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BRIEF REPORT

The Prognostic Role of Emotion Regulation Dynamics in the Treatment of Major Depressive Disorder

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Objective: The potential prognostic role of emotion regulation in the treatment of major depressive disorder (MDD) has been highlighted by transtheoretical literature and supported by promising empirical findings. The majority of the literature is based on self-report observations at a single snapshot, thus little is known about the prognostic value of moment-to-moment dynamic evolvement of emotion. The present study is the first to examine the prognostic value of both intra- and interpersonal, moment-to-moment emotion regulation dynamics, and the potential moderating effect of the type of treatment. ***Method:*** To assess the prognostic value of emotion regulation dynamics, we focused on the first session, using 6,780 talk-turns within 52 patient–therapist dyads. Emotion regulation dynamics were measured using fundamental frequencies of the voice and were calculated using empirical Bayes residuals of the actor–partner interdependence model. Symptomatic change was measured using the Hamilton Rating Scale for Depression across 16 weeks of supportive treatment (ST) or supportive–expressive treatment (SET). ***Results:*** Findings suggest that patients who show less regulated intrapersonal dynamics during the first session show less reduction of symptoms throughout treatment ($\beta = .26$, $p = .019$). Findings further suggest that this association is mitigated when these patients receive SET, as opposed to ST ($\beta = .72$, $p = .020$). ***Conclusions:*** The findings demonstrate the ability of first-session emotion regulation dynamics to serve as a prognostic variable. The findings further suggest that the adverse effect of emotion regulation dynamics on the patient's prognosis can be mitigated by explicit work on changing maladaptive emotional patterns.

What is the public health significance of this article?

This study is the first to demonstrate the role of first-session emotion regulation dynamics in predicting symptomatic change throughout treatment. The findings suggest that patients who show less regulated intrapersonal dynamics during the first session might benefit less from treatment. The findings further suggest that the adverse effect of emotion regulation dynamics on the patient's prognosis can be mitigated by providing treatment that works explicitly on changing maladaptive emotional patterns. The findings may support identification of individuals with a risk of poorer prognosis based on their emotional dynamics, as early as the first session of treatment. The findings may further inform personalized treatment selection.

Keywords: emotional dynamics, emotion regulation, moderation, depression

Supplemental materials: https://doi.org/10.1037/ccp0000835.supp

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Major depressive disorder (MDD), the leading cause of disability worldwide (Friedrich, 2017), is characterized by major emotional difficulties (Aldao et al., 2010) that can manifest in maladaptive patterns of emotion regulation, such as difficulties downregulating emotional arousal. Even though there are effective treatments for MDD, studies suggest that these only work for about 50% of patients (Cuijpers et al., 2014). These moderate efficacy rates highlight the importance of identifying, as early as possible in the course of treatment, whether the treatment is effective for the individual. Identifying individuals with poorer prognoses may prevent lengthy trial-and-error processes that result in prolonged patient suffering and increased risk of poor outcomes, including suicide (Gaynes et al., 2009).

It has been suggested that patients' emotional difficulties may serve as a prognostic variable determining who may benefit the most from treatment (e.g., Carryer & Greenberg, 2010). Current literature examining the ability of emotional difficulties to serve as a prognostic variable mostly focuses on emotional aspects that can be reported by the individual (i.e., experience; e.g., Watson et al., 2011). These studies focus on snapshot observations sampled at a single time point and find that patients who report higher levels of emotional difficulties are less stable in their emotional experience during treatment (Fisher et al., 2019), show lower levels of emotion processing (Watson et al., 2011), and are less likely to show symptomatic improvement at the end of treatment (Scherer et al., 2017). While these studies were instrumental in demonstrating the ability of emotional difficulties to serve as a prognostic variable, the use of self-report measures is restricted to what the individual can explicitly report, whereas patterns of emotion regulation are not always consciously accessible for the individual (Quigley et al., 2014). Furthermore, the use of self-report measures as implemented in psychotherapy research is restricted to a low resolution of assessment (e.g., single time point, between-sessions examination) and therefore is incapable of capturing the moment-to-moment dynamics of emotion regulation (Kuppens, 2019).

