Published in final edited form as:
Behav Ther. 2017 September ; 48(5): 614–623. doi:10.1016/j.beth.2017.01.002.

Mobile phone-based mood ratings prospectively predict psychotherapy attendance

Emma Bruehlman-Senecal[a], **Adrian Aguilera**[a,b], and **Stephen M. Schueller**[c]

[a]University of California, Berkeley, School of Social Welfare, Berkeley, CA, USA

[b]University of California, San Francisco, San Francisco General Hospital, Department of Psychiatry, San Francisco, CA, USA

[c]Northwestern University, Feinberg School of Medicine, Chicago, IL, USA

Abstract

Objective—Psychotherapy non-attendance is a costly and pervasive problem. While prior research has identified stable patient-level predictors of attendance, far less is known about dynamic (i.e., time-varying) factors. Identifying dynamic predictors can clarify how clinical states relate to psychotherapy attendance and inform effective “just-in-time” interventions to promote attendance. The present study examines whether daily mood, as measured by responses to automated mobile phone-based text messages, prospectively predicts attendance in group cognitive-behavioral therapy (CBT) for depression.

Method—Fifty-six Spanish-speaking Latino patients with elevated depressive symptoms (46 women, mean age = 50.92 years, SD = 10.90 years), enrolled in a manualized program of group CBT, received daily automated mood-monitoring text messages. Patients’ daily mood ratings, message response rate, and delay in responding were recorded.

Results—Patients’ self-reported mood the day prior to a scheduled psychotherapy session significantly predicted attendance, even after controlling for patients’ prior attendance history and age (OR = 1.33, 95% CI [1.04, 1.70], p = .02). Positive mood corresponded to a greater likelihood of attendance.

Conclusions—Our results demonstrate the clinical utility of automated mood-monitoring text messages in predicting attendance. These results underscore the value of text messaging, and other mobile technologies, as adjuncts to psychotherapy. Future work should explore the use of such monitoring to guide interventions to increase attendance, and ultimately the efficacy of psychotherapy.

Keywords

text messaging; attendance; mHealth; psychotherapy; depression

Correspondence should be addressed to Adrian Aguilera (aguila@berkeley.edu) and Emma Bruehlman-Senecal (emma.bruehlman-senecal@berkeley.edu).

Non-attendance of psychotherapy is a pervasive problem—one that is linked to poor therapeutic outcomes (Mitchell & Selmes, 2007) and significant costs to clinics (Lefforge, Donohue, & Strada, 2007). Mobile phone-based short messaging service (i.e., SMS or "text messaging") has increasingly been used to reduce the problem of non-attendance through the delivery of appointment reminders (Branson, Clemmey, & Mukherjee, 2013; Sims et al., 2012), and to encourage between-session psychotherapy engagement (e.g., by enabling two-way interactions between patients and clinicians; Aguilera, & Muñoz, 2011). However, no research has examined whether information sent by patients via text during psychotherapy can be used to predict when patients are most at risk of missing scheduled sessions. This information could provide a window into patients' daily lives, helping to clarify how clinical states relate to important treatment processes, such as psychotherapy attendance. Moreover, data that enables clinicians to identify instances at which patients are at heightened risk of non-attendance could prove invaluable to increasing attendance, powering "just-in-time" outreach to patients when they need additional support to stay engaged. In depression, daily mood, which has been found to index depressive symptom severity (Aguilera, Schueller, & Leykin, 2015), may be a particularly important predictor of attendance. The present research explores whether responses to daily mood-monitoring messages predict future psychotherapy attendance among patients with depression.

Non-attendance of Psychotherapy

Non-attendance of psychotherapy is recognized as a significant barrier to effectively implementing evidence-based mental health interventions in the community, posing substantial costs to patients and their health care providers (Mitchell & Selmes, 2007). Sporadic attendance can lead to missed opportunities to learn, review, and practice psychotherapeutic skills, and consequentially may result in less than optimal benefit from psychotherapy (Aguilera, & Muñoz, 2011). Psychotherapy no-shows also lead to loss of income for clinics, wasted staff time and resources, and increased wait times for others in need (Chen, 1991; Lefforge et al., 2007).

The importance of regular, sustained engagement with psychotherapy is further supported by the dose-effect literature, which demonstrates that patients' likelihood of making and maintaining meaningful treatment gains increases with the number of psychotherapy sessions attended (Hansen, Lambert, & Forman, 2002). Reflecting these findings, early termination, defined as attending fewer than a specified "optimal" number of sessions (Swift & Greenberg, 2012), has been linked to a number of detrimental outcomes, including increased rates of medication non-adherence, lesser improvement in psychiatric symptoms, and higher rates of readmission and rehospitalization (Baekeland & Lundwall, 1975; Chen, 1991; Killaspy, Banerjee, King, & Lloyd, 2000; Mitchell & Selmes, 2007). Given the benefits of regular attendance, and the costs associated with early termination, it is important to have a better understanding of factors that predict attendance.

Prior research has identified a number of patient-level demographic factors that predict whether patients will attend psychotherapy regularly enough to be classified as "completers" rather than "early terminators". Attendance has been found to be lower among low-income and ethnic minority patients (Barrett, Chua, Crits-Christoph, Gibbons, & Thompson, 2008; Reis & Brown, 1999; Wierzbicki & Pekarik, 1993), as well as patients with lower education levels (Barrett et al., 2008; Garfield, 1994; Swift & Greenberg, 2012). Younger patients have also been found to have lower attendance rates (Barrett et al., 2008; Swift & Greenberg, 2012), although this link has not been consistently demonstrated (Garfield, 1994; Reis & Brown, 1999; Wierzbicki & Pekarik, 1993).

