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Patterns of Early Change in Interpersonal Problems and Their Relationship to Nonverbal Synchrony and Multidimensional Outcome

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Early change is an increasing area of investigation in psychotherapy research. In this study, we analyzed patterns of early change in interpersonal problems and their relationship to nonverbal synchrony and multiple outcome measures for the first time. We used growth mixture modeling to identify different latent classes of early change in interpersonal problems with 212 patients who underwent cognitive–behavioral treatment including interpersonal and emotion-focused elements. Furthermore, videotaped sessions were analyzed using motion energy analysis, providing values for the calculation of nonverbal synchrony to predict early change in interpersonal problems. The relationship between early change patterns and symptoms as well as overall change in interpersonal problems was also investigated. Three latent subgroups were identified: 1 class with slow improvement (n = 145), 1 class with fast improvement (n = 12), and 1 early deterioration class (n = 55). Lower levels of early nonverbal synchrony were significantly related to fast improvement in interpersonal change patterns. Furthermore, such patterns predicted treatment outcome in symptoms and interpersonal problems. The results suggest that nonverbal synchrony is associated with early change patterns in interpersonal problems, which are also predictive of treatment outcome. Limitations of the applied methods as well as possible applications in routine care are discussed.

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Some of the ideas and results presented in the current study were presented at German Psychological Association (DGPs) Clinical Psychology Meeting in Erlangen in May 2019. Part of the data analyzed in this study were published in Paulick et al. (2018). In the current study, we used the algorithm by Altmann (2013; script publicly available at GitHub: https://github.com/10101-00001/MEA).

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Public Significance Statement

This study suggests that lower levels of nonverbal synchrony may be a predictor of early improvement in interpersonal problems, which furthermore predict treatment outcome in symptoms and interpersonal problems. Given further research, nonverbal synchrony might become a useful addition to monitor successful treatment processes.

Keywords: patterns of early change in interpersonal problems, nonverbal synchrony, growth mixture modeling, motion energy analysis

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Early change, defined as substantial change during the early phase of psychotherapy, has been shown to be predictive of treatment outcome at termination and follow-up (e.g., Haas, Hill, Lambert, & Morrell, 2002; Lutz, Stulz, & Köck, 2009; Nordberg, Castonguay, Fisher, Boswell, & Kraus, 2014; Rubel, Lutz, & Schulte, 2015). Its predictive value has been confirmed in samples with different age groups (e.g., Gunlicks-Stoessel & Mufson, 2011), psychological and pharmacological treatments (e.g., Hofmann, Schulz, Meuret, Moscovitch, & Suvak, 2006; van Calker et al., 2009), in different diagnostic groups (e.g., Aderka, Nickerson, Bøe, & Hofmann, 2012; Lutz et al., 2014), and for diverse instruments used to measure early change and symptomatic outcome (e.g., Leucht, Busch, Kissling, & Kane, 2007).

In one of the earlier investigations of early change, a sample of 147 college students receiving psychotherapy at a university counseling center was assessed using symptom measures within the first three therapy sessions. Early improvement was related to positive treatment outcome. In addition, those who were categorized as having early improvement maintained their therapy goals up to two years later (Haas et al., 2002). In subsequent investigations, advanced statistical models such as growth mixture modeling (GMM) were often used to define different patterns of change for patient subgroups, whereby the subgroup early rapid improvement turned out to be an especially good predictor of outcome. For example, Stulz, Lutz, Leach, Lucock, and Barkham (2007) used GMM to identify multiple subpopulations early in therapy. The mixed sample consisted of 192 patients from an outpatient clinic. The results suggested a relation between early change and outcome. More precisely, 96% of rapid responders were also categorized as recovered or improved at the end of treatment. In contrast, the nonrapid responders improved much less during treatment (22%). This study was replicated and extended by Nordberg and colleagues (2014) on a mixed sample of 147 patients at an university-based training clinic. Early change patterns were identified using GMM within the first 15 sessions of therapy.

However, although early change has repeatedly been shown to be a powerful predictor of global and disorder specific symptoms under different circumstances, there is a limited amount of research on the relation between early change and other treatment outcomes or treatment processes variables, for example, interpersonal problems and/or potential interpersonal or dyadic mechanisms. In one of the few studies, Zilcha-Mano and Errázuriz (2017) investigated early change patterns in therapeutic alliance within the first four sessions of therapy in a mixed sample of 166 patients. In this study the effect of early alliance patterns on treatment outcome was moderated by interpersonal problems at the beginning of therapy.

There is evidence for a reciprocal relation between interpersonal problems and disorder specific symptoms. Such interpersonal problems related to psychological disorders might be social skills deficits and dysfunctional social behavior (Alden & Taylor, 2004; Erickson & Newman, 2007; Stangier, Esser, Leber, Risch, & Heidenreich, 2006). Furthermore, psychological disorders do not only have an impact on intrapersonal emotions as well as cognitive and behavioral symptoms but can also result in interpersonal problems, for example, low self-esteem can lead to dysfunctional social behavior (Hames, Hagan, & Joiner, 2013).

For example, interpersonal processes in social anxiety patients are often characterized by submissive and inhibited behavior. In social interactions, these patients try to avoid conflicts and show a lack of the expression of warmth and dominance (Russell, Moskowitz, Zuroff, Bleau, Pinard, & Young, 2011). Patients with depressive disorders experience interpersonal problems caused by reassurance-seeking and complaining (Erickson & Newman, 2007; Hames et al., 2013). In addition, depressed patients express more sadness, poor posture, and infrequent gesturing (Hames et al., 2013).

Putative interpersonal mechanisms such as patient–therapist dyadic synchrony may also influence early change of interpersonal problems. Moreover, patients with severe interpersonal problems tend to elicit specific interpersonal reactions in other people, including the therapist (e.g., Kiesler, 1983). According to Kiesler's (1983) theory of interpersonal complementarity, interpersonal behaviors are classified based on two dimensions: agency (ranging from dominant to submissive) and affiliation (ranging from hostile to friendly). Interaction partners of patients with interpersonal problems tend to display more intense interpersonal and emotional reactions toward these patients, even if their reaction is not necessarily helpful to the person. For example, if a patient diagnosed with chronic depression displays submissive and somewhat hostile interpersonal behavior (Constantino et al., 2008; McCullough, 2003), this provokes others to react in a dominant and angrily directive way (e.g., Erickson & Newman, 2007). This reaction stabilizes the patient's dysfunctional interpersonal pattern of being submissive. In addition, it reinforces the patient's negative expectations and furthers their disrupted self-identity. A trained psychotherapist should be able to detect the interpersonal pull triggered by the patient and act in a more noncomplementary way, even on a nonverbal level, to support patients' ability to react flexibly and solve interpersonal problems. Therapists should be better able to

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react to the extreme sadness, reduced gesture, and motoric movements by not being overwhelmed by these depressive symptoms or adapting the same depressive nonverbal behavior. Some treatment concepts focusing on current interpersonal patterns such as, for example, interpersonal therapy or cognitive behavioral analysis system of psychotherapy train therapists specifically in such skills (interpersonal discrimination learning) to handle patient's immediate interpersonal deficits (McCullough, 2003; Wagner & Safran, 2010).