To close this gap, a growing number of studies have started to examine patterns of emotion regulation as dynamic processes (e.g., Bryan et al., 2018). To be able to zoom-in on dynamic patterns occurring within a session, studies have started to use automatic measures of emotion that can capture within-session dynamics of emotion regulation of both the patient and the therapist. Vocal acoustic markers, especially the fundamental frequency (F0) of the voice, are among the automatic measures that are being used with increasing frequency over the last decade. F0 refers to the lowest frequency harmonic that is created by the vibration of the vocal cords during speech and has proven to be a reliable indicator of emotional arousal (Juslin & Scherer, 2005). Using F0 as an emotional measure enables researchers to capture implicit aspects of emotional dynamics in high temporal resolution (Juslin & Scherer, 2005).

Two main types of dynamics have been identified in the literature (e.g., Bryan et al., 2018): (a) intrapersonal dynamics, defined as processes occurring separately for the patient and the therapist, and (b) interpersonal dynamics, defined as interdependence between the patient and the therapist. Less regulated intrapersonal dynamics can manifest in an escalation of emotional arousal, such that deviations in patients' F0 increase from the general emotional trajectory over time. Less regulated interpersonal dynamics can manifest in an escalation effect between the therapist and patient, such that increases in F0 of the therapist from the therapist's general emotional trajectory predict an increase in the patient's F0 at the next moment (Perry et al., 2017). Existing evidence suggests that intrapersonal dynamics are relatively stable during psychotherapy sessions and that interpersonal dynamics commonly manifest as therapist arousal facilitating the patient's regulation of emotional arousal (Wieder & Wiltshire, 2020). Studies that examined associations between interpersonal dynamics and therapeutic processes found that the regulating effect of a therapist on the patient was associated with patients perceiving exposure interventions as more plausible (Wieder & Wiltshire, 2020), and with higher levels of the patient's emotional bond to the therapist (Bryan et al., 2018). Yet, the ability of intra- and interpersonal dynamics to serve as a prognostic variable is yet to be examined.

To close this gap in the literature, the present study aims to investigate whether first-session intra- and interpersonal emotion regulation dynamics (Perry et al., 2017) predict the trajectory of treatment outcome. We expect that, at the sample level, patients within dyads with less regulated emotional dynamics will show less reduction of symptoms throughout treatment relative to those in dyads showing more regulated emotional dynamics. We further explore whether this association will be weaker for patients with more (vs. less) regulated dynamics when receiving treatments that focus on changing maladaptive emotional responses (supportive–expressive vs. supportive treatment). Due to the lack of empirical literature on this subject, we regard this hypothesis as exploratory.

Method

Participants

Data of 52 patients, from the training and active phases of a randomized controlled trial (RCT; Zilcha-Mano et al., 2021), were included. This subsample includes all active patients of the RCT ($N = 100$), excluding (a) patients whose data do not meet the recommended standards for high quality of acoustic data ($N = 40$; Rochman & Amir, 2013; see online Supplemental Material), and (b) a further 14 patients whose data became available later and were analyzed as a sensitivity analysis. An additional sample of pilot patients was also included ($N = 6$). Ethical approval for the study was obtained from Haifa University (Grant 186/15). Demographic and diagnostic information for this subsample appears in Table 1.

