Physiological Synchrony in Psychotherapy Sessions

Wolfgang Tschacher & Deborah Meier

Postprint: Wolfgang Tschacher & Deborah Meier (2019): Physiological synchrony in psychotherapy sessions. *Psychotherapy Research*, DOI: 10.1080/10503307.2019.1612114

Physiological synchrony in psychotherapy sessions

Abstract

In this proof-of-principle study, a convenience sample of 55 dyadic psychotherapy sessions conducted by one therapist was analyzed. The electrocardiograms and respiration behavior of both therapist and client were monitored simultaneously. Four clients were included, and session outcome was documented by session reports in two clients. From electrocardiograms, heart rate and heart rate variability were derived in consecutive 15-second intervals throughout sessions. Entire sessions (average duration, 51 minutes) were assessed for physiological synchrony of therapist's and client's respiration, electrocardiogram, heart rate, and heart rate variability. Two methods of synchrony computation were applied to the time series: windowed cross-correlation and correlation of local slopes (concordance). Both methods included surrogate controls using segment-wise shuffling. Significant synchrony of three measures, but not of electrocardiograms, was present in this dataset. In regression models, we found associations between synchronies and alliance ratings, and further self-report variables. Results support the existence of physiological synchrony in this collection of psychotherapy sessions, which speaks for the sympathetic and parasympathetic coupling between this therapist and her client and its link with ratings of therapy process. The feasibility of deriving signatures of synchrony of physiological signals with the described methodology was corroborated. The findings now await generalization by further research.

Introduction

A minimal definition of psychotherapy says it is a cure based on processes of learning, which unfold in the interaction between a therapist and a client. Accordingly, the scientific study of psychotherapy must focus on such learning processes – the change mechanisms and ingredients of psychotherapy – and on the specific kind of alliance that constitutes the therapeutic interaction. The therapist-client alliance is a foundational factor common to all psychotherapy approaches, and accordingly has attracted much attention in process research. In this article, we will analyze one aspect of psychotherapeutic interaction that possibly constitutes a core aspect of alliance – therapist-client synchrony.

Synchrony is generally defined as the social coupling of two (or more) individuals in the here-and-now of a communication context that emerges alongside, and in addition to, their verbal exchanges (Tschacher & Ramseyer, 2017; Koole & Tschacher, 2016). This broad synchrony concept calls for operationalization: one needs to decide which observables allow the quantification of nonverbal synchrony. In the wake of the embodiment turn in cognitive science, awareness of the bi-directional influences between bodily and mental processes has increased (Tschacher & Bergomi, 2012). Consistent with embodiment thinking, we conceive of the therapeutic alliance as nonverbally and physiologically grounded, and we believe that nonverbal and physiological variables open up new opportunities to study therapeutic alliance at high detail through embodied synchrony.

Motor behavior offers a straightforward approach to study nonverbal synchrony by quite economical and non-invasive data acquisition methods, such as Motion Energy Analysis (MEA, Ramseyer & Tschacher, 2011; Grammer et al., 1998) and other motion capture methods. Nonverbal data may also concern paraverbal attributes of speech, especially the pitch and loudness of verbal utterances (e.g. Imel et al., 2014), which can likewise be monitored in a non-invasive way in psychotherapy sessions. In this article, however, we will elaborate solely on the coupling of client's and therapist's physiological processes in the psychotherapy session. We will also leave aside central nervous processes (their synchrony is called hyperscanning) as well as endocrinal, retinal and eye-movement parameters. These variables either require sophisticated measurement devices, or laboratory settings, or cannot be monitored with high sampling frequencies. To our knowledge, there are as yet no studies on the synchronization of these measures in psychotherapy settings.

The psychological meaning of physiological data

Physiological time series constitute embodiments of psychological variables, yet they do not possess unambiguous psychological meaning. Anatomically, all peripheral physiological processes, such as cardiac, electrodermal and respiratory activity, are governed by the autonomous nervous system (ANS), which generally regulates vital functions of the body via the energy supply and activation of organs and tissues (Birbaumer & Schmidt, 2007; Pocock, Richards & Richards, 2013). This regulation is called autonomous because it occurs outside conscious awareness and volition. At the same time, ANS activation is closely associated with emotional and cognitive processes: activation of the sympathetic branch of the ANS prepares the body and mind for fight and flight responses in critical situations, whereas the parasympathetic branch of the ANS regulates functioning in rest and relaxation, and supports sexual behavior. The two ANS branches complement one another, and they also correspond to antagonistic emotions. Sympathetic states of mind and emotion are activated-energetic, whereas parasympathetic states are rather relaxed and subdued (Geller & Porges, 2014; Palumbo et al., 2017).