So far, this kind of patient–therapist dyadic interaction was difficult to assess in psychotherapy research, with time-consuming rating systems commonly being applied to only a few patients (Baesler & Burgoon, 1987; Bernieri, 1988). The investigation of interpersonal behavior based on nonverbal synchrony is a relatively new field in psychotherapy process research, which is based on new technological developments allowing automated video analysis of treatments sessions. *Nonverbal synchrony* can be defined as movement coordination between interacting persons (Ramseyer & Tschacher, 2011). It originates from research in developmental and social psychology, showing associations with higher resonance and rapport (e.g., Bernieri, Davis, Rosenthal, & Knee, 1994), higher involvement (e.g., Katsumata, Ogawa, & Komori, 2009), and relationship quality (e.g., Grammer, Honda, Juette, & Schmitt, 1999), as well as interactions in positive situations (e.g., Altmann, 2011). In mother–neonate interactions, it has been connected to healthy child development (e.g., Lindsey, Mize, & Pettit, 1997). To date, studies seem to show that movement synchrony between two people generates emotional security and a sense of being receptively attuned to one another (Geller & Porges, 2014). However, interpersonal and/or nonverbal synchrony by itself may not always be beneficial—particularly when interaction partners mutually amplify or escalate each other's ineffective interpersonal processes (Butler, 2015; Feldman, 2003; Tronick, 1989).

Whereas former studies investigating nonverbal synchrony used human ratings to analyze body movements (e.g., Chartrand & Bargh, 1999), recent studies make use of more economic automatic video analysis systems, finding comparable results (e.g., Altmann, 2013; Tschacher, Rees, & Ramseyer, 2014). In this line of research working with automatic video analysis systems, motion energy analysis (MEA; e.g., Altmann, 2011, 2013; Ramseyer & Tschacher, 2011; Watanabe, 1983) is the most commonly applied approach in clinical research. It assesses simultaneous and slightly time-lagged movements of interacting persons within a video clip (generated values based on pixel changes are subsequently used to calculate synchrony). This procedure, which was also applied in this study, provides information on the dynamic quality of synchrony in terms of the relations between movements (changes in postures, gestures, and even facial expressions), whereas the static quality (in terms of which posture) is not assessed.

In psychotherapy research, automatically analyzed nonverbal synchrony has been shown to be related to different process variables. For example, previous studies have found positive associations with the therapeutic relationship (e.g., Ramseyer & Tschacher, 2011), patient self-efficacy (Ramseyer & Tschacher, 2011), and treatment outcome and dropout (e.g., Paulick et al., 2018). Despite the growing number of studies using automatically analyzed synchrony, its association with early change in interpersonal problems has yet to be investigated. This article attempts to extend the existing early change literature and its application to clinical practice in several ways. First, it focuses on early change in interpersonal problems, rather than focusing on early change in symptomatic outcome. Such a focus can help therapists to gain more awareness of interpersonal processes during therapy and to understand how to achieve positive outcomes. Second, the article introduces a novel clinically relevant predictor of early interpersonal change, namely nonverbal synchrony. The study of new, trainable process variables such as nonverbal synchrony is an important step toward increasing the clinical relevance of the early change literature (e.g., in the context of treatment monitoring and feedback systems). Concretely, this work focuses on identifying specific therapist behaviors that relate to an adaptive early interpersonal change trajectory and better ultimate outcomes. Third, this article uses a novel and so far understudied automatized method to measure nonverbal synchrony. Given the limited knowledge of mediators and mechanisms of change in psychotherapy (e.g., Kazdin, 2014), automatized measures of psychotherapeutic processes applied to larger databases in association with modern statistical tools for data analyses might have the potential to achieve a better identification and understanding of core change parameters in psychotherapy.

With these aims in mind, we examine if patient–therapist dyadic nonverbal behavior or synchrony at the beginning of treatment helps to predict early change in interpersonal problems. Early nonverbal synchrony could be a possible indicator that the therapist might be less impacted by the interpersonal behavior of the patient and more able to nonverbally handle the dysfunctional interpersonal pattern. Patient–therapist dyads with lower early synchrony might result in faster improvement of interpersonal problems. However, it is also possible that higher nonverbal synchrony improves alignment and attunement between therapist and patient, therefore resulting in interpersonal problems being alleviated more quickly.

In this study, we therefore first investigated patterns of early change in interpersonal problems. Second, on the basis of early change patterns in interpersonal problems, we explored whether nonverbal synchrony was related to early change. Third, we tested if these early change patterns were related to multiple posttreatment outcomes (interpersonal problems and symptoms).

Method

Patients and Therapists

The study is based on a sample of 212 patients treated by 78 therapists between 2007 and 2016 at an outpatient clinic in southwest Germany. The data used in this study is an extension (an additional 95 cases were subsequently assessed in the same clinic) of a dataset also used in a study on dropout published by Paulick et al. (2018). Eligible patients had to meet the following criteria: (a) baseline measurements, (b) one additional measurement within the first 10 sessions, (c) eligible video clip of Session 3 (alternatively Session 4 or 5, for criteria, see section below), (d) no substance dependency or psychosis (as both disorders may have severe effects on nonverbal behavior, possibly distorting the data), and (e) no transfer to a different therapist during the course of therapy. Patients were over 15 years of age (M = 35.66, SD = 12.72) and 52.89% were male. Patients in this study had varying diagnoses: anxiety disorders (n = 101; 47.64%), depression (n = 96; 45.28%), personality disorders (n = 6; 2.82%), and others (e.g., eating disorders: n = 8; 3.76%). One hundred forty-seven patients (69.34%) received two or more diagnosis (see Table 1). Patients were diagnosed based on the Structured Clinical Interview for Axis I *DSM–IV* Disorders (SCID-I; Wittchen, Wunderlich, Gruschwitz, & Zaudig, 1997). The interviews were conducted by intensively trained independent clinicians before actual therapy began. Subsequently, the videotaped interviews and diagnoses were discussed in expert consensus teams comprised of four senior clinicians. Final diagnoses were determined by consensual agreement of at least 75% of the team members.