While prior research provides important information about *who* is at risk of non-attendance, considerably less research speaks to the question of *when* patients are least likely to attend psychotherapy. Information about time-varying factors that predict attendance is critical, because this information could be used to efficiently time outreach to patients who are at particularly high risk of non-attendance in a given week. It could also be used to shape intervention content—for example, if non-attendance is linked to low mood states, this suggests that it may be important to integrate cognitive and behavioral interventions that motivate patients to attend psychotherapy despite a low mood.

Identifying Time-Varying Predictors of Psychotherapy Attendance

Traditional intervention research collects patient data only at a few key points (i.e., at initial intake, during psychotherapy sessions, and at follow-ups). This misses patients' daily experiences as they relate to clinical disorders. Depression, for example, tends to be characterized by high levels of negative affect and low levels of positive affect (Watson et al., 1995), which is evident in depressed individuals' self-reported daily affective experiences (Bylsma, Taylor-Clift, & Rottenberg, 2011). For patients receiving psychotherapy for depression, fluctuations in daily mood may serve as an important time-varying predictor of missed appointments. Daily and weekly mood has been found to be a reliable proxy for elevated depressive symptoms (Aguilera et al., 2015), and symptoms of depression are more commonly expressed when low moods occur (Miranda, Person, & Byers, 1990). Many depressive symptoms, including reduced motivation (Treadway & Zald, 2011), reduced gross motor activity (Sobin & Sackeim, 1997), and social withdrawal (Segrin, 2000) may interfere with attendance in psychotherapy. Indeed, retrospective reports from both psychotherapy patients (Killaspy et al., 2000) and clinicians (DeFife, Conklin, Smith, & Poole, 2010) indicate that elevated psychiatric symptoms are a common reason patients skip scheduled sessions.

Mobile technology adjuncts to psychotherapy, such as text messaging, may be a particularly useful tool for identifying time-varying predictors of attendance, such as low mood, because they allow for a naturalistic assessment of processes in flux between scheduled psychotherapy sessions (Aguilera & Muench, 2012; Luxton, McCann, Bush, Mishkind, & Reger, 2011). They also facilitate sampling of patients' experiences in close proximity to scheduled sessions. While not empirically demonstrated, it seems plausible that patients' experiences just prior to a scheduled psychotherapy session may predict their likelihood of attendance more robustly than more distant experiences. Mobile technology adjuncts also allow for data collection from patients who fail to show up to scheduled sessions, providing relevant information about predictors of attendance from a wider range of patients than would otherwise be possible. Additionally, these adjuncts enable novel forms of data collection, such as information about the frequency and speed of responding to treatment-related messages, which may index patients' level of engagement with psychotherapy, and predict future attendance. While mobile technology adjuncts show promise for identifying time-varying predictors of psychotherapy attendance, to the best of our knowledge no prior research has used them to achieve this goal.

The Present Research

The goal of the present research was to determine whether patient responses to mood-monitoring text messages—sent daily between scheduled group CBT (GCBT) sessions—could be used to prospectively predict patients' likelihood of psychotherapy attendance. We expected that three types of information, gleaned from these mood-monitoring texts, would predict attendance: (1) daily mood, (2) consistency and frequency of responding, and (3) speed of responding. We outline our rationale for each prediction below.

Daily mood

As described above, mood at the daily level, as well as averaged over the course of a week, has been found to index depressive symptom severity (Aguilera et al., 2015). As such, daily mood measurements may provide critical information about when patients may miss psychotherapy due to elevated psychiatric symptoms. Furthermore, mood monitoring is a core feature of many evidence-based treatment programs, including CBT (Cohen, Edmunds, Brodman, Benjamin, & Kendall, 2013), so having patients respond to daily mood monitoring texts is consistent with the therapeutic rationale. Given past research, we predicted that low mood in close proximity to a scheduled psychotherapy session would predict a lower likelihood of attendance.

Response rate

We expected that consistent and frequent responding to daily mood-monitoring texts would positively predict attendance. Self-monitoring of mood is a common homework assignment in CBT, and completion of self-monitoring homework is theorized to both require and reinforce motivation to engage with psychotherapy (Cohen et al., 2013; Detweiler & Whisman, 1999). Thus, consistent and frequent responding to mood-monitoring texts may positively predict future attendance, because this response pattern may reflect sustained engagement with psychotherapy. The expectation that more frequent responding would positively predict attendance is also consistent with research demonstrating a link between more frequent homework completion and lower attrition rates (Burns & Nolen-Hoeksema, 1992; Persons, Burns, & Perloff, 1988).

Response delay

We expected that faster responses to incoming mood-monitoring text messages might positively predict attendance. Although there is no empirical literature that directly speaks to speed of response as an index of engagement, it seems plausible that response delay, like response rate, might capture patient willingness to engage with psychotherapy. Given the lack of prior research on this variable, we treat analyses including response delay as exploratory.

