Administration and Policy in Mental Health and Mental Health Services Research
https://doi.org/10.1007/s10488-023-01310-w

ORIGINAL ARTICLE

Facing Change: Using Automated Facial Expression Analysis to Examine Emotional Flexibility in the Treatment of Depression

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Accepted: 2 October 2023

Abstract

Objective Depression involves deficits in emotional flexibility. To date, the varied and dynamic nature of emotional processes during therapy has mostly been measured at discrete time intervals using clients' subjective reports. Because emotions tend to fluctuate and change from moment to moment, the understanding of emotional processes in the treatment of depression depends to a great extent on the existence of sensitive, continuous, and objectively codified measures of emotional expression. In this observational study, we used computerized measures to analyze high-resolution time-series facial expression data as well as self-reports to examine the association between emotional flexibility and depressive symptoms at the client as well as at the session levels.

Method Video recordings from 283 therapy sessions of 58 clients who underwent 16 sessions of manualized psychodynamic psychotherapy for depression were analyzed. Data was collected as part of routine practice in a university clinic that provides treatments to the community. Emotional flexibility was measured in each session using an automated facial expression emotion recognition system. The clients' depression level was assessed at the beginning of each session using the Beck Depression Inventory-II (Beck et al., 1996).

Results Higher emotional flexibility was associated with lower depressive symptoms at the treatment as well as at the session levels.

Conclusion These findings highlight the centrality of emotional flexibility both as a trait-like as well as a state-like characteristic of depression. The results also demonstrate the usefulness of computerized measures to capture key emotional processes in the treatment of depression at a high scale and specificity.

Keywords Emotional flexibility · Facial expression · Process-outcome research · Computerized measures

Deficits in emotional flexibility are posited to be at the epicenter of Major Depressive Disorder (MDD), a highly prevalent and debilitating condition (Rottenberg, 2017). Emotional flexibility is defined as the capacity to dynamically modulate one's emotional responses from one moment to the next (Kuppens et al., 2010). When an affective state persists over time unchanged and unmodulated by a wider range of emotions, an increase in distress and symptoms may ensue (Bonanno et al., 2004; Gupta & Bonanno, 2011; Kashdan & Rottenberg, 2010; Wichers et al., 2015). There is evidence that depressed individuals tend to experience inflexible emotions and find it difficult to adjust to environmental vicissitudes (Kashdan & Rottenberg, 2010; Koval et al., 2012; Pe et al., 2015).

Moreover, many psychotherapy models from a variety of approaches postulate that clients' distress often stems from inflexible patterns of experienced emotions. One of the main goals of treatment is to help clients expand the repertoire of their emotional experiences, which is posited to lead to better well-being (Fosha, 2001; Greenberg, 2012; Lane, 2020; McCullough & Magill, 2009). Indeed, many studies have shown that more adaptive emotional processes in psychotherapy coincides with an improvement in clients' ability to experience a wider range of emotions (e.g. Bar-Kalifa &

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Published online: 25 October 2023

Atzil-Slonim, 2020; Herrmann et al., 2016; Kramer et al., 2015; Pos et al., 2009).

Most studies examining the range of emotions in psychotherapy and its association with clients' symptoms have relied on clients' *subjective* reports of their emotions (e.g. Bar-Kalifa & Atzil-Slonim, 2020). Because emotions tend to fluctuate and change from moment to moment, these measures are limited in their ability to capture emotional dynamics that occur *within* a session. Other studies have used observer ratings of clients' emotional processes in treatment (e.g. Herrmann et al., 2016; Pascual-Leone & Greenberg, 2007). These studies provided rich and detailed view of emotional processes in psychotherapy, yet, because observational human coding is extremely labor-intensive and expensive, these studies have typically focused on the analyses of two or three sessions per treatment, limiting the examination of the ways in which fluctuations in emotional patterns are associated with changes in symptoms level from session to session throughout treatment. Advances in technology, in particular computerized facial expression methods, however, have made it possible for psychotherapy researchers to identify clients' emotions on a large scale and with high specificity tapping into momentary fine-grained emotional fluctuations (Imel et al., 2017). In the past few years, mental health practitioners and researchers have made concerted efforts to devise methods to passively monitor clients' mental conditions, so that clients and clinics can be relieved of the considerable burden of filling out questionnaires. Automatic facial recognition measures are particularly good candidates for a number of reasons. Facial recognition technology can deliver insights about clients' emotional state more objectively (than self-report questionnaires), non-intrusively (unlike other measures such as electrodes to assess physiological responses), continuously (by contrast to non-continuous measures such as voice), and with high temporal resolution. Facial expressions are a primary way to signal emotional states to one's environment (Cohn et al., 2007). Recent work has highlighted the importance of facial expressions in depression as a mechanism of emotional expression and non-verbal communication (Girard & Cohn, 2015). Although there are numerous approaches to the automated analysis of facial expressions (for a review, see Cohn & De la Torre, 2015), most are based on the Facial Action Coding System (FACS; Ekman & Friesen, 1976). This system classifies facial movements in terms of action units composed of movements of one or a set of facial muscles. Different facial expressions are produced by contracting different combinations of muscles (Freitas-Magalhães, 2012).