Table 1
Demographic and Clinical Features of the Present Sample

Variable	Values (M, SD, %, and frequencies)
Demographics	
Age, *y*, M (SD)	31.2 (8.9)
Education, *y*, M (SD)	14.6 (1.7)
Female	33 (63.5)
Income > Average	12 (23.1)
Married/cohabitating	8 (15.4)
Employed	30 (57.7)
Religion, Jewish	42 (80.8)
Clinical features	
Current medication, yes	6 (11.5)
Previous medication, yes	8 (15.4)
Previous psychotherapy, yes	21 (40.4)
Comorbidities	
Any disorder	37 (71.2)
Any anxiety disorder	36 (69.2)
Any personality disorder	43 (82.7)

Note. $N = 52$.

Treatment and Therapists

Patients received 16 weekly sessions of a time-limited manualized psychodynamic treatment adapted for depression. Patients received either an expressive-focused treatment ($N = 26$; SET; Luborsky et al., 1995), in which emotional dysregulation is addressed by focusing on the patient's emotional responses in interpersonal contexts, or a supportive-focused treatment (ST), using the same manual but excluding the expressive component. Seven therapists participated in the study (case load of: $M = 4.35$, $SD = 2.69$). Further details on therapists' demographic characteristics, clinical experience, training process, and demonstration of fidelity are described elsewhere (Zilcha-Mano et al., 2021).

Measures

Vocally Encoded Emotional Arousal

Mean fundamental frequency (F0) was used as the measure of vocally encoded emotional arousal. Patients' and therapists' mean F0 values during the session were extracted in a four-step analysis: (a) the volume of audio files was normalized using the Audacity software (Audacity Team, 2018), (b) each file was manually trimmed (segmented) into separate patient's and therapist's talk-turns, (c) overlapping speech and irrelevant noises were excluded from the analysis, as recommended by Bryan et al. (2018), and (d) mean F0 values were estimated using the Praat software package Version 6.0.24 (Boersma & Weenink, 2009) with a time step of 0.25 s (Bryan et al., 2018) and a bandpass filter to restrict F0 values to the normal range of adult speech (between 75 and 300 Hz; Juslin & Scherer, 2005). A mean F0 was calculated for every talk-turns.

Trajectory of Treatment Outcome

Patients' depression level (main outcome) throughout treatment was assessed using the Hamilton Rating Scale for Depression (HRSD; Hamilton, 1967). The HRSD was administered to patients by well-trained diagnosticians (for details, see Zilcha-Mano et al., 2021). Interjudge reliability in the active trial was .98.

Procedure

After describing the study to patients, written informed consent was obtained. The first session was recorded (see online Supplemental Material) and the midphase of the session was selected for acoustical analysis, due to its potential to represent the SE therapeutic dialogues in a more comprehensive manner. Each dyad's segment of analysis started at the 20th min, with a complete sentence of the therapist, and ended 15 min later. The HRSD was administered before each session.

Statistical Analyses

Data Preparation

F0 data was detrended using recommended methods (Curran & Bauer, 2011). Detrending allowed us to control for time and between-individual differences (e.g., therapist effect; Falkenström et al., 2016), such that pure within-individual moment-to-moment changes of F0 could be the focus of subsequent analysis (see online Supplemental Material).

Calculating Emotion Regulation Dynamics

Following previous studies (e.g., Bryan et al., 2018), within-session emotional dynamics were estimated using an actor–partner interdependence model (APIM, Kenny et al., 2006) to characterize cross-lagged associations between patient and therapist F0 across subsequent talk-turns. To calculate intra- and interpersonal emotional dynamics *for each individual*, random effects were included on patient and therapist actor and partner effects, in addition to the intercept. These random effects were extracted for each patient and therapist in each dyad using empirical Bayes residuals (EBRs; Raudenbush & Bryk, 2002; for equation of the model, see online Supplemental Material).

Main Analysis

To examine whether patients' and therapists' intra- and interpersonal emotional dynamics predict the trajectory of treatment outcome, a longitudinal hierarchical model was estimated, where session number was nested within individual. A model of fixed and random effect of log of time was found to demonstrate the best model fit in predicting the trajectory of treatment outcome, based on the Bayesian information criterion (BIC). Cross-level interactions between individuals' actor and partner coefficients and log time were included to predict the trajectory of treatment outcome.

