communicate fluctuations in their mental functioning. While residential treatment programs may be an ideal setting to pilot the use of EMA and wearable technology, some of the data

collected is limited by the structure of the program. For example, the sleep and activity levels are partially constrained by group activities and the daily schedule. Collecting EMA and activity data may be more informative when collected during outpatient treatment, when the patient's activities are naturalistic and unconstrained.

However, in any treatment setting, communication to members of the treatment team allows patients to feel contained in order to delay or eliminate self-harming actions. The hope is that the self-containing function may be internalized over time, without the need for violent expression. Helping patients realize the of digital tools and the pathway to subjective containment contributes to a therapeutic alliance that can be suicide preventing. JITAIs can be extremely useful in this regard, especially when the patient is in outpatient or no treatment, promoting self-awareness in the moment to prevent violent self-attack.

Traumatic responses to suicide attempts linger with patients, loved ones, and clinicians for long periods of time following the violent action itself.<sup>34</sup> Prevention of self-violence reduces interpersonal conflict, stress, and burnout. Psychoeducation about the effectiveness of self-monitoring develops from interpersonal connections with members of the treatment team.

This encouragement supports patients in their efforts to monitor and articulate their inchoate desires for relief through self-violence, which in turn promotes containment and deepens interpersonal



**Figure 8.** Relationship between Active Suicidal Thoughts and Stress. Graph of daily average of stress ratings and active suicidal thinking as reported by email. No significant relationship was found.

connections. In this way, self-attacking actions may be decreased as affective distress calms down. EMAs can play an important role in helping patients and staff recognize indicators of psychic distress and approaching suicidal dangers, enabling alternative actions that encourage growth and avoid the intrapsychic experience of trauma. However, further research is needed to identify the categories of data that are most useful in predicting risk and improving self-monitoring in order to justify wide-scale use of wearable devices and EMA data collection.

The evolving uses of technology in the clinical care of self-destructive behavior highlights innovative thinking and a therapeutic commitment to suicide prevention for patients with BPD. Further studies are needed to evaluate these interesting and potentially valuable tools, including the use of EMA, for areas of effectiveness.

#### Chelsey R. Wilks, PhD

BPD is a complex disorder characterized by instability in affect, interpersonal relationships, behavior, and identity. Among the interventions that are effective for BPD, dialectical behavior therapy (DBT)<sup>30</sup> is among the most disseminated and studied.<sup>35</sup> DBT centers around Linehan's biosocial theory,<sup>36</sup> which conceptualized BPD as a disorder of pervasive emotion dysregulation that developed due to a transaction between a biological vulnerability toward high emotionality and a pervasive invalidating environment. In this way, individuals with BPD learn ineffective behavioral strategies (e.g., nonsuicidal self-injury [NSSI],

anger outbursts) to manage their emotions. DBT therapists conceptualize that problem behaviors develop or are maintained due to these skill deficits, and therefore, work with clients to impart more skillful behavior to supplant functionally equivalent ineffective behaviors. Individual DBT therapists prioritize treatment targets by the severity of their clients' condition.

Individuals who are actively engaging in life-threatening behaviors such as NSSI or other suicidal behaviors are considered "stage one" clients, and their life-threatening behaviors are closely monitored and managed. In the case of Jane, she had evidenced several episodes of suicidal behavior, including potentially lethal suicide attempts and ongoing self-injurious behaviors. It is the top priority of a DBT therapist to closely monitor and track the client's suicidal behaviors, which is done using a daily diary card. The DBT diary card serves two important functions: to monitor target behaviors that occur outside therapy and to guide each individual session. If a client reports that she engaged in a "target behavior" (defined as an ineffective behavior directly targeted in therapy), the therapist will typically conduct both a chain and solution analysis. Via the chain analysis, the therapist and client work backward to try to understand the controlling variables that led to engaging in the target behavior(s). Along the way, the therapist and client work collaboratively to identify and rehearse more effective strategies that could have been employed and may have interrupted the chain of events that caused the target behavior.



Unfortunately, the DBT diary card and subsequent chain analyses hinge on whether clients accurately complete it. In the case of Jane, her inability to accurately fill out the diary card hampered her progress. She was continuing to engage in life threatening behaviors and the self-reported content from the diary card was insufficient to facilitate treatment.

The clinical team overseeing Jane's treatment decided to implement a variety of objective and subjective data collection methods to better understand and more accurately evaluate Jane's emotional and behavioral dysfunction. These included a three-time daily EMA to assess for activities, enjoyment, and stress level, and a Garmin Vivofit 4 smartwatch to monitor physical activity and sleep, as well as access to Jane's emails and medical chart. These adjunctive data streams have the capacity to provide useful, real time clinical data that can augment the course of DBT. In particular, EMA captures momentary mood, urges, and behaviors that are an accurate snapshot of an individual's current state whereas the diary card assesses for a day-level peak. Moreover, clients are expected to complete the diary card daily, but the paper and pencil format makes it less convenient to complete as intended. For Jane, it was observed that she tended to report more stress than enjoyment, and that her stress was pervasive, while enjoyment was more fleeting and rarer. Wearable sensor data provide a novel opportunity for evaluating objective behavioral data such as steps, sleeping patterns, and heart rate. In Jane's case, her wearable data indicated that her sleep and activity patterns were highly irregular. Finally, Jane's emails provided highly relevant contextual information about her functioning, mood, and well-being. Jane's emails revealed explicit mentions of suicide that prospectively predicted her hospitalization. Interestingly, there were no correlations between Jane's explicit mentions of suicide via email and her EMA or activity data.