Based on this antagonism, most somatic and vegetative processes in humans are controlled by a synergy of sympathetic and parasympathetic efferences. The heart is dually innervated, i.e. cardiac dynamics represents, in addition to cortical and endocrinal inputs, both sympathetic-activating and parasympathetic-damping influences (Thayer, Hansen, Saus-Rose, & Johnsen, 2009). Thus, heart rate (HR) increase is related to arousal and stress, and linked with activating emotions such as joy, anger, or fear. Phasic HR decrease can be due to the orienting response, a passing state when novel information is presented (Graham & Clifton, 1966); enduringly lowered HR goes back to the parasympathetic influence in relaxation.

Heart rate variability (HRV) is a complex signal, which again reflects the antagonistic interplay of both ANS systems. HRV is generally related to health and disease: lowered HRV is commonly linked to reduced affect-regulation abilities and increased depressiveness and anxiety. Induction of congruent, positive mood is associated with increased HRV (Kop, Synowski, Newell, Schmidt, Waldstein, & Fox, 2011). Persons with low HRV appear to react more defensively even to non-threatening stimuli, which corresponds well to findings of positive correlations of HRV with the Big-Five personality trait 'Openness to experience' (Williams, Rau, Cribbet, & Gunn, 2009) and to negative correlations of HRV with 'Neuroticism' (Ode, Hilmert, Zielke, & Robinson, 2010). Aesthetic appreciation while viewing artworks was found associated with increased HRV (Tschacher et al., 2012).

Electrodermal activity (EDA) is commonly measured by electrodes attached to the fingers, sampling skin conductance. EDA is a signal that is only under sympathetic control, and is generally indicative of emotional and mental activation irrespective of its valence (Sequeira, Hot, Silvert, & Delplanque, 2009). Phasic electrodermal responses reflect orienting responses (like HR). In the absence of external stimuli, spontaneous fluctuations of skin conductance are common, whose frequency correlates with emotional arousal. Anxiety patients, for example, show both more fluctuations and higher tonic skin conductance. Unexpected events that generate emotional responses can be readily detected in EDA.

Breathing activity is controlled, in addition to ANS inputs, by a number of neuronal and neurochemical factors, very generally by pacemakers in the brainstem and the CO_2 concentration in the blood. On top of this, breathing can be regulated voluntarily (other than cardiac activity), which is obvious in speech because verbal utterances depend on the passage of air when exhaling. The contraction of bronchial muscles is enhanced by parasympathetic influence and counteracted by sympathetic activity and adrenaline (Birbaumer & Schmidt, 2010); hyperventilation can be a result of stress, i.e. sympathetic activation. In reverse, deep and slow breathing is connected with parasympathetic activity, which is commonly used in meditative practices to enter mindful states.

Research on physiological synchrony in psychotherapy and psychotherapy-related contexts

Only few studies have used measures of physiological synchrony to explore psychotherapy process. A recent general review (Palumbo et al., 2017) found eight articles on psychotherapy in English, yet the number of pertinent publications is presently growing (Kleinbub, 2017). Most of the psychotherapy studies targeted electrodermal activity (EDA). The study by Marci and Orr (2006) introduced EDA concordance as a measure of synchrony in experimental structured interviews, finding a relationship of synchronized tonic skin conductance changes with emotional closeness and empathy. These links were supported by a subsequent study (Marci, Ham, Moran & Orr, 2007), which was one of the first to explore physiological synchrony in psychotherapy. Karvonen, Kykyri, Kaartinen, Penttonen & Seikkula (2016) also reported evidence of EDA concordance in a setting of systemic couple therapies with two therapists. Palmieri et al. (2018) found higher EDA synchrony in clinical interviews when the interviewer had received a secure-attachment prime. Coutinho et al. (2018) supported the significant synchrony findings in a sample of romantic couples, yet not with the concordance index but with the cross-correlational method of surrogate synchrony (concordance and surrogate synchrony are introduced in the methods section below).

Only few studies used cardiac activity in terms of heart rate (HR) or heart rate variability (HRV) as signatures of physiological synchrony in psychotherapy. The occurrence of HR synchrony was described in various non-therapeutic contexts, e.g. in the synchronization of observers' with actors' HR in a fire-walking ritual (Konvalinka et al., 2011). Di Mascio et al. (1955) were likely the first to study the interpersonal correlation of HR, exploring three single cases of psychoanalytic interviews. Kodama et al. (2018) reported a single-case study where HR synchrony correlated with qualitative measures. Interpersonal HRV was again first explored by the Di Mascio group (Di Mascio et al., 1957), who reported in-phase HRV synchrony in observer-coded tension segments and anti-phase synchrony in antagonistic segments. Further findings derived from research on romantic dyads: HRV synchrony was found related to marital conflict (Gates, Gatzke-Kopp, Sandsten, & Blandon, 2015). Helm, Sbarra, & Ferrer (2014) reported higher HRV coregulation in couples with higher relationship satisfaction in laboratory tasks.