We examined each of these three types of texting variables (i.e., daily mood, response rate, and response delay) over two relevant time frames: 1) the week leading up to a scheduled psychotherapy session and 2) the day immediately prior to that session. We were uncertain which time frame would more robustly predict future attendance. On one hand, average weekly responses may be a stronger predictor, because they may better capture sustained low mood and/or loss of motivation characteristic of individuals with elevated depressive symptoms. Weekly responses are also less likely to be affected by momentary situational influences. Conversely, patients' emotional and/or motivational state just prior to a scheduled psychotherapy session might have a larger impact on attendance, because patients may be deciding whether to attend in close proximity to a scheduled session. The possibility that patients' emotional state just before psychotherapy may influence their decision to attend is consistent with research demonstrating that emotions that are experienced at the time of decision-making can exert a powerful influence on individuals' decisions (e.g., by shaping memory processes, probability judgments, etc.; Lowenstein & Lerner, 2003). Given the compelling arguments for both time frames, we examined both, and did not have strong hypotheses regarding which time frame would more robustly predict attendance.

We explored these questions within a sample of low income, Spanish-speaking Latino patients. We focused on Latino patients because Latinos constitute a plurality of the patients treated within the public sector hospital in which this study was conducted (San Francisco Department of Public Health, 2014–2015). Additionally low income and ethnic minority patients, including Latinos, have been found to have lower psychotherapy attendance rates. Thus, information regarding time-varying predictors of attendance is arguably most needed within these populations (see Swift and Greenberg (2012) for a similar argument).

Method

Participants

Participants were 56 patients (46 women, mean age = 50.92 years, *SD* = 10.90 years, range = 28–68 years) referred by their primary care providers to an embedded mental health service at a public sector hospital (San Francisco General Hospital). All patients identified as Latino/a, were Spanish-speaking, and were low-income, as evident by their eligibility for public health insurance (e.g., Medicaid). The University of California, San Francisco IRB approved this study, and all participants provided informed consent.

Structure and Processes of Group CBT and the Text-based Adjunct

Referral and initial screening—Patients' primary care providers referred them to a behavioral health clinician when there were concerns about depression due to qualitative symptom expression or a positive screen based on the PHQ-9 (Kroenke, Spitzer, & Williams, 2001). Patients were considered eligible for GCBT for depression if they had a PHQ-9 score of 10 or above at the time of initial assessment by the behavioral health clinician. Patients with comorbid substance abuse disorders, psychosis, or whose primary problem was grief were not considered for group psychotherapy, and were referred to more appropriate services. Patients who attended at least one GCBT session, and who interacted with the text-messaging component of psychotherapy, were included in this study. Most patients (68%) already knew how to text prior to this study, but those who did not were trained by study staff. Mobile phone ownership was not a requirement of the study, although all but one patient did own a mobile phone. This patient was provided one for the duration of the study.

Content and structure of the group psychotherapy sessions—Clinicians used the Manual for Group Cognitive-Behavioral Therapy of Major Depression (Muñoz et al., 2000) from 2010–2014 and the updated BRIGHT manual (Miranda et al., 2006) from 2014–2016. The BRIGHT manual has the same structure and similar content as the Manual for Group Cognitive-Behavioral Therapy of Major Depression, but contains revisions for increased readability and graphics. The content of both manuals is based on cognitive, behavioral, interpersonal, and health-based strategies for mood management, with all sessions emphasizing mood monitoring as a key component of psychotherapy.

Both depression treatment manuals are updated versions of a 1986 manual developed for use with public sector patients (Muñoz, Aguilar-Gaxiola, & Guzmán, 1986), which has been found to be efficacious in low-income and ethnic minority populations (Organista, Muñoz, & Gonzalez, 1994) (for additional details on cultural adaptations to the protocols, see Aguilera, Garza, & Muñoz, 2010; Muñoz & Mendelson, 2005). The groups were led by two bilingual therapists—a licensed clinical psychologist and/or a licensed clinical social worker with expertise in CBT and in treating low-income and Latino patients. Both the GCBT sessions, and all of the text messages and measures, were delivered in Spanish.

Psychotherapy was structured as a continuously running group, and was designed to last 16-weeks, with group sessions offered weekly. Patients were admitted to the group on a rolling basis to minimize wait times. Some patients were allowed to continue to attend group psychotherapy after the 16-week mark as space permitted (e.g., if they were still symptomatic or if they wished to make up missed content), but we focused our analyses on the first 16 weeks of psychotherapy offered to patients, as this time frame represented potential completion of all content within the treatment manuals.

Structure of text-based adjunct—All patients received a daily, automated mood-monitoring text (i.e., “What is your mood right now on a scale of 1–9?”), at a randomly determined time each day between 8am and 9pm, with the time of receipt varying each day for each patient. Patients were asked to reply to each message via text with a number between 1–9 indicating their mood.[1] Patients were told that the clinic was implementing text messaging as a method of helping patients practice CBT-based skills in their daily lives, as well as to let therapists know how they were doing throughout the week. Prior qualitative research provides evidence that depressed Spanish-speaking Latino patients perceive this text-based adjunct as a helpful and supportive mood management tool (Aguilera & Berridge, 2014; Aguilera & Muñoz, 2011).

[1]If a patient texted more than one numerical response to this mood-monitoring message, which occurred on approximately 4.7% of all days on which patients responded, their responses were averaged at the daily level to create a single daily measure of mood.