Exploratory Analysis

To examine whether emotional dynamics, time, and treatment type (SET vs. ST) predict the trajectory of treatment outcome, an additional model was run where the main effect for and interactions involving treatment type, and the two-way interactions between log time and actor/partner effects, were added. All analyses were conducted using the SAS PROC MIXED procedure (Littell et al., 2006). Descriptive statistics of the variables are presented in Table S1.

Results

Calculating Emotion Regulation Dynamics

No actor or partner effects were found at the sample level. Estimated variance of the actor and partner random effects revealed significant between-person variability in actor but not in partner coefficients (see Table S2).

Main Analysis

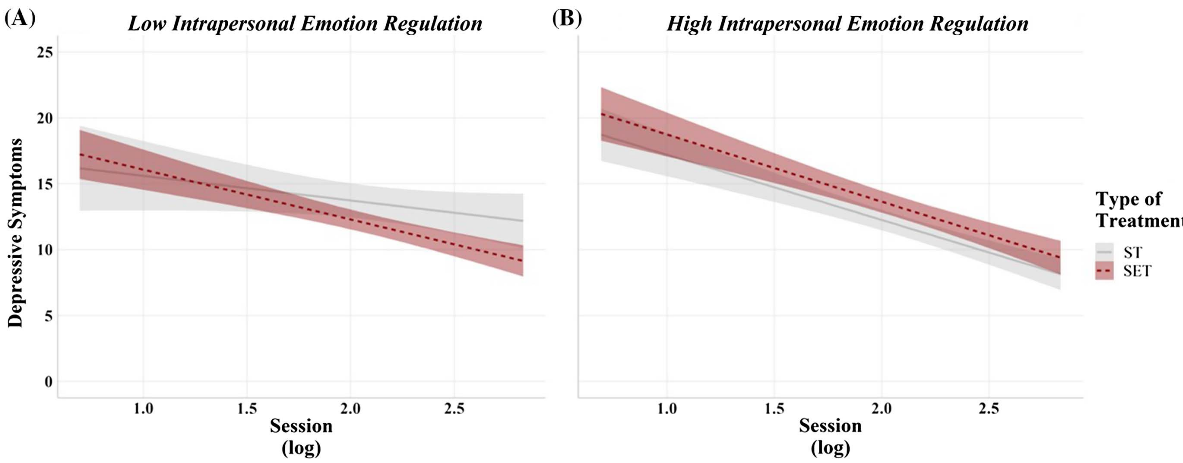
The interaction between patients' intrapersonal emotional dynamics and time significantly predicted the trajectory of treatment outcome ($\beta = .258$; Table S3): patients who showed greater increase in emotional arousal during the first session showed less reduction of symptoms throughout treatment. Other interactions were not significant.

Exploratory Analysis

The interaction between patients' intrapersonal emotional dynamics, time, and treatment type significantly predicted the trajectory of treatment outcome ($\beta = .751$; Table S4, Figure 1): patients who

Figure 1

Figure Demonstrates the Three-Way Interaction Between Patient Intrapersonal Emotion Regulation Dynamics and Treatment Type, in Predicting the Trajectory of Treatment Outcome



Note. The two panels describe the associations between emotion regulation (low (A) and high (B)), treatment type (ST (gray line) and SET (red line)), and depressive symptoms over time. Note that "low intrapersonal regulation dynamic" is operationalized as actor coefficients greater than 0.25 standard above the mean of the patients' actor coefficients; $N = 19$, $B = -3.81$, $p = .028$, $\beta = -.77$. "High intrapersonal regulation dynamic" is operationalized as actor coefficients smaller than 0.25 standard below the mean of the patients' actor coefficients; $N = 16$, $B = .30$, $p = .756$, $\beta = .06$. These values were chosen in order to enable groups that are more equal in their size. The estimates in the models are unstandardized. ST = supportive treatment; SET = supportive–expressive treatment. See the online article for the color version of this figure.

showed greater increase in emotional arousal during the first session showed less reduction of symptoms when receiving ST as compared to these receiving SET. On the other hand, patients who showed smaller increase in emotional arousal during session did not significantly differ in their trajectory of treatment outcome when receiving ST versus SET.[1] Other interactions were not significant.