Recent studies have started to use these computerized facial expression measures to automatically capture features of depression (for reviews, see Nasser et al., 2020; Pampouchidou et al., 2017). Several studies have reported that these measures can differentiate between depressed clients and healthy controls (Gavrilescu & Vizireanu, 2019; Wang et al., 2018). However, most of these studies have examined cross-sectional data and assessed the association between depression and facial expressions at a single time point. Hence, they cannot examine whether facial expressions differ within individuals as a function of the severity of their depressive symptoms, or how such fluctuations are related to changes in depressive symptoms.

A few studies examined whether facial expression measures can automatically identify the severity of depressive symptoms over time (Girard et al., 2013; Harati et al., 2019). Girard et al. (2013) found that when participants experienced higher levels of depressive symptoms, they tended to manifest fewer facial expressions associated with the willingness to affiliate such as smiles. However, this study assessed participants' emotional expressions during a semi-structured interview at only two time points, using brief (about two minutes) time windows, thus, it was restricted in its ability to capture within-session patterns of emotional expression or to determine whether changes in these patterns fluctuated with levels of depressive symptoms. Another study, by Harati et al. (2019) used unsupervised machine learning approach to classify levels of depression severity among clients before and after treatment for depression. Their study findings suggested that clients who exhibited higher emotional expressiveness had lower depression levels. However, these results were based on a relatively small sample size of only 12 participants, and the evaluation of depressive symptoms was conducted during semi-structured interviews rather than psychotherapy sessions. Recent reviews of the literature have emphasized the need for more studies that will use computational facial expression measures continuously to examine how markers of depression vary between and within individuals (Girard & Cohn, 2015; Nasser et al., 2020; Pampouchidou et al., 2017). Examining the association between facial expression and depressive symptoms repeatedly across treatment may shed light on the question whether depressed clients tend to have lower emotional flexibility as a stable trait-like characteristic or whether emotional flexibility and depressive symptoms tend to fluctuate and change together over time as a state-like characteristic.

The Current Study

We employed time-intensive, session-by-session, measurements of clients' depressive symptoms. In addition, we used a computerized emotion recognition system to a continuous assessment of facial expressions within sessions.

Combined, these measures allowed us to examine the associations between depressive symptoms and emotional flexibility at the treatment level as well as at the session level. Specifically, the following hypotheses were tested:

(a) Clients with higher levels of depressive symptoms will tend to have lower levels of emotional flexibility across treatment on average.
(b) Sessions characterized by higher levels of clients' depressive symptoms will tend to have lower session-level emotional flexibility.

We expected that these associations would hold above and beyond the influence of mean emotional valence of the emotional expression.

Method

The data for this study were drawn from a larger project examining interpersonal and emotional processes in short-term psychodynamic psychotherapy modified to treat depression. This project was conducted in [removed for blind review] and approved by the associated IRB. All participating clients signed an informed consent form. The data set has been used in (REMOVED FOR BLIND REVIEW). However, none of the measures reported in the present study were used in that study. The data, materials, and analysis code for this study can be accessed from the first author.

Clients

Participants ($n = 178$) were screened on the Beck Depression Inventory-II (BDI-II; Beck et al., 1996) as part of an ongoing study. Of this cohort, 64 individuals with BDI-II scores ≥ 17 were asked to come for an intake interview during which the Mini-International Neuropsychiatric Interview Version 5.0 (MINI; Sheehan et al., 1998) was administered. The inclusion criteria were: (a) a primary diagnosis of major depressive disorder as indicated by the MINI, (b) a score of 14 or more on the 17-item clinician-administered semi-structured interview version of the Hamilton Rating Scale for Depression (HAMD; Hamilton, 1960; Williams, 1988). The exclusion criteria were: (a) active suicidality, (b) substance abuse or dependence, (c) current or past bipolar disorder, (d) presence of psychotic features, (e) past severe head injury, (f) pending legal proceedings, and (g) current pregnancy or a medical condition warranting hormonal treatment. Out of the 64 participants who began therapy, two clients withdrew from therapy after session 4 and session 7. Because our analyses focused on data from five pre-selected sessions spaced evenly throughout the course of therapy, these two clients who dropped out early did not have sufficient data points and therefore were excluded from the analyses. Four other participants requested that their filmed therapy sessions not be used for research and were therefore removed from the original pool. The final cohort was thus composed of 58 clients (31 females and 21 males) diagnosed with MDD, with a mean age of 36.66 (standard deviation [SD] = 9.45; range: 21–61 years). The clients' mean BDI-II score at intake was 23.83 (SD = 8.57), indicating moderate depression levels (Beck et al., 1996).