Synchrony of respiration activity was not explored in psychotherapy sessions before. However, there are a number of findings in diverse contexts, such as respiration rate synchrony of audience members and dancers in a dance performance (Bachrach, Fontbonne, Joufflineau, & Ulloa, 2015), or respiratory coordination found in concert audiences (Upham, Egermann, & McAdams, in print) and among singers of a choir (Vickhoff et al., 2013). Studies in couple research also analyzed respiration, finding synchrony of respiration and interpreting respiration as a driver of cardiac synchrony (Ferrer & Helm, 2013). Thus, although respiration synchrony belongs to wide-spread folklore in applied psychotherapy and coaching (e.g. in so-called Neurolinguistic Programming, NLP), very few research results are available.

The present study is an observational case study of 55 psychotherapy sessions, which were conducted by a single psychotherapist in a naturalistic day-hospital setting. The goal of the analysis was to arrive at proof-of-principle for physiological synchrony by evaluating a physiological dataset with modern statistical methodology in order to determine the extent of physiological synchrony manifested in these psychotherapy sessions. We wished to show that our methodological approach is feasible in principle when using physiological signals. Due to the limited nature of the available dataset, one therapist and her four clients, no general findings were expected beyond proof-of-principle. We hypothesized that the synchrony of client's and therapist's respiratory activity, heart rate, and heart-rate variability should exceed surrogate controls, and thereby support the existence of these types of physiological synchrony in the documented cases (hypothesis 1). We further assumed, based on previous studies, that physiological synchrony is associated with ratings of alliance quality and other process ratings (hypothesis 2). Methodologically, we expected that the two synchrony algorithms implemented would provide differing results, also with respect to their associations with self-report ratings (hypothesis 3). In an additional analysis, we explored the possibility of electrocardiogram synchrony (exploratory hypothesis 4).

Materials and methods

Psychotherapy sessions

The dataset consists of four psychotherapy courses conducted by a female psychologist in a day-hospital setting at a university psychiatric hospital in Switzerland. The therapist was not a member of the team of investigators and was not involved in the planning or analysis of the research project. She administered psychodynamic psychotherapy in seated position. Sessions were held over a time-period of 15 months in the years 1995 and 1996, usually at weekly intervals. During this period, a total of 93 psychotherapy sessions were provided to four regular clients, each with durations of up to 60 minutes. Of all sessions, 55 were monitored; they had a mean duration of 51 minutes (SD=8.6, range 25-65). Monitored sessions were unevenly distributed between the four therapy courses (therapy codes: 37 sessions vreni, 10 vreme, 5 chrta, 3 chran). The vreni and vreme therapies concerned two female, chrta and chran two male clients. No further personal or psychopathological information is available, as patient records are stored not longer than 15 years – the data are effectively anonymous. The reasons for not monitoring all 93 sessions were technical failures in five sessions, and premature termination of monitoring after completion of the feasibility study during the chran therapy. Also, initial sessions were not considered to allow some time before asking for a client's consent. Thus the sampled sessions constitute an unbalanced convenience sample of psychotherapies.

The original goal of data acquisition was to assess the feasibility of detailed physiological and behavioral measurements in a naturalistic psychotherapy setting, on the background of a hypothesized 'sociophysiological coupling' between therapist and client (Tschacher, 1997). This observational study was completed in 1996; in the absence of appropriate methodological tools, the data however were never systematically analyzed with the exception of a merely correlational overview (Tschacher & Scheier, 1997) and a tentative surrogate analysis of a subsample (N=10) of respiration data (Tschacher, 1997). More recently, an analysis of nonverbal synchrony was performed restricted to the hand movement data (N=27) in the vreni therapy course (Ramseyer & Tschacher, 2016).

Session reports

Upon termination of a session, session report questionnaires were provided by which the therapist and the client independently assessed the session using seven-point Likert scales. We used the German-language session reports developed by the Grawe group (Grawe & Braun, 1994), whose revised form was later validated and psychometrically described by Flückiger, Regli, Zwahlen, Hostettler, & Caspar (2010). Session reports were filled out in 10 vreme therapy sessions and 37 vreni sessions. The therapist report consisted of 17 items, the client report of 15 items. The items of the therapist session report questionnaire load on three scales, the quality of therapeutic relationship (Alliance_th), the therapist’s evaluation of patient's cooperation (Cooperation_th), and the therapist’s evaluation of progress in therapy (Progress_th). Alliance_th and Cooperation_th may be considered aspects of therapist-assessed alliance. Three scales capture the client’s assessment of the therapy session: the quality of therapeutic relationship (Alliance_cl), the client’s evaluation of own well-being (Well-being_cl) and therapy progress (Progress_cl).