While the majority of patients began receiving texts during their first week of psychotherapy ($n = 42$), a subset of patients ($n = 14$) started receiving texts more than a week after GCBT began ($M = 33.3$ days into GCBT, $SD = 23.7$ days). The day at which patients first began receiving texts did not interact with any of the texting variables to moderate the reported findings (all *z*s < 1.60 in absolute value, all *p*s >.10), so this variable is not discussed further.

Measures

Weekly attendance—Patients received an attendance score of 1 (attended) or 0 (absent) for each of the 16 weeks of GCBT. Patients attended an average of 6.98 sessions, with considerable variation around this mean ($SD = 4.95$, range = 1 to 16 sessions).

Measures derived from mood-monitoring texts[2]—Patients received an average of 91.23 mood-monitoring texts in the first 16 weeks of psychotherapy ($SD = 24.72$ texts). Due to system errors, texts were not sent to patients on a small percentage of the days that they were scheduled to go out (3.7%). Additionally, upon their request, eleven patients stopped receiving text messages within the 16-week treatment period (average day at which messages were stopped = day 70, $SD = 29$ days). Patients who stopped receiving messages before the end of psychotherapy did not differ from other patients in their age, gender, or baseline depressive symptoms (all *p*s >.12). On average, patients responded to 42.71 texts (47% of those received; $SD = 28.20$ texts).

Three types of text-messaging variables were derived from patients' text responses— mood ratings, response rates, and response delays —corresponding to the two aforementioned time frames: a) the week leading up to a scheduled psychotherapy session and b) the day immediately prior to a session.

Mood ratings

Prior-week mood: Patients' numerical responses to mood-monitoring texts (i.e., "What is your mood right now on a scale of 1–9? (9 being the best)") received in the week prior to each scheduled psychotherapy session were averaged to measure patients' prior-week mood ($M = 6.95$, $SD = 1.16$).[3]

Prior-day mood: Patients' numerical responses to mood-monitoring texts received *the day before* a scheduled psychotherapy session were recorded ($M = 6.73$, $SD = 1.29$).

Response rate

Prior-week response rate: Patients' response rates to mood-monitoring texts sent in the week prior to a scheduled session were calculated by dividing the number of mood-monitoring texts to which a patient responded in this seven-day window by the number of texts received ($M = 47\%$ response, $SD = 27\%$).

[2]The descriptive statistics for all of the text-based variables were derived by first averaging within patients across time, and then averaging across patients.

[3]In computing the daily and weekly text-messaging measures, if the patient did not reply to a mood-monitoring message until the day after it was received, which occurred in 3.7% of all cases, their response was not included in the daily and weekly scores.

Prior-day response: Patients were assigned a score of 1 (*responded*) or 0 (*did not respond*) to each mood-monitoring text received the day before a scheduled session (M = 43% response, SD = 29%).

Response delay: Response delay was operationalized as the number of minutes that elapsed from the time that a mood-monitoring text was sent to a patient, to the time the patient's reply to that text was received.

Prior-week response delay: Patients' delay in responding to mood-monitoring texts received in the week prior to each scheduled session was averaged to measure prior-week response delay (M = 86.86 minutes, SD = 76.57 minutes). The distribution of this variable was highly skewed, so following recommendations for transforming reaction-time data (Ratcliff, 1993), we took the natural log to normalize the distribution.

Prior-day response delay: Patients' delay in responding to mood-monitoring texts sent the day before a scheduled session was recorded (M = 68.05 minutes, SD = 78.27 minutes). As with prior-week delay, we took the natural log to normalize the distribution.

Data-Analytic Strategy

The data consisted of up to 16 data points nested within each patient, corresponding to the 16 weeks of psychotherapy. To predict weekly attendance from the texting variables, we used multilevel logistic regressions, which allowed us to model dependencies in the same patient's data across time. Across all models, error terms for the intercepts at level 1 were allowed to vary at level 2. These analyses were performed with the melogit command in Stata 13 using adaptive quadrature with 30 integration points (Rabe-Hesketh & Skrondal, 2012). Melogit includes the data for participants (j) and occasions (i) where neither the response y_{ij} nor the covariate(s) x_{ij} are missing. The data of the eleven patients who stopped receiving texts before the end of psychotherapy were included in the analyses up until the point at which they stopped receiving text messages.

Our central research question was whether a patient's responses to mood-monitoring texts in the week or the day prior to a scheduled psychotherapy session predicted attendance. Because we were interested in whether earlier texting behaviors predicted later attendance, we conducted lagged analyses in which we predicted current-week attendance from prior-week and prior-day texting behaviors. For example, to examine whether patients' self-reported mood in the week prior to a scheduled psychotherapy session predicted their likelihood of attending that session, we constructed a multilevel logistic regression model in which we predicted current-week attendance from prior-week (i.e., lagged) mood.

We conducted these analyses in three steps. First, we entered each of the respective lagged daily and weekly texting variables into separate multilevel logistic regressions, which allowed us to examine each texting variable's individual contribution to predicting attendance. Second, we retained those lagged texting variables that significantly predicted attendance in step one, and entered them together into a model in which we controlled for prior-week attendance. Controlling for prior-week attendance allowed us to assess whether the texting variables provided information about the likelihood of future attendance above and beyond that provided by patients' prior attendance history. It also allowed us to assess whether texting behaviors were associated with *change* in attendance from one week to the next. Because attendance at week 1 was a constant (i.e., all patients, by definition, attended their first psychotherapy session), we excluded week 1 data from those lagged analyses containing the lagged attendance variable.[4] Third, we controlled for patient age, a well-recognized demographic predictor of attendance. We did not control for ethnicity or SES, two other demographic factors linked to attendance, as the composition of our sample on these variables was largely homogenous.