Treatment and Therapists

The clients underwent brief (16 session) supportive-expressive (SE) psychodynamic psychotherapy (Luborsky & Mark, 1991) adapted to the treatment of depression (Luborsky et al., 1995). The key treatment features included supportive techniques, such as affirmation and empathic validation, as well as expressive techniques such as interpretation and confrontation. SE therapy has been reported to be effective in the treatment of depression (Beck et al., 1996; Sheehan et al., 1998). The therapists were trained and supervised by senior clinicians with extensive expertise in SE therapy and received weekly individual and group supervision. Thirteen therapists (7 females and 6 males) participated in this study; five therapists treated 6 to 9 clients each, seven others treated 2–4 clients each and the remaining therapist treated 1 client. The therapists were advanced trainees in a university clinic with 3 to 7 years of experience.

Measures and Procedure

All sessions were recorded using a 1,920 × 1,080 pixel HD camera positioned behind the therapist and aimed at the client in a way that allowed it to be positioned in front of the client's face without disturbing eye contact with the therapist. The position of the chairs was marked on the floor so that at the beginning of each session the relative position between the camera and the client was optimal. Five preselected sessions evenly distributed throughout the course of therapy (sessions 2, 5, 8, 11, and 14) were analyzed, resulting in a total of 283 sessions (the video recordings of seven sessions were excluded from the analysis due to technical issues with the camera orientation or the computer filming system).

Automated facial expression recognition to assess emotion flexibility FaceReader-9 was used to extract emotional responses from the video recordings. The FaceReader allows assessment of emotional responses through video imagery analysis (Höfling et al., 2020; Lewinski et al., 2014) and is based on the FACS system (Ekman & Friesen, 1976). The

FaceReader provides built-in facial action unit analysis and emotional expression scoring without needing additional training or customization. The validity of FaceReader's affective measures was examined and found to be highly associated with the ratings of external professional annotators (Skiendziel et al., 2019). The software achieved 88% accuracy in identifying basic emotions compared to expert human coders (Lewinski et al., 2014) and the latest version, FaceReader-9 which was used in this study, has over 96% accuracy in measuring emotions from facial expressions (Noldus, 2022).

The entire 50 min of each session were analyzed. The FaceReader system automatically analyzes video frames to detect the intensities of 20 facial action units on a continuous scale from 0 to 1. From these action unit intensities, it calculates the intensity scores from 0 to 1 for each of the six basic facial expressions (happy, sad, angry, surprised, scared, disgusted). It uses the "circumplex model of affect" (Russell, 1980) to compute a valence score ranging from −1 (most negative emotion) to +1 (most positive emotion) based on the highest scoring positive and negative expressions, which are captured at a rate of 25 frames per second. In line with previous research in this field (e.g., Kuppens et al., 2010; Ogbaselase et al., 2020) which used a 1 s time interval, we used the mean valence score in each second during the session to evaluate the emotional responses of the participants from moment to moment. A total of 884,022 observations were obtained (M= -0.05; SD = 0.26), allowing for the examination of changes in emotional valence over time. Figure 1 illustrates the setting and the analysis that was conducted using the FaceReader software.

As in previous studies (e.g., Coifman & Summers, 2019), emotional flexibility was indexed as the standard deviation (SD) of clients' valence scores during the therapy session where higher SD values indicate greater emotional flexibility during a session.

Beck Depression Inventory (BDI-II; Beck et al., 1996). The BDI-II is a 21-item self-report measure of depression that asks respondents to rate the severity of their depressive symptoms during the previous week on a variable Likert scale (i.e., 19 items use a 4-point scale and 2 items use a 7-point scale but have equivalent scores ranging from 0 to 3). Individual item scores are summed to create a total severity score with a range of 0 to 63. The BDI-II has been shown to have high internal consistency (α = 0.93) and concurrent validity (Subica et al., 2014). In the current sample, the levels of reliability for within-person and between-person