All patients finished the diagnostic phase before treatment (see below), received individual psychotherapy with an average of 34.31 treatment sessions (SD = 16.71) and 17% (n = 36) dropped out of treatment.

All therapists in this study were enrolled in a 3-year (full-time) or 5-year (part-time) postgraduate training program with a CBT focus, which also included interpersonal and emotion-focused elements (Castonguay, Eubanks, Goldfried, Muran, & Lutz, 2015; Lutz, Schiefele, Wucherpfennig, Rubel, & Stulz, 2016). They had received at least 1 year of training before beginning to see patients and were supervised by a senior therapist every 4th session. Therapists (82.05% female) treated between one and 13 patients (M = 2.75 patients, SD = 2.87) in this study.

Table 1
Sample Characteristics: Demographic and Clinical Variables

Variables	M	Rage
Patient age (in years)	35.61	15–68
Therapy duration (number of sessions)	33.88	12–81
	n	%
Patient sex (female)	102	48.11
Therapist sex (female)	64	82.05
Dropout frequency	36	16.98
Marital status	210	
Married	40	19.00
Separated	19	9.00
Single	80	38.10
In relationship	61	29.05
Divorced	9	4.29
Widowed	1	.48
Education	211	
No graduation	8	3.80
Lower secondary	46	21.80
Middle secondary	55	26.10
Higher secondary	100	47.40
Other	2	.90
Primary SCID diagnosis	212	
Depression	97	45.54
Bipolar	5	5.15
Major depression	78	80.41
Dysthymia	14	14.43
Anxiety	101	47.89
Social phobia	45	21.13
Panic disorder	5	2.35
Obsessive compulsive disorder	8	3.76
Posttraumatic stress disorder	5	2.35
Somatization disorder	7	3.29
Other	17	8.02
Personality	6	2.82
Other	8	3.76
Comorbid (second SCID diagnosis)	147	69.48
Depression	36	24.95
Anxiety	68	45.95
Personality	21	14.19
Others	22	14.86

Note. SCID = Structured Clinical Interview for Axis I *DSM-IV* Disorders.

Procedure

Intake examinations was carried out by senior clinicians in the first session, followed by a diagnostic interview (SCID-I) in Session 2. Therefore, Session 3 was the patient's first session with his or her regular therapist. Patients participated in the routine assessment system within the clinic over the course of treatment and therapy sessions were consistently videotaped. All patients gave informed consent with regard to the use of their data and videos for research. The study was also approved by the ethical board of the University of Trier.

Instruments

Inventory of Interpersonal Problems. The Inventory of Interpersonal Problems (IIP-12; Lutz, Tholen, Schürch, & Berking, 2006) is a self-report inventory that assesses interpersonal problems. It is a 12-item short-version of the Inventory of Interpersonal Problems (IIP; Horowitz, Rosenberg, Baer, Ureño, & Villaseñor, 1988). The instrument includes change sensitive items from the four subscales based on the circumplex model of interpersonal behavior and items are scored on a 5-point Likert scale ranging from 0 (*not*) to 4 (*very*). It is highly correlated with the IIP-Deutsch (r = .89) and has good reliability scores (r_{tt} = .76, α = .74; Lutz et al., 2006). The IIP-12 was assessed every 5 sessions during treatment. In the current study, we used its global score (a sum of all items), which showed good internal reliability at pretreatment (Cronbach's alpha = .74), Session 5 (Cronbach's alpha = .79), Session 10 (Cronbach's alpha = .74), and posttreatment (Cronbach's alpha = .89).

Outcome Questionnaire 30. The Outcome Questionnaire 30 (OQ-30) is a 30-item self-report measure and was designed to assess the outcome and course of psychotherapy. The items are answered on a 5-point Likert scale ranging from 0 (*never*) to 4 (*almost always*). The OQ-30 has three primary dimensions: (a) subjective discomfort, (b) interpersonal relationships, and (c) social role performance. All 30 items can be aggregated to create a total score. The OQ-30 is a short form of the Outcome Questionnaire 45 (OQ-45) comprising the 30 items that are most sensitive to client change and has demonstrated high levels of congruence with the OQ-45 (Ellsworth, Lambert, & Johnson, 2006; Vermeersch, Lambert, & Burlingame, 2000; Vermeersch et al., 2004). The OQ-30 also showed good internal consistency in our sample of N = 212 patients (α = .91). Pre–post mean scores were used to test for symptomatic change.

Penn Helping Alliance Questionnaire. The Penn Helping Alliance Questionnaire (HAQ; Alexander & Luborsky, 1986; German translation by Bassler, Potratz, & Krauthauser, 1995) is an 11-item self-report questionnaire, which assesses the therapeutic relationship and process. It has a 6-point Likert scale ranging from 1 (*strongly disagree*) to 6 (*strongly agree*). Internal consistency

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was high in our sample (HAQ: α = .84) and comparable to that of the German version of the HAQ reported in the literature (α = .89; Bassler et al., 1995). The therapeutic relationship assessed at the third session with the therapist (Session 5) was used as a predictor in this study.

Measurement of Nonverbal Behavior With MEA

A detailed sourcebook for using MEA is provided in the online supplementary material. All therapy sessions were recorded using two cameras joined into a split-screen image. Video quality was ensured through a static camera position, stable light conditions, and digitized film material. We only analyzed the first 15 min of each therapy session, because the interaction was frequently interrupted by the use of whiteboards or roleplays (where patient and therapist left their seating places) later in the session. Former studies have demonstrated that nonverbal synchrony during the first 15 min and the entire 50 min of the session is highly correlated ($r > .80$; Paulick et al., 2018; Ramseyer & Tschacher, 2011). Nonverbal behavior was measured via the automated video analysis algorithm MEA, implemented in the statistics software MATLAB (MathWorks, 2012). The method has a high convergent validity. Altmann et al. (2019) applied three MEA algorithms on the same video and found that high correlation between time series of different implementations: *r*(Ramseyer, Paxton) = .895, *r*(Ramseyer, Altmann) = .996, and *r*(Paxton, Altmann) = .894 with $p < .001$.