Sensitivity Analyses

To test the stability of the findings, analyses were reconducted using a data set that included additional, completely new, 14 patients (total of 66 individuals; 7,766 talk-turns), in which talk-turns were decomposed automatically, using a diarization algorithm (see online Supplemental Material). The findings were replicated, showing a significant interaction of patients' intrapersonal emotional dynamics and time in predicting the trajectory of treatment outcome, and a significant three-way interaction of moderation of treatment type. Thus, the additional data supported the validation of the study's findings.

Discussion

The present findings suggest that patients who show less regulated intrapersonal dynamics during the first session show less reduction of symptoms throughout treatment. These findings are consistent with previous knowledge, suggesting that patients reporting emotion regulation difficulties would benefit less from treatment (e.g., Scherer et al., 2017). Yet, the present findings expand previous knowledge by using rigorous methodology to examine both the predictors and the outcome variables. Accordingly, emotional dynamics were assessed using automatic measures of emotion, by which implicit aspects of emotional dynamics can be captured in high temporal resolution. Additionally, treatment outcome was assessed session-by-session, using a gold standard clinical interview (HRSD; Hamilton, 1967). Future studies may elaborate the present findings by examining the characteristics of patients who tend to less regulated intrapersonal dynamics during the first session.

The present study further aimed at investigating whether treatments focusing on changing maladaptive emotional dynamics (SET vs. ST) have a moderating effect on such poor prognosis. The study found that SET, in which much of the therapeutic work focuses on the patient's maladaptive emotional responses (Luborsky et al., 1995), mitigated the negative effect of less regulated intrapersonal dynamics on the patient's prognosis. These findings add to previous knowledge by suggesting that the association between less regulated emotional dynamics and poorer prognosis can be experimentally manipulated using RCT in which participants are randomized to receive SET rather than ST (Zilcha-Mano et al., 2021). If replicated in future studies, these findings may inform personalized treatment selection.

As for the null results of the interpersonal dynamics in predicting the trajectory of treatment outcome, a possible explanation could be the low between-person variability in the partner coefficients. It is possible that examination of emotional dynamics within the first session may capture only initial aspects of the dyadic interaction, as the therapeutic relationship is yet to be developed. Future studies should further examine this issue.

The main limitation of the present study lies in its small sample size. Yet, sensitivity analysis suggests the potential replication of the findings, as the current findings were replicated using a sample that

[1] For conditional slopes of the three-way interaction according to treatment type (ST vs. SET), see Table S5.

included additional new patients, in which talk-turns were decomposed using a different method. The present study used the APIM to model interpersonal dynamics, as has been done repeatedly in the literature (e.g., Bryan et al., 2018). Future studies may use additional methods (e.g., "most highly aroused moments"; measure of *K*; Kenny & Ledermann, 2010) and may distinguish between different types of dysregulations (e.g., escalation and de-escalation) to complement the picture provided in the present study. Additionally, the present study used EBRs to calculate intra- and interpersonal emotional dynamics *for each individual*, a methodology that may result in uncertainty of—and shrinkage in—the point estimate of the EBR. These limitations are mitigated in the present study due to the high reliability of measuring F0, and the focus on the relative magnitude of actor and partner associations as opposed to their absolute values. Notwithstanding these limitations, using a rigorous design, the present study contributes innovative findings regarding the prognostic value of emotional dynamics, and the role of type of treatment in mitigating the risk of poorer prognosis. Such knowledge may be utilized in the future for clinical practice, among other voice technologies (Imel et al., 2017).