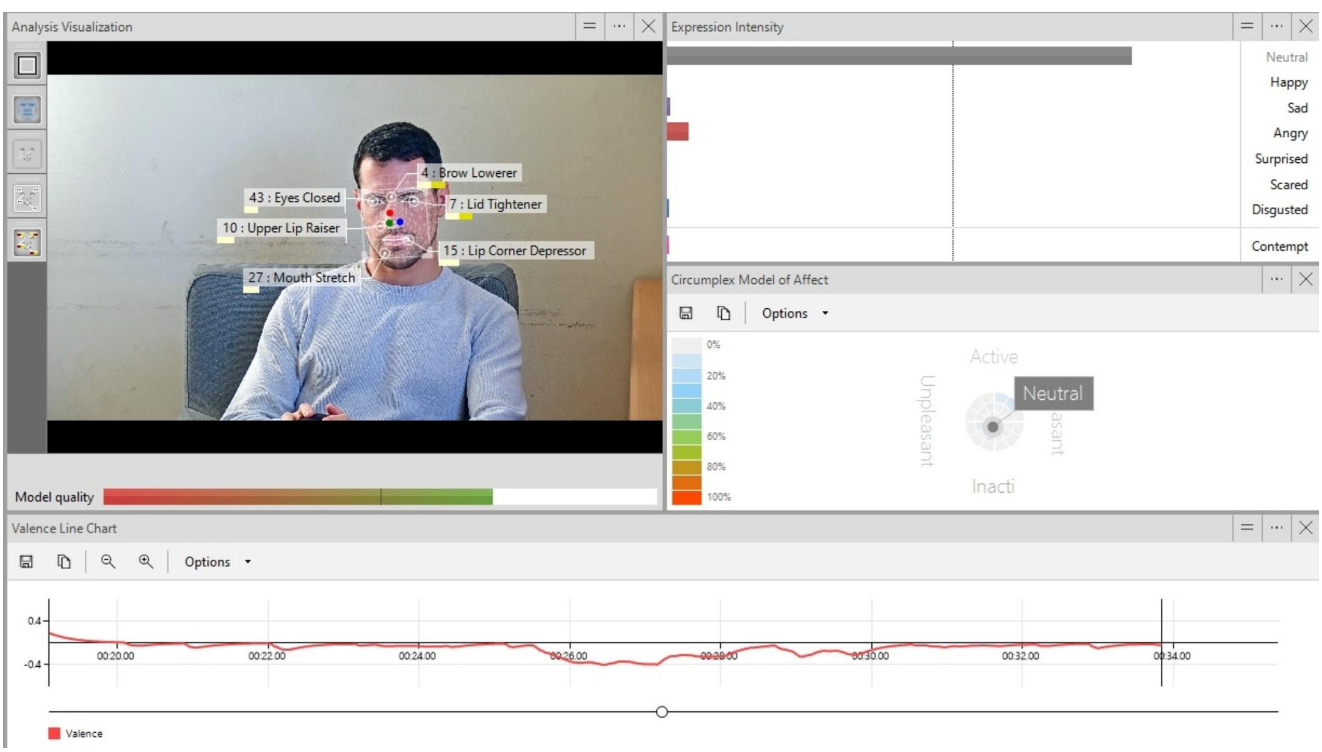

Fig. 1 Automated facial expression to assess clients' emotional responses during the entire session moment-by-moment. *Note* An illustration of the setting and the analysis that was conducted using FaceReader-9 software

measures were 0.67 and 0.98, respectively. Clients completed the BDI-II at the beginning of each session.

Data Analytic Strategy

The dataset had a hierarchical structure, with session ratings nested within clients. Therefore, we used multilevel modeling (MLM; Raudenbush & Bryk, 2002) to test whether emotional flexibility was associated with clients' BDI scores. The variable ValenceSD (the standard deviation of clients' valence scores during the session) was client mean-centered (MC; centered around each client's mean) for within-client effects, as well as grand-mean-centered (GMC; centered around the grand mean of all clients) for between-client effects. The model was adjusted for mean facial expression valence. The following two-level (session nested within clients) model was estimated:

Level 1

$$BDI_{ij} = \beta_{0j} + \beta_{1j} * MeanValenceMC_{ij} + \beta_{2j} * SDValenceMC_{ij} + e_{ij}$$

Level 2

$$\beta_{0j} = \gamma_{00} + \gamma_{01} * MeanValenceGMC_j + \gamma_{02} * SDValenceGMC_j + \mu_{0j};$$

$$\beta_{1j} = \gamma_{10}; \beta_{2j} = \gamma_{20};$$

$$(\mu_{0j}) \sim N\left[(0), (\tau_{00})\right]$$

In this model, the reported BDI score of client j at session i was modelled at the session level (Level 1) by client emotional flexibility scores (β_{2j};within clients) while controlling for the mean valence scores. On Level 2, the intercept (β_{0j}) was modelled to include the fixed effect (γ_{00}) and the emotional flexibility score at the client level (γ_{02}) while controlling for the mean valence score at the client level (γ_{01}). The residual (e_{ij}, i.e., the level 1 random effect) and the level 2 random effect were modeled for the intercept (μ_{0j}).

Results

Table 1 presents the results of the MLM analysis. The association between measure of emotional flexibility (ValenceSD) and depression severity (BDI scores) was tested at the between and within client levels. Results were consistent with both of our hypotheses. Consistent with hypothesis 1, the fixed between-client effect indicated that higher levels of clients' average emotional flexibility were associated with lower depression severity. Consistent with hypothesis 2, the fixed within-client effect indicated that sessions with higher levels of emotional flexibility were associated with lower depression severity.

Figure 2 illustrates a session characterized by high levels of depression and low flexibility and a session characterized by low levels of depression and high flexibility. Taken together, both client averages and session levels of emotional flexibility were associated with lower reported depression symptoms[1].