Before MEA was applied, several preprocessing steps were conducted. Videos were collected with different camera systems. To ensure the comparability of the videos, they were converted to avi format and scaled to the least common video size (640:480, with a frame rate of 25 frames/sec, 2000 Kbit per second) using the Any Video Converter 3.0. Next, videos were cut to a length of 15 min. In line with former studies using MEA, we defined the upper body beginning at the seat of the chair as a specific region of interest (ROI), as the patients' and therapists' legs were often covered by the table or one person's feet were visible on the others person's split screen. Furthermore, two background ROI (10 × 10 pixels) were drawn in the upper half of each split-screen to measure noise (e.g., due to light changes in the therapy room), which was subsequently controlled for (Altmann, 2013).

After these preprocessing steps, MEA was applied, that is, the grayscale pixel differences between consecutive video frames for each interacting person were computed according to the definition of motion energy (Grammer et al., 1999). A threshold for movement detection was empirically determined according to Altmann (2013) and set to a pixel change of 12 to automatically exclude minimal light changes or video noise. Afterward, time series were standardized to the size of each ROI (divided by the number of pixels in each ROI and multiplied by 100) to control for different ROI sizes and avoid over-/underestimation of movements. This resulted in motion energy values being equivalent to percent values as a value of 100 represented an activation of 100% of the ROI. Subsequently, we corrected the time series for coding and video image errors as follows: If the background ROI had a value higher than five, the associated sections in the respective time series were replaced by missing values. Furthermore, if the difference between three consecutive pixels was higher than 15 (representing an increase of 15% from one frame to the next, followed by an appropriate decrease, or vice versa), this leap was identified as an image error and the corresponding values were coded as missing. This procedure was based on a data-driven analysis to find a cut-off for movements that can be produced by humans. All missing values were subsequently linearly interpolated by neighboring values and complemented by noise to avoid artificial synchronization, which may occur if both time series are interpolated at the same place and the neighbors are very similar. If more than eight frames in a row were set to missing, the analysis stopped and the videos were excluded. Finally, a moving median with a bandwidth of five was applied to each time series to smooth small signal irregularities.

Quantification of Nonverbal Synchrony

Nonverbal synchrony was measured using an automated algorithm using windowed cross-lagged correlation (WCLC) and a peak-picking algorithm implemented by Altmann (2011, 2013; publicly available at https://github.com/10101-00001/sync_ident). Before WCLC was run, the time series of both patient and therapist were logarithm transformed to account for different peak heights. WCLC calculates correlations of time series segments, so called windowed correlations. It was applied as follows: First, a reference window or starting point was selected. Then, cross-lagged correlations with a time lag of +/−125 frames (= 5 s; in cases of positive time lags, person B was the initiator of synchronous movements, negative time lags pertained to synchronous movements where person A was the initiator) were estimated. This way, not only simultaneous, but also slightly delayed patient and therapist movements were examined. Therefore, the reference window was rolled over the time series in steps of one frame (= 0.04 s; so called overlapping rolling windows) and cross-correlations were computed for each new position of reference window. This was repeated until the end of time series was reached. All correlations were tested against zero using a parametric test. If a correlation failed to reach significance, it was set to zero to account for randomly occurring synchrony. Afterward, correlation coefficients were squared to highlight the distinctions between low and high correlation indices and to produce solely positive values. Furthermore, a squared correlation corresponds to the variance of the later window, which can be explained by the variance of the former window. All squared correlations were stored in a matrix. A matrix element with the "coordinates" (k, l) refers to the (squared) cross-correlation of window A at frame (position) k and window B at frame k + l. The choice of parameter settings was based on the extensive validation by Schoenherr, Paulick, Worrack, et al. (2019). The applied parameter settings (e.g., type of transformation, bandwidth) showed the highest identification rate of synchronization intervals for simulated motion energy time series pairs (sync intervals generated by simulation) as well as for motion energy time series pairs of naturalistic interactions (sync intervals rated by human raters). The choice of maximum time lag was made according to settings by Altmann et al. (2019); Paulick et al. (2018) and Ramseyer and Tschacher (2011).

To identify synchronization intervals, a peak-picking algorithm was applied (for details, see Altmann, 2011, 2013; Schoenherr, Paulick, Worrack, et al., 2019). The algorithm includes three steps: First, all local maxima (peaks) within the matrix of squared correlations (R^2) were identified. Second, neighboring peaks were

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summarized as peak crests. Third, when peak crests overlapped, the peak crests with the lower correlation were removed. The time interval of resulting peak crests are called synchronization intervals which characterized by a high and significant cross-lagged correlation (Altmann, 2013). Finally, a list of synchrony intervals for each analyzed video was generated, whereas each interval may have a different time lag, initiator of movement, starting point, ending point, and correlation strength (average R^2). Synchronization intervals were then filtered when they lasted longer than 0.4 s (Altmann, 2013) and their average R^2 value was higher than 0.25. As shown in a validation study, intervals with lower R^2 values may reflect randomly identified synchrony (Schoenherr, Paulick, Worrack, et al., 2019). The global synchrony score was calculated by dividing the time with significant synchronization by the total duration of the sequence and then multiplying it by 100. Thus, the resulting value represents the percentage of synchronous movements (simultaneous as well as time-lagged) of patient and therapist.

In sum, values represent simultaneous and time-lagged movements of patients and therapists, whereas higher values refer to higher temporal accordance between both movements. Synchronous movements can be demonstrated in both persons changing their seating positions, but also in one person raising his arm and the other person nodding his head. Thus, values do not provide information on the type of movement.

Data Analytic Strategy

GMM was used to identify patterns of early change in interpersonal problems (a sourcebook for using GMM is provided in the online supplementary material). GMMs allow the identification of multiple meaningful subgroups that differ with regard to their characteristics compared to the total sample. Further, estimates of between-person differences in within-person change can be made (e.g., Curran, Obeidat, & Losardo, 2010; Jung & Wickrama, 2008). There are several advantages in terms of including partially missing data, unequally spaced time points, and time-varying covariates (Curran et al., 2010). Whereas conventional growth models estimate an overall growth curve on basis of individual variations around a global mean intercept and slope, GMM allows the estimation of mean growth curves for each latent class and captures within-class variation (Muthén & Muthén, 2000; Ram & Grimm, 2009; Wang & Bodner, 2007). GMMs are known as a conservative method to identify patterns of early change and are favored over rational definitions (e.g., reliable change; Wang & Bodner, 2007) and traditional longitudinal methods.