These sorts of data are being used to better understand and predict psychological disorders and other forms of behavioral dysfunction such as depression,<sup>26</sup> and suicide.<sup>22</sup> More work is needed to better incorporate these data in clinical practice; in particular, they are messy, require computationally complex systems, and are hard to interpret. Paper-and-pencil daily diaries are ubiquitous in DBT because therapists can quickly glance at and understand the patterns and correlations and assess for the client's thoughts if more context is needed. The inherent complexity of sensor, EMA, and email (or text) data preclude their application in real time clinical care—in this case report, several analytic techniques were used to contextualize the data. The data would be more meaningful if they could be aggregated within a larger sample in order to compare trajectories with other individuals. Furthermore, data cleaning and analyses occurred after the client discontinued therapy, inhibiting its clinical utility. That being said, there is significant promise of incorporating these sorts of data into clinical practice, particularly in cases where traditional assessment methods are insufficient or unreliable.

Finally, it is important to note that Jane fully consented to the treatment team using and interpreting these data to facilitate

treatment. In an era of big data and artificial intelligence, consent should be the guiding principle, especially in predicting and monitoring mental health conditions.

### Ipsit Vahia, MD

Jane's case is an elegant illustration of how clinical care is in essence a process of collecting, analyzing and reacting to data. The "traditional" and "digitally enhanced" approaches to care are fundamentally identical processes, distinguished primarily by the volume and sources of data involved. Here, the clinical team gathered three different tiers of data: 1) clinical history and mental status examination, 2) ongoing assessment of the patient's response to the evidence-based treatments provided on the unit, and 3) data gathered digitally in real time via EMA and motion tracking. The first tier, represented here by Jane's clinical history, remains foundational for diagnosis and clinical formulation across psychiatry and mental health care. Based primarily on self-report from patients or caregivers and augmented by other collateral information (e.g., lab tests, neurocognitive evaluations, neuroimaging), its goal is to capture the breadth of clinical symptomatology and help clinicians narrow diagnostic considerations.

The second tier of clinical data represents objective, clinician-reported/observed data. In Jane's case, this captured an understanding of a higher level of risk on admission to the specialized care unit, and the use of daily diary cards. The second tier incorporates objective information that clinicians consider in the context of the first layer of data to help refine treatment approaches. While not applied in this case, measurement-based care also represents a systematized form of collection of the second layer of data.

Historically, these two tiers of data collection have represented the totality of clinical care. However, their limitations have long been recognized. A significant issue is that these approaches are not able to capture behavior changes, or responses to triggers that happen in real time. This is of particular relevance and urgency for persons such as Jane who are in treatment for volatile, high-risk behaviors that could get triggered spontaneously and lead to negative outcomes. It is only over the past five to ten years that the emergence and subsequent ubiquity of digital devices such as smartphones or wearables has opened the possibility of gathering a third tier of real time data on such behaviors. The case of Jane illustrates how such data can lead to new and highly personalized insights. In her case, it led clinicians to identify triggers for suicidality. Other studies have demonstrated that this approach can be applied for a range of clinical scenarios, including detection of behavioral and psychological symptoms in dementia and relapse of symptoms in schizophrenia.<sup>37,38</sup>

However, significant challenges will have to be overcome before such approaches can become the standard of care. One is the effort and resources required to store, manage and analyze the extraordinary volumes of data collected through digital assessment methods. Even EMA, which collects far fewer data points than motion trackers, still requires a high degree of

analytic capability. The vast majority of data are not of clinical relevance, and it is time-consuming and effort intensive to identify which data points may inform clinical decision-making. Most publications outlining the effectiveness of such data-based approaches are small case studies, conducted in tertiary academic environments that have the resources to support the necessary analytics. To replicate this approach at scale will require higher levels of investment in developing the computational infrastructure needed to provide real time insights. It is not a coincidence that the literature on such approaches overwhelmingly involves post hoc rather than real time analysis of data, despite the potential for such data to inform real time intervention. It is likely that the cost effectiveness of these approaches will need to be demonstrated as institutions and clinical services make the investment in such infrastructure.

Beyond data-related challenges, however, there are two broader concerns that may be far more relevant in determining whether digitally augmented care achieves its full potential. The first is the risk of technologically driven care creating new health care disparities. While it has the potential improve access and reach of care, to achieve this requires that devices such as smartphones and infrastructure such as internet access and adequate data plans are equitably distributed, yet it is well established that this is not the case.<sup>39–41</sup> This must be considered and mitigated while digitally augmented care is in relative infancy.

The second issue is of clinician data fatigue and burnout.<sup>42</sup> Studies have demonstrated that a high volume of messages and information can lead to clinician burnout, and the responsibility for processing and responding to additional digital data is likely to amplify this. To address this risk will require a multi-pronged approach that includes development of reliable analytic algorithms that can process data and achieve sensitivity and specificity in detecting relevant signals. It will also involve the creation of best practices and regulatory frameworks that balance the importance of incorporating digital insights into care without creating new potential liabilities. Jane's case demonstrates how digital tools can fundamentally alter clinical outcomes for the better, but implicit in the narrative are the significant barriers that will need to be overcome before this approach can be scaled.

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