Discussion

Our research aimed to enhance the understanding of the role of emotional flexibility in the treatment of depression. To that end, we assessed clients' emotional flexibility, using computerized facial expression measures, and examined the association with clients' depression levels, based on their session-by-session self-reports. Our results supported our hypotheses. Consistent with our first hypothesis, we found

Table 1 Longitudinal MLM of emotional flexibility as a predictor of BDI score (Model 1)

Parameters	Estimate (*SE*)	*p*	95% CI	95% CI	Effect size
Fixed effects					
Intercept (γ_{00})	17.77(1.13)***	< 0.001	[15.54, 20.01]	[15.54, 20.01]	− 0.001
Slope MeanValenceMC	-0.74(1.63)	0.65	[-3.95,2.48]	[-3.95,2.48]	− 0.016
Slope SDValenceMC (γ_{20})	-24.07(10.72)*	0.03	[-45.19,-2.95]	[-45.19,-2.95]	− 0.07
Slope MeanValenceGMC	8.41(12.8)	0.51	[-17.24,34.06]	[-17.24,34.06]	0.07
Slope SDValenceGMC (γ_{02})	-53.49(17.27)**	< 0.01	[-88.09,-18.89]	[-88.09,-18.89]	− 0.35
Random effects					
Level 1 (sessions)					
Residual	6.6				
Level 2 (clients)					
Intercept	7.47		[5.63,9.89]	[5.63,9.89]	[5.63,9.89]

Note. Effect size was obtained by standardizing the raw scores and re-running the model (Baldwin et al., 2014)

*p < .05, **p < .01, ***p < .001

[1] The random effect of the clients' average BDI scores was also significant, indicating significant between-client variability.

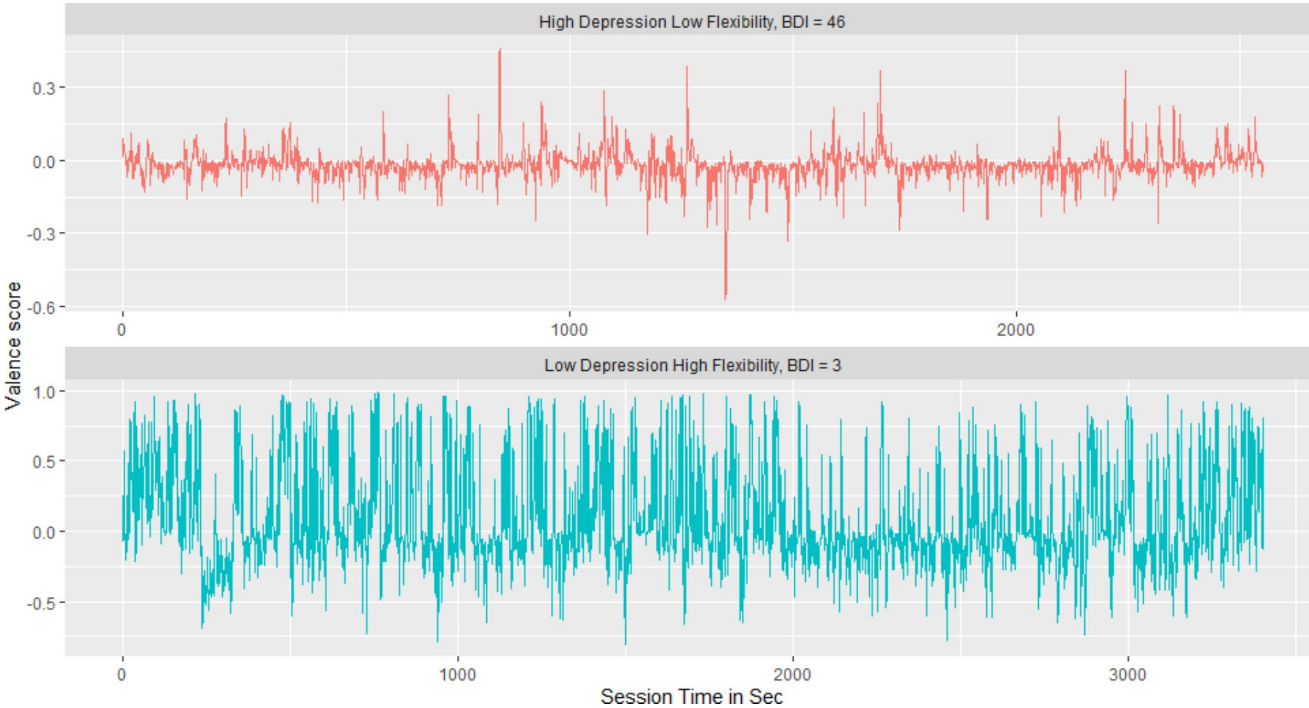

Fig. 2 Valence score traces in one-second intervals from two sessions. This figure illustrates the relationship between depression and emotional flexibility levels in two different sessions. One shows "High Depression Low Flexibility" and the other shows "Low Depression High Flexibility"

that clients who (on average) experienced higher levels of depressive symptoms, tended to exhibit lower levels of emotional flexibility during treatment. This finding supports and extends previous research indicating that higher levels of depression are associated with lower emotional flexibility (Brose et al., 2015; Kuppens et al., 2010). Notably, our study significantly broadens the scope of previous research, encompassing a much larger number of assessment sessions and utilizing a more fine-grained time resolution for measuring emotional flexibility that captures moment-to-moment emotional fluctuations. Taken together, these findings highlight the role of emotional flexibility as a central factor in depression (Kashdan & Rottenberg, 2010).