In the present study, intercept variances were estimated without restriction, whereas the variances around the class-specific slopes were fixed to zero. Thus, heterogeneity of change had to be captured completely by the differences between mean slopes of different latent classes (for similar approaches, see also Hunter, Muthén, Cook, & Leuchter, 2010; Lutz et al., 2014; Uher et al., 2010). To model the early change patterns, IIP-12 was regressed on the logarithmized time variable. Dose-effectiveness research has shown a consistent pattern of rapid response early in therapy (e.g., Lambert, 2007). A log-linear transformation of time is a common and parsimonious approximation of this consistent curvilinear pattern (see also Stulz, Lutz, Kopta, Minami, & Saunders, 2013).

Prior research investigated different methods to estimate best model fit (Jung & Wickrama, 2008). In the present study, we chose the bootstrapped likelihood ratio test (BLRT) to be decisive factor for the best solution. According to Nylund, Asparouhov, and Muthen (2007), the BLRT proved superiority among the information criteria-based indices. We started with a one-class solution and successively added one more class in each subsequent run. First, we chose the best model based on the criteria-based indices (Bayesian information criterion [BIC], sample size adjusted BIC [SABIC], and Akaike information criterion [AIC]). Second, we tested the best k-class solution (based on criteria-based indices) to a model with k + 1-classes using the BLRT. A significant p value ($p < .05$) revealed the best solution. In case of a nonsignificant p value, the model was rejected and the k-class was tested against a k − 1 class solution.

A consensual definition of how many sessions can be seen as "early" is lacking. In accordance with previous studies on early change, we used about one third of the average treatment length (33.88 sessions on average $\times$ ⅓ $= 11.29 \approx 10$) as the definition of early change within this study (e.g., Lutz et al., 2014, 2017). Therefore, we used three time points of the IIP-12 to generate early change patterns: pretreatment, Session 5, and Session 10.

To examine whether nonverbal synchrony at the beginning of treatment predicted early change patterns, we applied multinomial logistic regression analysis, also including age and gender as patient characteristics as well as therapeutic alliance at the beginning of therapy in the analysis.

Finally, to address the association between patterns of early change in interpersonal problems and outcome in symptoms as well as interpersonal problems, we used analyses of covariance (ANCOVAs) and effect sizes. Therefore, we applied general linear models. In the first of these models, IIP-12 posttreatment was set as the dependent variable, IIP-12 pretreatment as the covariate, and class membership as a fixed factor. In the second model, OQ-30 posttreatment served as the dependent variable, OQ-30 pretreatment as the covariate and class membership as a fixed factor. In addition, we calculated Cohen's d using the pre- to posttreatment change on the IIP-12 as well as the OQ-30. One-way analysis of variance were performed to test the association between class membership and mean d for pre to post change. If the final outcome assessment was missing (dropout of $n = 36$), we carried IIP-12 and OQ-30 values forward from the last available assessment (which was at a maximum four sessions before the dropout).

Results

Patterns of Early Change

Table 2 presents the model fit indices. The increase in the BIC from the one- to the four-class solution, indicates the one-class solution to be superior. In contrast to the BIC, the SABIC, as well as the AIC decreased from one-class to three-class solutions and suggested a three-class solution. In addition, the entropy value in Class 3 was closest to 1. Furthermore, the BLRT of comparing the two- with the three-class solution was significant ($p < .05$), supporting the superiority of the three-class solution. Therefore, we used the three-class solution for further analyses.

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Table 2
Information Criteria, Entropy, and p Values in Bootstrapped Likelihood Ratio Test for Up to Four Latent Classes

Number of classes	BIC	SABIC	AIC	Entropy	BLRT *p* value
1	769.37	750.36	749.23		
2	777.75	749.24	747.55	.52	.12
3	777.45	739.43	737.17	.77	<.05
4	788.37	741.19	738.37	.75	.60

Note. BIC = Bayesian information criterion; SABIC = sample size adjusted BIC; AIC = Akaike information criterion; BLRT = bootstrapped likelihood ratio test.

Table 3 presents the average membership probabilities, which ranged from 0.87 for patients in Class 3 to 0.91 for patients in Class 1.

The estimated latent growth curves for the three-class solution (see Figure 1) showed one group with slow improvement (Class 1), one group with fast improvement (Class 2), and one early deterioration group (Class 3). The moderate symptoms of Class 1 members (n = 145; 68.40%) decreased slowly but significantly (B_{C1}: −0.47, $p < .001$) during the first 10 sessions with a moderate effect size of $d = 0.50$. Interpersonal problems decreased for members of Class 2 (n = 12; 5.66%) steadily from Sessions 1 to 10, with a significant negative slope (B_{C2}: −2.13; $p < .001$) and a positive large early change effect size of d = 1.69. The low initial symptoms of Class 3 members (n = 55; 25.94%) increased steadily from Sessions 1 to 10, with an significant positive slope (B_{C3}: 0.93, $p < .001$) and a negative early change effect size of $d = -0.81$. The mean IIP-12 value at pretreatment assessment differed significantly between the classes, $F(1, 209) = 12.91$, $p <$ .001. Class 2 members showed a significantly higher IIP-12 value at pretreatment than members of class 1, $t(155) = -2.09$, $p < .05$ and 3, $t(66) = -3.67$, $p < .001$. In addition, the IIP-12 pretreatment values of members of class 1 were significantly higher than those of Class 3, $t(199) = -4.54$, $p < .001$. There was no significant association between class membership and diagnostic categories, $\chi^2(6) = 6.20$, $p = .40$.

Prediction of Early Change Based on Nonverbal Synchrony and Patient-Intake Characteristics

After defining patterns of early change in interpersonal problems, we investigated the associations between class membership, nonverbal synchrony, age, gender, and therapeutic alliance. Therefore, we added these variables to multinomial logistic regressions. Age, gender and therapeutic alliance showed no predictive power for class membership—age: $\chi^2(2) = 2.06$, $p = .36$; gender: $\chi^2(2) = 3.58$, $p = .17$; and therapeutic alliance: $\chi^2(2) = 4.49$, $p =$ .11. Nonverbal synchrony was the only variable that showed predictive power, $\chi^2(2) = 9.84$, $p < .01$ and significantly discriminated between classes (see Table 4). High nonverbal synchrony at session three was associated with a higher probability of belonging to Class 1 or 3 compared to Class 2. There was no significant difference when Class 1 was compared to Class 3.

Associations Between Early Change and Treatment Outcome

An ANCOVA with IIP-12 posttreatment as the dependent variable, IIP-12 pretreatment as the covariate and class membership as a fixed factor showed that class membership was significantly associated with outcome, $F(3, 208) = 22.03$, $p < .001$, $\eta^2 = 0.18$. In an additional ANCOVA with OQ-30 posttreatment as the dependent variable, OQ-30 pretreatment as the covariate and class membership as a fixed factor, class membership was significantly associated with symptomatic outcome, $F(3, 208) = 4.33$, $p < .05$. Table 5 shows the effect sizes between pre- to postchange on the IIP-12 and OQ-30. In both questionnaires, Class 2 (fast improvement) showed the largest effect.