Data Transparency Statement

Data of this article are retrieved from a randomized controlled trial (RCT) examining supportive–expressive psychotherapy for major depressive disorder (published). This RCT has yielded several articles with separate foci. Of these, one study has been published on acoustical data as measured before the start of treatment (published), and one study on the treatment main outcome (published). Whereas the previous study that was published on acoustical data focused on the intake session between the evaluator and the patient, the present study focuses on the first session, meaning between the patient and the therapist. In addition, the present study includes treatment condition and treatment outcome data, which were not included in the previous study. The present study is the first to combine acoustical data, treatment condition, and treatment main outcome. Thus, there is no overlap with any previous studies.

References

Aldao, A., Nolen-Hoeksema, S., & Schweizer, S. (2010). Emotion-regulation strategies across psychopathology: A meta-analytic review. *Clinical Psychology Review*, *30*(2), 217–237. https://doi.org/10.1016/j.cpr.2009.11.004

Audacity Team. (2018). *Audacity®: Free, open source, cross-platform audio software*. https://www.audacityteam.org/

Boersma, P., & Weenink, D. (2009). *Praat: Doing phonetics by computer* (Version 5.1. 05) [Computer program].

Bryan, C. J., Baucom, B. R., Crenshaw, A. O., Imel, Z., Atkins, D. C., Clemans, T. A., Leeson, B., Burch, T. S., Mintz, J., & Rudd, M. D. (2018). Associations of patient–rated emotional bond and vocally encoded emotional arousal among clinicians and acutely suicidal military personnel. *Journal of Consulting and Clinical Psychology*, *86*(4), 372–383. https://doi.org/10.1037/ccp0000295

Carryer, J. R., & Greenberg, L. S. (2010). Optimal levels of emotional arousal in experiential therapy of depression. *Journal of Consulting and Clinical Psychology*, *78*(2), 190–199. https://doi.org/10.1037/a0018401

Cuijpers, P., Karyotaki, E., Weitz, E., Andersson, G., Hollon, S. D., & van Straten, A. (2014). The effects of psychotherapies for major depression in adults on remission, recovery and improvement: A meta-analysis. *Journal of Affective Disorders*, *159*, 118–126. https://doi.org/10.1016/j.jad.2014.02.026

Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology*, *62*(1), 583–619. https://doi.org/10.1146/annurev.psych.093008.100356

Falkenström, F., Ekeblad, A., & Holmqvist, R. (2016). Improvement of the working alliance in one treatment session predicts improvement of depressive symptoms by the next session. *Journal of Consulting and Clinical Psychology*, *84*(8), 738–751. https://doi.org/10.1037/ccp0000119

Fisher, H., Atzil-Slonim, D., Bar-Kalifa, E., Rafaeli, E., & Peri, T. (2019). Growth curves of clients' emotional experience and their association with emotion regulation and symptoms. *Psychotherapy Research*, *29*(4), 463–478. https://doi.org/10.1080/10503307.2017.1411627

Friedrich, M. J. (2017). Depression is the leading cause of disability around the world. *JAMA*, *317*(15), Article 1517. https://doi.org/10.1001/jama.2017.3826

Gaynes, B. N., Warden, D., Trivedi, M. H., Wisniewski, S. R., Fava, M., & Rush, A. J. (2009). What did STAR*D teach us? Results from a large-scale, practical, clinical trial for patients with depression. *Psychiatric Services*, *60*(11), 1439–1445. https://doi.org/10.1176/ps.2009.60.11.1439

Hamilton, M. (1967). Development of a rating scale for primary depressive illness. *The British Journal of Social and Clinical Psychology*, *6*(4), 278–296. https://doi.org/10.1111/j.2044-8260.1967.tb00530.x

Imel, Z. E., Caperton, D. D., Tanana, M., & Atkins, D. C. (2017). Technology-enhanced human interaction in psychotherapy. *Journal of Counseling Psychology*, *64*(4), 385–393. https://doi.org/10.1037/cou0000213

Juslin, P. N., & Scherer, K. R. (2005). Vocal expression of affect. In J. A. Harrigan, R. Rosenthal, & K. R. Scherer (Eds.), *The new handbook of methods in nonverbal behavior research* (pp. 65–135). Oxford University Press.