The results also supported the second hypothesis by showing that higher depressive symptoms in a session were associated with lower session-level emotional flexibility. Thus, in sessions in which clients' depressive symptoms were higher, their emotional flexibility was lower, and vice versa. These findings are not only consistent with previous studies that have pointed to the usefulness of computerized measures to capture facial expression patterns that characterize depressed individuals (e.g., Gavrilescu & Vizireanu, 2019; Wang et al., 2018), but extend them by indicating that computerized measures can capture the dynamic nature of emotional flexibility and the ways in which it changes in relation to levels of depressive symptoms session-by-session throughout treatment.

Importantly, the association between emotional flexibility and depressive symptoms was significant above and beyond the mean valence of the experienced emotions, both at the client as well as at the session levels. These findings are consistent with current views suggesting that depression is more than an imbalance between negative and positive emotions – it also involves the inflexibility of emotional expression (Barrett, 2017; Kashdan & Rottenberg, 2010; Werner-Seidler et al., 2020). In line with recent recommendations to assess processes in psychotherapy both at the between as well as at the within-client levels (e.g., Huibers et al., 2022; Zilcha-Mano, 2021), our findings highlight the centrality of emotional flexibility both as a trait-like as well as a state-like characteristic of depression. The results also demonstrate the ability of computerized measures to capture key emotional processes in the treatment of depression.

This study's contributions should be considered in light of its limitations. One limitation is the use of facial expressions as the sole measurement method. Emotions are known to be expressed through multiple modalities, including the vocal, physiological, and linguistic channels. Future research would benefit from including such modalities and examining the generality versus specificity of the facial channel in depression. Second, the current study focused on emotional flexibility in the valence dimension of the affective space. While this approach is consistent with previous studies (Coifman & Summers, 2019; Koval et al., 2012; Kuppens et al., 2010), given that affective states can be situated in a two-dimensional space of valence and arousal (Russell, 1980), future studies would benefit from examining affective flexibility in valence and arousal jointly. Third, the reliance on trainee therapists and the focus on psychodynamic psychotherapy may also limit the generalizability of the findings. Future studies may examine the associations between emotional flexibility and depressive symptoms in therapies conducted by more experienced clinicians as well as in other treatment models. Fourth, there is evidence suggesting that automated assessments of emotional valence correlated with therapist assessments of client emotions but not with the clients' own assessments of their emotions (Terhürne et al., 2022). This raises the possibility that our measurement of emotional flexibility might be more indicative of clients' capacity to express emotions flexibly, rather than their ability to experience a broad spectrum of emotions. Future research should delve into the congruence between flexibility in facial expression and flexibility in subjectively experienced emotions to discern if both, or only one, are associated with shifts in depressive symptoms. Finally, although we found a correlation between emotion flexibility and depression, we did not address the questions of causality.

These limitations notwithstanding, the current findings extend the study of emotional processes during psychotherapy and have theoretical, methodological, as well as clinical, implications. Theoretically, the role of emotional flexibility in depression is highlighted. Methodologically, the value of using automatic emotional expression recognition software as diagnostic tools to assess depression is supported. Clinically, our findings suggest the importance of enhancing and enlarging the repertoire of emotional expression in therapeutic work. The integration of computerized facial expression assessments of emotional flexibility into existing feedback and monitoring systems may allow clinicians and mental health providers to seamlessly monitor clients' mental states without burdening them with completing questionnaires, assist clinicians in diagnosing signs of depression, and help their clients increase their emotional flexibility.

Declarations

The authors have no relevant financial or non-financial interests to disclose.
The authors have no competing interests to declare that are relevant to the content of this article.
All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non-financial interest in the subject matter or materials discussed in this manuscript.
The authors have no financial or proprietary interests in any material discussed in this article.
The study was approved by Bar-Ilan University Review Board (Num. AS/01507/2019) and was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.
The study followed guidelines from The REporting of studies Conducted using Observational Routinely-collected health Data (RECORD).

References

Baldwin, S. A., Imel, Z. E., Braithwaite, S. R., & Atkins, D. C. (2014). Analyzing multiple outcomes in clinical research using multivariate multilevel models. *Journal of Consulting and Clinical Psychology*, *82*(5), 920.