How Could Nonverbal Synchrony Be Useful in Clinical Practice? A Case Example

In clinical practice, a fine-grained monitoring and feedback system could be used based on repeated outcome measures (e.g., IIP-12) and process measures (e.g., nonverbal synchrony) to report information to the therapist session by session. Such a system could indicate whether a patient is still on track or he or she has a high probability of treatment failure. For example, the therapist receives feedback on the patient's IIP-12 mean score for each session starting after the initial session, where values at waitlist, pretreatment and the first 10 sessions are pictured in a graph. In addition, the therapist receives information about the level of nonverbal synchrony (high or low) in comparison to the mean synchrony of the three groups of interpersonal change (fast improvement, slow improvement and early deterioration). For example, a patient could show a negative development of interpersonal change as well as a high nonverbal synchrony score. Given our findings are replicated in future studies, this could be an indicator of a specifically risky situation in terms of the interaction taking place within the therapist–patient dyad. A corresponding decision rule might include two steps: (a) a negative reliable change in the IIP-12 is identified and (b) nonverbal synchrony is within the confidence interval of the early deterioration group. The following feedback and notification to the therapist could possibly include additional information about specific techniques or suggest an intervention with colleagues. Both options would have the goal of increasing awareness of nonverbal processes within that specific treatment and might help the therapist to better handle a very strong interpersonal pull and improve his or her nonverbal behavior toward the patient.

Table 3
Average Latent Class Probabilities for Most Likely Latent Class Membership (Row) by Latent Class (Column)

Most likely latent class membership	Average latent class probabilities		
	Class 1	Class 2	Class 3
Class 1	.91	.02	.07
Class 2	.10	.90	.00
Class 3	.13	.10	.87

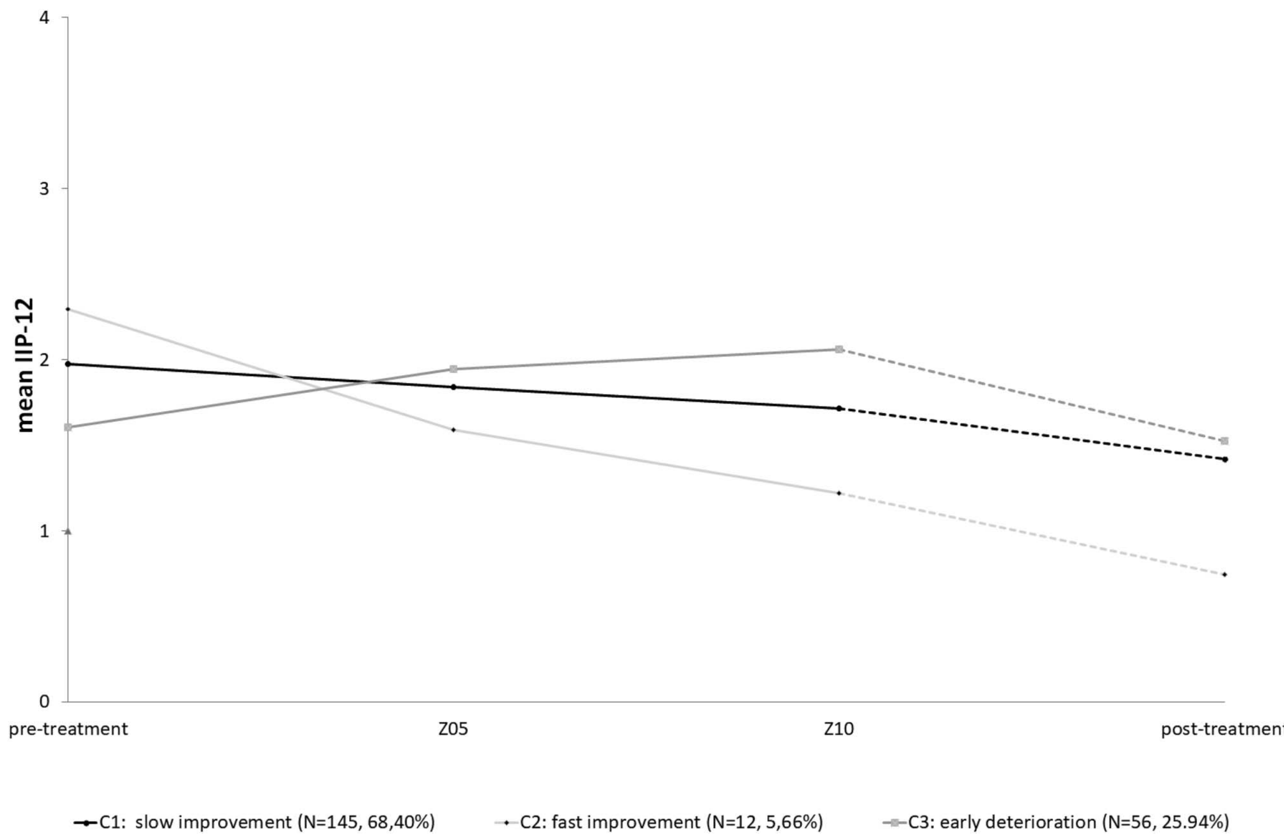

Figure 1. Mean latent growth curves for growth mixture modeling solution with three latent classes within the first 10 sessions and observed mean score (Inventory of Interpersonal Problems 12, IIP-12) in the respective classes after the therapy.

Discussion

The aim of this study was to investigate early change of interpersonal problems and its associations with nonverbal synchrony and posttreatment outcome in interpersonal problems and symptoms. To our knowledge, this is the first study examining the relation between interpersonal problem change and nonverbal synchrony. Accordingly, we found three early change patterns in interpersonal problems over the first 10 sessions of therapy: Class 1 showed a slow improvement, Class 2 was characterized by rapid improvement of interpersonal problems, and in Class 3 interpersonal problems worsened over the first 10 sessions. Furthermore, nonverbal synchrony at the beginning of treatment predicted early change patterns in interpersonal problems insofar as low nonverbal synchrony was related to a higher probability of being a member of the rapidly improving subgroup of patients. In addition, the three change patterns showed significantly different results with regard to posttreatment outcome in interpersonal problems as well as symptoms.