Results

Results from all steps of the analyses are displayed in Table 1. In the text, we highlight the notable significant findings. In the first step, only one of the six lagged texting variables—patients' mood the day prior to a scheduled psychotherapy session—significantly predicted current-week attendance (OR = 1.33, 95% CI [1.05, 1.68], p = .02). The estimated odds ratio of 1.33 indicates that, for every one-point increase in a patient's mood, their estimated odds of attending their next scheduled psychotherapy session increased by 33%. None of the other lagged daily or weekly variables significantly predicted attendance (all other ps > .06). Because prior-day mood was the only significant lagged predictor of attendance, it was the only variable retained in the second step of the model. We also analyzed the within-patient effect of prior-day mood on next day attendance using a conditional logistic regression. The odds ratio was extremely similar in magnitude (OR = 1.32, 95% CI [1.03, 1.70], p = .03), indicating that these results are not purely driven by patients in a chronically low mood being less likely to attend, but instead that attendance is less likely when one's mood is below one's personal average. Because of the similarity in findings, we did not explore within-patient effects in subsequent steps.

In the second step, prior-day mood remained a significant predictor of current-week attendance after controlling for prior-week attendance (OR = 1.35, 95% CI [1.05, 1.73], p = .02). This finding indicates that patients' mood the day before a scheduled session significantly predicts changes in patients' likelihood of attending group psychotherapy from one week to the next.

In a third step, patients' prior-day mood continued to significantly predict current-week attendance after controlling for patient age (OR = 1.33, 95% CI [1.04, 1.70], p = .02). Taken together, these findings suggest that patients' responses to mood-monitoring texts—specifically, their mood ratings the day before a scheduled psychotherapy session—provide a significant increment to the ability to predict future attendance, over and above established predictors of attendance, such as patient age and prior attendance history.

[4]Including week 1 data in the second step did not substantively change the reported findings. The estimated effect of prior-day mood was similar regardless of whether week 1 attendance data was included (OR= 1.30, SE= .15) or excluded (OR = 1.35, SE = .17, both ps < .05). The estimated effect of prior-week attendance was larger when the first week of attendance (a constant) was included (OR = 1.84, SE = .65) versus excluded (OR = 1.22, SE = .50), but was non-significant regardless (ps > .07).

Discussion

This study examined whether patients' responses to mood-monitoring text messages, sent during the course of group psychotherapy, prospectively predicted their likelihood of attendance. The primary finding was that patients' mood the day before a scheduled psychotherapy session positively predicted attendance, with a one point increase in a patient's mood (on a 1–9 scale) linked to approximately 33% higher odds of attendance, even after controlling for patient age and prior attendance history. In contrast, patients' *average* mood the week before a scheduled session did not significantly predict future attendance. These findings suggest that a patient's mood state in close proximity to a scheduled session may influence their decision to attend. Our results are consistent with prior survey research indicating that experiencing elevated psychiatric symptoms is a common reason that patients miss sessions (DeFife et al., 2010; Killaspy et al. 2000), as low daily mood has been found to index elevated depressive symptoms (Aguilera et al., 2015). They are also broadly consistent with research from the affect and decision-making literature, indicating that emotional states play a key role in decision-making (Lowenstein & Lerner, 2003). Unfortunately, these results suggest that patients may be *least* likely to receive psychotherapy at times in which they are feeling their worst, and thus are potentially in greatest need of psychotherapeutic support.

These findings have direct implications for targeting and tailoring interventions to increase attendance. Most clearly, they indicate that patients in a low mood the day prior to a scheduled psychotherapy session may benefit from additional outreach. "Just-in-time" interventions, such as triggered outreach from a clinician, or automated messages that acknowledge a patient's low mood while emphasizing the benefits of attendance, could potentially be delivered at these moments. Some considerations for how best to design such interventions are discussed below.

More broadly, this research underscores the value of text messaging, and other mobile health (mHealth) technologies, as adjuncts to psychotherapy. Text messaging enables the collection of information about patients' psychological states in close proximity to scheduled psychotherapy sessions, information that was critical to predicting attendance in the present study. Given the relative lack of information about time-varying predictors of attendance, this contribution is significant. In addition to improving the prediction of attendance, daily mood-monitoring texts may enhance patients' mood-state awareness and emotion-regulatory skills (Hill & Updegraff, 2012; Kauer et al., 2012), and may integrate easily into evidence-based psychotherapy programs that emphasize affect-monitoring as a core component of treatment, including CBT (Cohen et al., 2013), DBT (Rizvi, Dimeff, Skutch, Carroll, & Linehan, 2011), and ACT (Hayes, Strosahl, & Wilson, 2011). Moreover, prior pilot research has established the usability and feasibility of text-based mood monitoring within safety net settings, and among low income and ethnic minority patient populations, populations with higher rates of psychotherapy non-attendance (Aguilera & Berridge, 2014; Aguilera & Muñoz, 2011). Given the potential of mood-monitoring texts to predict and increase attendance, as well as to support broader psychotherapeutic goals, clinicians should consider incorporating such monitoring interventions as adjuncts to psychotherapy.