Bar-Kalifa, E., & Atzil-Slonim, D. (2020). Intrapersonal and interpersonal emotional networks and their associations with treatment outcome. *Journal of Counseling Psychology*, *67*(5), 580.

Beck, A. T., Steer, R. A., & Brown, G. K. (1996). *Beck depression inventory*.

Bonanno, G. A., Papa, A., Lalande, K., Westphal, M., & Coifman, K. (2004). The importance of being flexible: The ability to both enhance and suppress emotional expression predicts long-term adjustment. *Psychological Science*, *15*(7), 482–487.

Brose, A., Schmiedek, F., Koval, P., & Kuppens, P. (2015). Emotional inertia contributes to depressive symptoms beyond perseverative thinking. *Cognition and Emotion*, *29*(3), 527–538.

Cohn, J. F., Ambadar, Z., & Ekman, P. (2007). Observer-based measurement of facial expression with the Facial Action Coding System. *Handbook of emotion elicitation and assessment* (pp. 203–221). Oxford University Press.

Cohn, J. F., & De la Torre, F. (2015). *Automated face analysis for affective computing*

Coifman, K. G., & Summers, C. B. (2019). Understanding emotion inflexibility in risk for affective disease: Integrating current research and finding a path forward. *Frontiers in Psychology, 10*, 392. https://doi.org/10.3389/fpsyg.2019.00392.

Ekman, P., & Friesen, W. V. (1976). Measuring facial movement. *Environmental Psychology and Nonverbal Behavior*, *1*(1), 56–75. https://doi.org/10.1007/BF01115465.

Fosha, D. (2001). The dyadic regulation of affect. *Journal of Clinical Psychology*, *57*(2), 227–242.

Freitas-Magalhães, A. (2012). Microexpression and macroexpression. *Encyclopedia of Human Behavior*, *2*, 173–183.

Gavrilescu, M., & Vizireanu, N. (2019). Predicting depression, anxiety, and stress levels from videos using the facial action coding system. *Sensors (Basel, Switzerland)*, *19*(17), 3693.

Girard, J. M., Cohn, J. F., Mahoor, M. H., Mavadati, S., & Rosenwald, D. P. (2013). Social risk and depression: Evidence from manual and automatic facial expression analysis. *2013 10th IEEE International Conference and Workshops on Automatic Face and Gesture Recognition (FG)*, 1–8. https://doi.org/10.1109/FG.2013.6553748.

Greenberg, L. S. (2012). Emotions, the great captains of our lives: Their role in the process of change in psychotherapy. *American Psychologist*, *67*(8), 697.

Gupta, S., & Bonanno, G. A. (2011). Complicated grief and deficits in emotional expressive flexibility. *Journal of Abnormal Psychology*, *120*(3), 635.

Hamilton, M. (1960). A rating scale for depression. *Journal of Neurology Neurosurgery and Psychiatry*, *23*(1), 56.

Harati, S., Crowell, A., Huang, Y., Mayberg, H., & Nemati, S. (2019). Classifying depression severity in recovery from major depressive disorder via dynamic facial features. *IEEE Journal of Biomedical and Health Informatics*, *24*(3), 815–824.

Herrmann, I. R., Greenberg, L. S., & Auszra, L. (2016). Emotion categories and patterns of change in experiential therapy for depression. *Psychotherapy Research*, *26*(2), 178–195.

Höfling, T. T. A., Gerdes, A. B. M., Föhl, U., & Alpers, G. W. (2020). Read my face: Automatic facial coding versus psychophysiological indicators of emotional valence and arousal. *Frontiers in Psychology*, *11*. https://doi.org/10.3389/fpsyg.2020.01388. https://www.frontiersin.org/article/

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.

Kashdan, T. B., & Rottenberg, J. (2010). Psychological flexibility as a fundamental aspect of health. *Clinical Psychology Review*, *30*(7), 865–878. https://doi.org/10.1016/j.cpr.2010.03.001.

Koval, P., Kuppens, P., Allen, N. B., & Sheeber, L. (2012). Getting stuck in depression: The roles of rumination and emotional inertia. *Cognition and Emotion*, *26*(8), 1412–1427. https://doi.org/10.1080/02699931.2012.667392.

Kramer, U., Pascual-Leone, A., Despland, J. N., & de Roten, Y. (2015). One minute of grief: Emotional processing in short-term dynamic psychotherapy for adjustment disorder. *Journal of Consulting and Clinical Psychology, 83*(1), 187. https://doi.org/10.1037/a0037979.

Kuppens, P., Allen, N. B., & Sheeber, L. B. (2010). Emotional inertia and psychological maladjustment. *Psychological Science*, *21*(7), 984–991. https://doi.org/10.1177/0956797610372634.