To our knowledge, so far there is no research on early change patterns within interpersonal problems. Comparing our three-class solution with prior research on global or symptom-specific outcome measures, we found similar change patterns, although sizes of subgroups varied (e.g., Lutz et al., 2014, 2017). The group showing rapid early response was relatively small (Class 2) with 5.63%, whereas the early deterioration group (Class 3) was relatively large (26.29%). The majority of patients (68.08%) were assigned to Class 1, which was characterized by slow improvement. The differences between group sizes should not be considered a limitation, but rather than an indication to use GMMs. GMMs allowed the identification of such a small subpopulation, which differed extremely from the majority. In this regard, Jung and Wickrama (2008) suggested a minimum class size of 1%. This is in line with our three-class solution.

At this point, little is known about the reasons for early change of interpersonal problems (which seems to be a relatively small subgroup). New technical developments in automatized video analyses allow new possibilities to investigate mechanisms of change. One interesting new variable to investigate in this context is nonverbal synchrony measured by movement synchrony. The results of the present study indicate that lower levels of nonverbal synchrony at the beginning of therapy are related to early response and higher stability of early improvements in psychotherapy. At a first glance, this finding seems counterintuitive. Previous research has shown that higher nonverbal synchrony provides patients with a sense of emotional security and should therefore lead to an increased interpersonal change (Geller & Porges, 2014). However, this does not seem to necessarily be the case, especially for a subgroup of patients who benefited from more noncomplementary

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Table 4
Prediction of Class Membership by Patient Intake Characteristics and Patient–Therapist Dyadic Nonverbal Synchrony Via Multinomial Logistic Regression Analyses

Variables	Regression coefficient B	*p*	95% CI for odds ratio Lower	Odds ratio	Upper
Class 1[a] vs. Class 2[b]					
Intercept	3.67	.06			
NonVerbal_Sync	−10.56	<.01	<.001	<.001	.03
HAQ[d]	−1.18	.06	.31	.09	1.03
Age	−.02	.54	.98	.94	1.03
Gender	−.56	.39	.57	.16	2.06
Class 1[a] vs. Class 3[c]					
Intercept	.61	.54			
NonVerbal_Sync	−1.87	.30	.15	<.01	5.46
HAQ[d]	−.30	.31	.75	.43	1.31
Age	−.02	.18	.98	.96	1.01
Gender	.49	.13	1.63	.86	3.10
Class 3[a] vs. Class 2[b]					
Intercept	3.10	.13			
NonVerbal_Sync	−8.69	<.05	<.001	<.001	.22
HAQ[d]	−.90	.17	.41	.12	1.45
Age	<.01	.95	1.00	.95	1.06
Gender	−1.05	.12	.35	.09	1.34

Note. NonVerbal_Sync = patient–therapist dyadic nonverbal synchrony.
[a] Class 1 = slow improvement. [b] Class 2 = fast improvement. [c] Class 3 = early deterioration. [d] Penn Helping Alliance Questionnaire (HAQ) at Session 5. Four percent of the value were imputed using missForest (Stekhoven & Bühlmann, 2012).

interpersonal behavior, even on a nonverbal level. The present results seem to indicate that high initial nonverbal synchrony does not necessarily reflect a collaborative stance or “being in good contact” between patient and therapist. On the contrary, lower levels of nonverbal synchrony at the beginning of therapy may reflect better levels of therapists’ noncomplementary behavior (Atzil-Slonim et al., 2019). Dyads with lower nonverbal synchrony might reflect therapists’ ability to not immediately react to the interpersonal pull triggered by the patient, even on a nonverbal level. An alternative explanation might be that fast responders, who started with higher levels of interpersonal problems, tended to use their nonverbal behavior to maintain or increase interpersonal distance at the beginning of treatment (see Girard, Cohn, Mahoor, Mavadati, Hammal, & Rosenwald, 2014), which possibly affected the therapists, leading them to be less synchronized. Future studies should investigate nonverbal synchrony in later therapy phases and look at change in nonverbal synchrony in those patient groups to see whether they start indicating a willingness to affiliate, which may lead to increased synchrony later in treatment. Support for the interpretation that participants increase their expressiveness (e.g., therapists are less synchronized) when the expressiveness of their partners is attenuated (e.g., clients have more affiliation problems) comes from studies by Yang, Fairbairn, and Cohn (2013), as well as Boker et al. (2009). Another possible explanation could be that the fast improvement of that patient group at the beginning of treatment lead to calmer therapists, who made less effort to synchronize with their patients’ body movements. Therapists’ perception of an at-risk patient who wants to quit therapy may lead to overcompensating behavior (e.g., therapists are more synchronized).

In summary, nonverbal synchrony seems to be an important factor in interpersonal relationships that needs further investigation, especially over the course of treatment and regarding its relation to the alliance. Our results pose a new research question, as it remains unclear how to interpret nonverbal synchrony in relation to the alliance. Recent studies have discussed it as an embodied component of the therapeutic alliance (Ramseyer & Tschacher, 2011). However, given our nonsignificant findings regarding the alliance (at Session 5) as a predictor of early change patterns, nonverbal synchrony might indeed measure a different or specific component of the therapeutic alliance, which is not adequately covered by patient self-report measures of the alliance. This component might reflect the therapeutic alliance of therapist–

Table 5
Pre–Post Change During Treatment on the Inventory of IIP-12 and the OQ-30 (Effect Sizes) by Early Change Patterns

Sample	*n*	Final treatment outcome: Effect size change in IIP-12 during treatment (*d*)	Effect size change in OQ-30 during treatment (*d*)
All patients	212	.77	1.04
Class 1[a]	145	.98	1.07
Class 2[b]	12	2.26	1.80
Class 3[c]	55	.11	.83
p value		<.001[d]	<.01[d]

Note. IIP-12 = Inventory of Interpersonal Problems 12; OQ-30 = Outcome Questionnaire 30.
[a] Class 1 = slow improvement. [b] Class 2 = fast improvement. [c] Class 3 = early deterioration. [d] One-way analyses of variance were performed testing the association between class membership and mean pre- to postchange.

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patient dyads, where therapists do not react complimentarily to the interpersonal pull triggered by the patient, even on a nonverbal level. It could also be that patients with higher levels of interpersonal problems display less synchrony with their therapist in order to maintain interpersonal distance at the beginning of treatment. These complementary and more fine-grained aspects of the therapeutic alliance might be able to explain additional variance, not confounded with the traditional patient or therapist-rated alliance measures. Given the preliminary nature the results and this research area in general, this topic needs further elaboration.