Limitations

One limitation is the unclear generalizability of these findings to other patient groups. Our sample was exclusively comprised of low-income, Latino, and Spanish-speaking patients, the majority of which were female and middle aged. While it seems plausible that low mood before psychotherapy may negatively predict attendance within the broader patient population, future research is needed to directly evaluate this possibility. It is important to note that although our sample may not represent the larger US patient population, psychotherapy non-attendance is a more pronounced problem within low-income and ethnic minority populations (Barrett et al., 2008; Garfield, 1994, Wierzbicki & Pekarik, 1993), and so research aimed at increasing attendance in these populations is particularly needed. A second limitation was that our sample size was relatively small, which may have limited our ability to detect weaker, but non-trivial, predictors of attendance, as might be the case for response rate and response delay. Thus, replication of this research within larger samples would be valuable. Also, given that attendance was generally low, but representative of attendance in public sector settings (e.g., Wang et al., 2005), predictors of attendance would be worth exploring in other clinical settings.

An additional limitation was patients' degree of engagement with the text-based adjunct. Mobile technologies are useful for predicting future attendance only to the extent that patients are willing to engage with them regularly. As noted in the methods, eleven patients asked to stop receiving text messages before the end of psychotherapy. An additional seven patients (6 women, mean age = 49.99 years, SD = 9.90 years) received texts, but never responded to them. This latter group, which was not included in the analyses as they provided no texting data, did not significantly differ from the reported sample in age, gender, or the severity of their baseline depressive symptoms. Nonetheless, future research is needed to better characterize and understand the perspective of patients who are unable or unwilling to use texting as a psychotherapeutic tool, and to find alternative approaches to predicting and encouraging regular attendance for these patients. As mHealth interventions increasingly rely on passive sensing from smartphones to detect activity, location, and other variables related to depressive symptoms (e.g., Saeb et al., 2015), this data may also help predict important intervention points, without requiring regular responding on the part of patients.

Future Directions

While this study suggests that patients who report low mood the day prior to psychotherapy may benefit from additional outreach, it does not indicate what type(s) of outreach would effectively increase attendance. Future research is needed to determine *why* low mood states in proximity to psychotherapy are a predictor of non-attendance. It is possible that low mood may reflect anhedonia, a hallmark symptom of depression, which decreases motivation for engaging in healthy activities (Dichter, 2010). Another possibility is that low mood might result from other life circumstances or difficulties that interfere with attendance (e.g., difficulty taking time off work (Alegria et al., 2008), physical pain or illness (Charles & Almeida, 2006)). Identifying the causes of patients' low mood states can inform the content of interventions aimed at reducing barriers to regular attendance.

Future research is also needed to determine the most effective outreach modality. Given the resource intensive nature of direct clinician outreach, a series of stepped interventions could be piloted. For example, if a patient is participating in a mobile intervention and reports low mood the day before a session, that patient could receive automated text messages that acknowledge barriers to attendance and suggest problem-solving techniques, or remind the patient of mood benefits accrued from past sessions. If this approach does not result in increased attendance, clinicians could reach out directly to select patients before scheduled sessions to encourage attendance. A series of such interventions, if successful, may result in a patient receiving an adequate and consistent amount of psychotherapy before termination of treatment, and thus ultimately benefiting from psychotherapy.

Conclusions

The present research demonstrates the value of mood-monitoring text messages in the prospective prediction of psychotherapy attendance. Mood the day before a scheduled psychotherapy session, as measured via text message, was a significant time-varying predictor of attendance. Given the high rate and high costs of psychotherapy non-attendance, future research should explore how to apply this information to develop content and time-tailored (i.e., “just in time”) interventions to increase attendance.

Acknowledgments

We would like to thank the clinicians (Heather Ladov, LCSW, Sandra Larios, PhD, Marta Perez, LCSW, and Laura Pullen, LCSW), clinic directors (Susan Scheidt, PhD and Christina Weyer Jamora, PhD), and lab managers (Patricia Avila and Julia Bravin) for their support. We would also like to thank Ricardo Muñoz, PhD for his guidance in running the groups, and the patients in the groups for sharing their data with us. This work was supported by grants 5K23MH094442 (PI: Aguilera) and K08MH102336 (PI: Schueller) from the National Institute of Mental Health.

References

Aguilera A, Berridge C. Qualitative feedback from a text messaging intervention for depression: Benefits, drawbacks, and cultural differences. Journal of Medical Internet Research. 2014; 46doi: 10.2196/mhealth.3660

Aguilera A, Muench F. There’s an app for that: Information technology applications for cognitive behavioral practitioners. Behavior Therapist. 2012; 35:65–73. [PubMed: 25530659]

Aguilera A, Muñoz RF. Text messaging as an adjunct to CBT in low-income populations: A usability and feasibility pilot study. Professional Psychology: Research and Practice. 2011; 42:472–478.

Aguilera A, Schueller SM, Leykin Y. Daily mood ratings via text message as a proxy for clinic based depression assessment. Journal of Affective Disorders. 2015:471–474. [PubMed: 25679202]

Alegria M, Chatterji P, Wells K, Cao Z, Chen CN, Takeuchi D, Jackson J, Meng XL. Disparity in depression treatment among racial and ethnic minority populations in the United States. Psychiatric Services. 2008; 59:1264–1272. [PubMed: 18971402]

Baekeland F, Lundwall L. Dropping out of treatment: A critical review. Psychological Bulletin. 1975; 82:738–783. [PubMed: 1103201]

Barrett MS, Chua WJ, Crits-Christoph P, Gibbons MB, Thompson D. Early withdrawal from mental health treatment: Implications for psychotherapy practice. Psychotherapy: Theory, Research, Practice, Training. 2008; 45:247–267.