Lewinski, P., Uyl, T., & Butler, C. (2014). Automated facial coding: Validation of Basic Emotions and FACS AUs in FaceReader. *Journal of Neuroscience Psychology and Economics*, *7*, 227–236. https://doi.org/10.1037/npe0000028.

Luborsky, L., & Mark, D. (1991). Short-term supportive-expressive psychoanalytic psychotherapy. In *Handbook of Short-Term Dynamic Psychotherapy*, 110–136.

Luborsky, L., Mark, D., Hole, A. V., Popp, C., Goldsmith, B., & Cacciola, J. (1995). *Supportive-expressive dynamic psychotherapy of depression: A time-limited version.*

McCullough, L., & Magill, M. (2009). Affect-focused short-term dynamic therapy. In *Handbook of evidence-based psychodynamic psychotherapy* (pp. 249–277). Springer.

Nasser, S. A., Hashim, I. A., & Ali, W. H. (2020). A review on depression detection and diagnoses based on visual facial cues. *2020 3rd International Conference on Engineering Technology and Its Applications (IICETA)*, 35–40.

Noldus (2022). *Facial expression analysis—FaceReader*. Facial Expression Analysis - FaceReader. https://www.noldus.com/facereader/facial-expression-analysis.

Ogbaselase, F. A., Mancini, K. J., & Luebbe, A. M. (2020). Indirect effect of family climate on adolescent depression through emotion regulatory processes. *Emotion*.

Pampouchidou, A., Simos, P. G., Marias, K., Meriaudeau, F., Yang, F., Pediaditis, M., & Tsiknakis, M. (2017). Automatic assessment of depression based on visual cues: A systematic review. *IEEE Transactions on Affective Computing*, *10*(4), 445–470.

Pascual-Leone, A., & Greenberg, L. S. (2007). Emotional processing in experiential therapy: Why the only way out is through. *Journal of Consulting and Clinical Psychology*, *75*(6), 875.

Pe, M. L., Kircanski, K., Thompson, R. J., Bringmann, L. F., Tuerlinckx, F., Mestdagh, M., Mata, J., Jaeggi, S. M., Buschkuehl, M., & Jonides, J. (2015). Emotion-network density in major depressive disorder. *Clinical Psychological Science*, *3*(2), 292–300.

Pos, A. E., Greenberg, L. S., & Warwar, S. H. (2009). Testing a model of change in the experiential treatment of depression. *Journal of Consulting and Clinical Psychology*, *77*(6), 1055.

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: Applications and data analysis methods* (Vol. 1). sage.

Rottenberg, J. (2017). Emotions in depression: What do we really know. *Annual Review of Clinical Psychology*, *13*(1), 241–263.

Russell, J. A. (1980). A circumplex model of affect. *Journal of Personality and Social Psychology, 39*(6), 1161.

Sheehan, D. V., Lecrubier, Y., Sheehan, K. H., Amorim, P., Janavs, J., Weiller, E., Hergueta, T., Baker, R., & Dunbar, G. C. (1998). The mini-international neuropsychiatric interview (MINI): The development and validation of a structured diagnostic psychiatric interview for DSM-IV and ICD-10. *Journal of Clinical Psychiatry*, *59*(20), 22–33.

Skiendziel, T., Rösch, A. G., & Schultheiss, O. C. (2019). Assessing the convergent validity between the automated emotion recognition software Noldus FaceReader 7 and Facial Action Coding System Scoring. *PloS One*, 14(10), e0223905.

Subica, A. M., Fowler, J. C., Elhai, J. D., Frueh, B. C., Sharp, C., Kelly, E. L., & Allen, J. G. (2014). Factor structure and diagnostic validity of the Beck Depression Inventory–II with adult clinical inpatients: Comparison to a gold-standard diagnostic interview. *Psychological Assessment*, *26*(4), 1106.

Terhürne, P., Schwartz, B., Baur, T., Schiller, D., Eberhardt, S. T., André, E., & Lutz, W. (2022). Validation and application of the non-verbal behavior analyzer: An automated tool to assess non-verbal emotional expressions in psychotherapy. *Frontiers in Psychiatry*, *13*, 1026015. https://doi.org/10.3389/fpsyt.2022.1026015

Wang, Q., Yang, H., & Yu, Y. (2018). Facial expression video analysis for depression detection in chinese patients. *Journal of Visual Communication and Image Representation*, *57*, 228–233. https://doi.org/10.1016/j.jvcir.2018.11.003.

Wichers, M., Wigman, J. T. W., & Myin-Germeys, I. (2015). Micro-level affect dynamics in psychopathology viewed from complex dynamical system theory. *Emotion Review*, *7*(4), 362–367.

Williams, J. B. (1988). A structured interview guide for the Hamilton Depression Rating Scale. *Archives of General Psychiatry*, *45*(8), 742–747.

Zilcha-Mano, S. (2021). Toward personalized psychotherapy: The importance of the trait-like/state-like distinction for understanding therapeutic change. *American Psychologist*, *76*(3), 516.