Furthermore, we found class membership to be a predictor of symptomatic change as well as change in interpersonal problems at the end of treatment. This result seems to extend earlier research, which found a relation between early response and treatment outcome (e.g., Haas et al., 2002; Nordberg et al., 2014). Although our results are based on the comparison of pre–post mean scores, we also calculated symptomatic change from Session 10 to posttreatment. As expected, in both cases—IIP-12: $F(3, 208) = 3.022$, $p = .051$, $\eta^2 = 0.03$ and OQ-30: $F(3, 208 = 2.03$, $p = .07$, $\eta^2 = 0.03$—class membership was not a significant predictor, due to the fact that the majority of change had already occurred between the beginning of treatment and Session 10 and later change was not as strong as before. Change patterns seem not to be linear for all patients over the entire course of treatment. Patients categorized as early improvement were more likely to experience higher symptom reduction. The mean effect size for the group of fast responders was nearly three times as large as the average overall effect size using the IIP-12. We found similar, but less strong results using the OQ-30. The fast improvement group showed the largest effect size, which was close to twice as large as the overall effect size. Compared to the fast improvement group, the slow improvement group showed only moderate effect sizes on both outcome measures.

As expected, patients with early deterioration showed the smallest effect sizes on the posttreatment IIP-12 and OQ-30 assessments. On average, these patients did not continue to deteriorate, but seemed only to reach their original level of interpersonal problems. In the future, such a subgroup of patients could be flagged using a monitoring system to ensure they receive special attention, for example, specific treatment options or interventions for interpersonal problems.

Limitations

Several limitations of this study are noteworthy. First, nonverbal synchrony was only measured for 15 min in one session. Future research should also investigate specific dyadic movement patterns over time, which may change over the course of therapy and therefore provide further information on symptomatic change. Another limitation refers to the measurement of nonverbal synchrony itself. The applied measurement provides information on the frequency of nonverbal synchronization. However, there are many different ways of defining and measuring nonverbal synchrony, which complicates the comparability of research results (e.g., Altmann, 2011; Boker, Rotondo, Xu, & King, 2002; Ramseyer & Tschacher, 2014). Furthermore, the applied automated measurement of nonverbal behavior only captures the association of movement dynamics between interacting persons, regardless of whether these movements are related to each other in terms of content. In this context, concerns may be raised with regard to the validity of the applied measurement methods and, indeed, correlations with human ratings of nonverbal synchrony are small (Schoenherr, Paulick, Worrack, et al., 2019). However, this is mainly because of different underlying definitions of the measured constructs. Although ratings of nonverbal synchrony pertain to meaningful behaviors (e.g., both persons laughing at the same time), MEA measures content-free nonverbal synchrony (e.g., also includes one person nodding their head while the other person changes their sitting position). Furthermore, MEA measures with a framerate of 25 (meaning that 25 pictures are taken a second), which is impossible for the human eye to detect. Nevertheless, several studies were able to confirm the validity of MEA, as synchrony values differed significantly from randomly generated "pseudo-synchrony" values (e.g., Paulick et al., 2018; Ramseyer & Tschacher, 2011). In addition, the applied synchrony measure showed good identification rates, detecting high correct positives and low false positives (Schoenherr, Paulick, Strauss, et al., 2019). In addition, many prior studies in social and developmental psychology research were able show reliable and promising results using these automated measurements (e.g., Grammer et al., 1999; Watanabe, 1983).

Another shortcoming of the present study relates to the phenomenon of early positive response. As in other studies of early change patterns, it cannot be ruled out completely that early response was also at least partially due to factors such as regression to the mean or placebo effects (e.g., Stewart et al., 1998). To eliminate these alternative explanations, it would be necessary to investigate additional change patterns among an untreated group of patients with the same pattern of disorders and compare the patients within early positive change classes. However, the fact that the early responder group showed additional substantial change beyond the early phase and until the end of treatment indicates that regression to the mean is unlikely to be the only explanation of the observed early change patterns. Concerning the application of early change, the choice of the optimal number of assessments has been a topic of some debate (for an overview, see Lambert, 2005; Rubel et al., 2015). Definitions range from the first three sessions (Haas et al., 2002) to the first 15 sessions (Nordberg et al., 2014), depending on overall treatment length. In the present study, early change was defined to capture about one third of the average treatment length in our sample, that is pretreatment to Session 10. This definition of early change is in accordance with previous studies (e.g., Lutz et al., 2014, 2017; Schibbye et al., 2014) and allows us to assume that beside anamnestic work, active treatment techniques were delivered. An associated argument is related to the reliability of the parameter estimates in the growth patterns. As the IIP-12 was assessed every five sessions, for example, we decided against an early change definition including only two assessments (and therefore less reliable estimates) in the GMM when using only pretreatment and Session 5 assessments.

Conclusion and Future Directions

This study investigated associations between patterns of early change in interpersonal problems and patient–therapist dyadic nonverbal synchrony as well as multiple posttreatment outcomes (interpersonal problems and symptoms). The findings demonstrated that nonverbal aspects can help to predict patterns of early change and provide further important information on nonverbal features of therapeutic processes. In future studies, it may be interesting to investigate whether the obtained results also hold for other samples. In future studies, it may be interesting to test whether the obtained results also hold for other samples. In this context, it might be especially fruitful to investigate the nonverbal synchrony–interpersonal change association depending on patients' baseline interpersonal functioning (e.g., attachment style, personality disorder, interpersonal problems, etc.). It might be that correlations depend on interpersonal baseline functioning and patient groups known to have especially high interpersonal problems (e.g., personality disorders) show specific patterns. Personality disorders are known to be disorders of social interaction, relationships, or shaping of relationships (Beeney et al., 2019). It can be expected that these subpopulations show specific nonverbal behavior and also provoke corresponding interpersonal pulls within the interaction partner or the therapist. For a better understanding of the potential mechanism of nonverbal synchrony, future research might investigate in patients 'intake interpersonal characteristics. For example, attachment style seems to be closely linked to interpersonal problems (Cameron, Finnegan, & Morry, 2012). Therefore, it can also be assumed that patient's attachment patterns have an influence on nonverbal synchrony.

Furthermore, with further knowledge of associations between nonverbal synchrony and interpersonal change, it seems promising to include such measures into clinical feedback systems to identify patients at risk for treatment failure. It is conceivable that the feedback of nonverbal synchrony to therapists may be a helpful supplemental tool to improve the process of treatment and to better handle nonverbal interactions (see the How Could Nonverbal Synchrony be Useful in Clinical Practice? A Case Example section).

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