Branson CE, Clemmey P, Mukherjee P. Text message reminders to improve outpatient therapy attendance among adolescents: A pilot study. Psychological Services. 2013; 10(3):298–303. [PubMed: 23937089]

Burns DD, Nolen-Hoeksema S. Therapeutic empathy and recovery from depression in cognitive behavioral therapy: A structural equation model. Journal of Consulting and Clinical Psychology. 1992; 60:441–449. [PubMed: 1619098]

Bylsma LM, Taylor-Clift A, Rottenberg J. Emotional reactivity to daily events in major and minor depression. Journal of Abnormal Psychology. 2011; 120(1):155–167. [PubMed: 21319928]

Charles ST, Almeida DM. Daily reports of symptoms and negative affect: Not all symptoms are the same. Psychology and Health. 2006; 21:1–7.

Chen A. Noncompliance in community psychiatry: A review of clinical interventions. Hospital and Community Psychiatry. 1991; 42:282–287. [PubMed: 1851496]

Cohen JS, Edmunds JM, Brodman DM, Benjamin CL, Kendall PC. Using self-monitoring: Implementation of collaborative empiricism in cognitive-behavioral therapy. Cogn Behav Prac. 2013; 20:419–428.

Conner, T., Barrett, LF., Tugade, MM., Tennen, H. Personality in context: The theory and practice of experience sampling. In: Robins, RW.Fraley, RC., Kreuger, R., editors. Handbook of research methods in personality psychology. New York, NY: Guilford Press; 2007. p. 190-192.

DeFife JA, Conklin C, Smith J, Poole J. Psychotherapy appointment no-shows: Rates and reasons. Psychotherapy: Theory, Research, Practice, Training. 2010; 47(3):413–417.

Detweiler JB, Whisman MA. The role of homework assignments in cognitive therapy for depression: Potential methods for enhancing adherence. Clinical Psychology Science and Practice. 1999; 6:267–282.

Dichter GS. Anhedonia in unipolar major depressive disorder: A review. The Open Psychiatry Journal. 2010; 4:1–9.

Garfield, SL. Research on client variables in psychotherapy. In: Bergin, AE., Garfield, SL., editors. Handbook of psychotherapy and behavior change. 4th. New York, NY: Wiley; 1994. p. 190-228.

Hansen NB, Lambert MJ, Forman EM. The psychotherapy dose-response effect and its implications for treatment delivery services. Clinical Psychology: Science and Practice. 2002; 9:329–343.

Hayes, SC., Strosahl, KD., Wilson, KG. Acceptance and Commitment Therapy: The Process and Practice of Mindful Change. 2nd. New York: Guilford Press; 2011.

Hill CLM, Updegraff JA. Mindfulness and its relationship to emotional regulation. Emotion. 2012; 12:81–90. [PubMed: 22148996]

Kauer SD, Reid SC, Crooke AHD, Khor A, Hearps SJC, Jorm AF, Sanci L, Patton G. Self-monitoring using mobile phones in the early stages of adolescent depression: Randomized controlled trial. Journal of Medical Internet Research. 2012; 14(3)doi: 10.2196/jmir.1858

Killaspy H, Banerjee S, King M, Lloyd M. Prospective controlled study of psychiatric out-patient nonattendance. British Journal of Psychiatry. 2000; 176:160–165. [PubMed: 10755054]

Kroenke K, Spitzer RL, Williams JBW. The PHQ-9: Validity of a brief depression severity measure. Journal of General Internal Medicine. 2001; 16:606–613. [PubMed: 11556941]

Lefforge NL, Donohue B, Strada MJ. Improving session attendance in mental health and substance abuse settings: A review of controlled studies. Behavior Therapy. 2007; 38(1):1–22. [PubMed: 17292691]

Luxton DD, McCann RA, Bush NE, Mishkind MC, Reger GM. mHealth for mental health: Integrating smartphone technology in behavioral healthcare. Prof Psychol: Res Pract. 2011; 42(6):505–512.

Miranda J, Persons JB, Byers CN. Endorsement of dysfunctional beliefs depends on current mood state. Journal of Abnormal Psychology. 1990; 99(3):237–241. [PubMed: 2212273]

Miranda, J., Woo, S., Lagomasino, I., Hepner, KA., Wiseman, S., Muñoz, R. BRIGHT CBT Depression Group Manuals. 2006. Full text available at: http://i4health.paloaltou.edu/manuals/bright-manuals.html

Mitchell AJ, Selmes T. Why don't patients attend their appointments? Maintaining engagement with psychiatric services. Adv Psychiatr Treat. 2007; 13:423–34.

Muñoz, RF., Aguilar-Gaxiola, SA., Guzmán, J. Manual de terapia de grupo para el tratamiento cognitivo-conductual de depresion [Group therapy for cognitive–behavioral treatment of depression]. San Francisco: San Francisco General Hospital Depression Clinic; 1986.