Kenny, D. A., Kashy, D. A., & Cook, W. L. (2006). *Dyadic data analysis*. Guilford Press.

Kenny, D. A., & Ledermann, T. (2010). Detecting, measuring, and testing dyadic patterns in the actor–partner interdependence model. *Journal of Family Psychology*, *24*(3), 359–366. https://doi.org/10.1037/a0019651

Kuppens, P. (2019). Improving theory, measurement, and reality to advance the future of emotion research. *Cognition and Emotion*, *33*(1), 20–23. https://doi.org/10.1080/02699931.2018.1536037

Littell, R. C., Milliken, G. A., Stroup, W. W., Wolfinger, R. D., & Oliver, S. (2006). *SAS for mixed models*. SAS publishing.

Luborsky, L., Mark, D., Hole, H. V., Popp, C., Goldsmith, B., & Cacciola, J. (1995). Supportive-expressive dynamic psychotherapy of depression: A time-limited version. In J. P. Barber & P. Crits-Christoph (Eds.), *Dynamic therapies for psychiatric disorders* (pp. 41–83). Basic Books.

Perry, N. S., Baucom, K. J. W., Bourne, S., Butner, J., Crenshaw, A. O., Hogan, J. N., Imel, Z. E., Wiltshire, T. J., & Baucom, B. R. W. (2017). Graphic methods for interpreting longitudinal dyadic patterns from repeated-measures actor–partner interdependence models. *Journal of Family Psychology*, *31*(5), 592–603. https://doi.org/10.1037/fam0000293

Quigley, K. S., Lindquist, K. A., & Barrett, L. F. (2014). Inducing and measuring emotion and affect: Tips, tricks, and secrets. In T. H. Reis & M. C. Judd (Eds.), *Handbook of research methods in social and personality psychology* (2nd ed., pp. 220–252). Cambridge University Press. https://doi.org/10.1017/CBO9780511996481.014

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods*. Sage Publications.

Rochman, D., & Amir, O. (2013). Examining in-session expressions of emotions with speech/vocal acoustic measures: An introductory guide. *Psychotherapy Research*, *23*(4), 381–393. https://doi.org/10.1080/10503307.2013.784421

Scherer, A., Boecker, M., Pawelzik, M., Gauggel, S., & Forkmann, T. (2017). Emotion suppression, not reappraisal, predicts psychotherapy outcome. *Psychotherapy Research*, *27*(2), 143–153. https://doi.org/10.1080/10503307.2015.1080875

Watson, J. C., McMullen, E. J., Prosser, M. C., & Bedard, D. L. (2011). An examination of the relationships among clients' affect regulation, in-session emotional processing, the working alliance, and outcome. *Psychotherapy Research*, *21*(1), 86–96. https://doi.org/10.1080/10503307.2010.518637

Wieder, G., & Wiltshire, T. J. (2020). Investigating coregulation of emotional arousal during exposure-based CBT using vocal encoding and actor-partner interdependence models. *Journal of Counseling Psychology*, *67*(3), 337–348. https://doi.org/10.1037/cou0000405

Zilcha-Mano, S., Goldstein, P., Dolev-Amit, T., Ben David-Sela, T., & Barber, J. P. (2021). A randomized controlled trial for identifying the most suitable treatment for depression based on patients' attachment orientation. *Journal of Consulting and Clinical Psychology*, *89*(12), 985–994. https://doi.org/10.1037/ccp0000696

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