Muñoz, RF., Ghosh Ippen, C., Rao, S., Le, HN., Dwyer, EV. Manual de Terapia de Grupo para el Tratamiento Cognitivo-Conductual de la Depresion: Aprendiendo a Manejar su Realidad Personal. 2000. Full text available at: http://medschool2.ucsf.edu/latino/cbtdengl.aspx

Muñoz RF, Mendelson T. Towards evidence-based interventions for disease populations: The San Francisco general hospital prevention and treatment manuals. Journal of Consulting and Clinical Psychology. 2005; 73:790–799. [PubMed: 16287379]

Organista KC, Muñoz RF, González G. Cognitive-behavioral therapy for depression in low-income and minority medical outpatients: Description of a program and exploratory analyses. Cognitive Therapy and Research. 1994; 18:241–259.

Persons JB, Burns DD, Perloff JM. Predictors of dropout and outcome in cognitive therapy for depression in a private practice setting. Cognitive Therapy and Research. 1988; 12:557–575.

Rabe-Hesketh, S., Skrondal, A. Multilevel and longitudinal modeling using Stata. 3rd. College Station, TX: Stata Press; 2012.

Ratcliff R. Methods for dealing with reaction time outliers. Psychological Bulletin. 1993; 114:510–532. [PubMed: 8272468]

Reis BF, Brown LG. Reducing psychotherapy dropouts: Maximizing perspective convergence in the psychotherapy dyad. Psychotherapy: Theory, Research, Practice, Training. 1999; 36:123–136.

Riley WT, Rivera DE, Atienza AA, Nilsen W, Allison SM, Mermelstein R. Health behavior models in the age of mobile interventions: Are our theories up to the task? Translational behavioral medicine. 2011; 1(1):53–71. [PubMed: 21796270]

Rizvi SL, Dimeff LA, Skutch J, Carroll D, Linehan MM. A pilot study of the DBT coach: An interactive mobile phone application for individuals with borderline personality disorder and substance use disorder. Behavior Therapy. 2011; 42(4):589–600. [PubMed: 22035988]

Saeb S, Zhang M, Karr CJ, Schueller SM, Corden ME, Kording KP, Mohr DC. Mobile phone sensor correlates of depressive symptom severity in daily-life behavior: An exploratory study. Journal of Medical Internet Research. 2015; 17doi: 10.2196/jmir.4273

Segrin C. Social skills deficits associated with depression. Clinical Psychological Review. 2000; 20:379–403.

Sims H, Sanghara H, Hayes D, Wandiembe S, Finch M, Jakobsen H, Kravariti E. Text message reminders of appointments: A pilot intervention at four community mental health clinics in London. Psychiatric Services. 63:161–168.

Sobin C, Sackeim HA. Psychomotor Symptoms of Depression. American Journal of Psychiatry. 1997; 154:4–17. [PubMed: 8988952]

Swift JK, Greenberg RP. Premature discontinuation in adult psychotherapy: A meta-analysis. Journal of Consulting and Clinical Psychology. 2012; 80:547–559. [PubMed: 22506792]

Treadway MT, Zald DH. Reconsidering anhedonia in depression: Lessons from translational neuroscience. Neuroscience and Biobehavioral Reviews. 2011; 35:537–555. [PubMed: 20603146]

Wang PS, Olfson LM, Pincus HA, Wells KB, Kessler RC. Twelve-month use of mental health services in the United States: results from the National Comorbidity Survey Replication. Arch Gen Psychiatry. 2005; 62:629–640. [PubMed: 15939840]

Watson D, Clark L, Weber K, Assenheimer JS, Strauss M, McCormick R. Testing a tripartite model: II. Exploring the symptom structure of anxiety and depression in student, adult, and patient samples. Journal of Abnormal Psychology. 1995; 104:15–25. [PubMed: 7897037]

Wierzbicki M, Pekarik G. A meta-analysis of psychotherapy dropout. Professional Psychology: Research and Practice. 1993; 24:190–195.

Author Manuscript
Author Manuscript
Author Manuscript

Highlights

- This study used text messaging to measure daily mood in patients with depression.
- Low mood the day prior to psychotherapy increased the risk of non-attendance.
- These findings can inform "just-in-time" interventions to improve attendance.

Table 1

Summary of Multilevel Logistic Regression Analyses for Variables Predicting Weekly Psychotherapy Attendance

	n[a]	*OR*	95% C.I.	*p*
Step 1: Lagged Texting Variables[b]				
Prior-week mood	55	1.12	0.90, 1.39	.32
Prior-day mood	46	1.33	1.05, 1.68	.02
Prior-week response rate	56	2.03	0.93, 4.41	.07
Prior-day response rate	56	1.03	0.63, 1.68	.90
Prior-week response delay	56	1.15	0.96, 1.37	.12
Prior-day response delay	48	1.16	0.98, 1.36	.08
Step 2: Controlling for Prior Attendance				
Prior-day mood	45	1.35	1.05, 1.73	.02
Prior-week attendance	45	1.22	0.54, 2.74	.64
Step 3: Controlling for Age				
Prior-day mood	45	1.33	1.04, 1.70	.02
Prior-week attendance	45	1.25	0.56, 2.83	.58
Age	45	1.05	0.99–1.12	.08

[a]The number of patients included in the analyses varied due to missing data.

[b]In step 1, each of the respective lagged texting variables were entered individually into separate multilevel logistic regressions.