Monitoring device

Both the clients and the therapist wore the Vitaport-4 ambulatory-measurement device (Mutz & Becker, 2006; Kölner Vitaport System, Becker Meditec) throughout the therapy sessions. The sensors consisted of three gel-filled silver electrodes fixed on the chest of each participant, therapist and client. The potential differences between the three leads were monitored with a sampling rate of 80 Hz, providing electrocardiograms (ECG) of each individual. From the ECG, heart rate and heart rate variability were derived. Further, a strain-sensitive belt was attached above the clothing of each participant for registration of respiratory behavior, i.e. breathing. This device measured the extension of the diaphragm and lower chest at a sampling rate of 16 Hz. The choice of an adequate sampling rate must consider the variability of the monitored behavior (Schiepek et al., 2016). It case of the oscillatory signals respiration and ECG, the sampling rates of 16 Hz and 80 Hz took the frequencies of the respective signals into account. In addition, each participant wore actimetric sensors at each wrist to register hand movements (not reported here, cf. Ramseyer & Tschacher, 2016). All sensors were attached by cable to the mobile Vitaport recording unit of each participant, which allowed unhindered movement. The two recording devices were aligned by their internal clocks, additionally manual markers were used to time-stamp the beginning and end of a session.

Recording was initiated at the time-stamp of the manual marker and ended with the second marker signal at the end of the respective session. All physiological data of ECG and respiratory behavior were available as time series in Vitaport format (*.vpd). For the present analyses, all files were transferred into text format (*.txt) using the software Variograf (Jain, Gehde, Feist, & Alfer, 2003). No smoothing or other filters were applied.

All pre-processing steps prior to synchrony computation were performed using JMP Pro 11 statistical software (SAS Institute Inc., 2013). The 80 Hz ECG time series were transferred to heart rate (HR) and heart-rate variability (HRV) in the following manner (cf. Fig.1). First, all R peaks of the ECG time series, which mark the highest ventricular contraction of each heart beat, were detected in the time series and saved with the corresponding time stamp. The periods between successive peaks, so-called interbeat intervals (IBI), measure the exact duration of each heart-beat period. From the IBI data, the 'momentary' HR was calculated in each successive quarter minute (i.e., 15s) of the therapy session by the mean IBIs. HRV is represented by the standard deviations of these IBIs (often abbreviated SDNN, standard deviation of interbeat intervals), also measured by quarter-minute periods.

Taken together, the physiological measurements comprised cardiac activity time series (ECG, sampling rate 80Hz), respiratory behavior (RESP, sampling rate 16Hz), time series of HR (sampling rate 4/minute, i.e. 1/15Hz) and of HRV (SDNN, sampling rate 4/minute). These data were available for therapist and clients to assess their physiological synchrony.

---Fig.1. here---

Computation of physiological synchrony

In general, synchrony means that two processes are, or become, correlated at a level exceeding chance correspondences (Moulder et al., 2018). Algorithms to estimate synchrony address the coupling between two processes, here the dyadic time series (ECG, HR, SDNN, and RESP) of client and therapist.

Most methods of synchrony computation function within the time domain, using cross-correlations of the paired time series. We applied two different algorithms, the surrogate synchrony approach (SUSY, cf. www.embodiment.ch) and the surrogate concordance approach (SUCO, cf. www.embodiment.ch). SUSY was the method used by Ramseyer & Tschacher (2011) and Tschacher, Rees & Ramseyer (2014). Concordance was introduced by Marci & Orr (2006).

SUSY is based on the cross-correlation function of the time series. The cross-correlations are computed segment-wise – time series are cut into segments of e.g. 60 seconds duration, and the cross-correlations within each segment are computed across a certain range of lags *L*. A default value in many studies is choosing lags up to 5 seconds ($-L_{\max} \leq L \leq L_{\max}$, where $L_{\max} = 5s$), i.e. all cross-correlations in a ten-seconds window are considered (10s windows were used by: Coutinho et al., 2018; Paulick et al., 2018; Ramseyer & Tschacher, 2011; Ramseyer & Tschacher, 2012; Tschacher, Rees & Ramseyer, 2014; Tschacher, Ramseyer, & Koole, 2018). Segment-size and window-size are basic parameters in SUSY. This operationalization thus includes the simultaneous (L=0) correlation as well as time-lagged (cross-)correlations, which derive from delayed responses of therapist to client and vice versa. To allow aggregation, all cross-correlations must be transformed using Fisher's *Z* transformation, hence Z_L. Synchrony in any segment *i* is then defined as the mean of all *m* cross-correlations of this segment, $\bar{Z}_i = \sum_{-L_{\max}}^{L_{\max}} Z_L \big/ m$. Absolute *Z* values $|Z_L|$ are averaged over all lags in each segment, then aggregated over all *n* segments of the session to obtain a value of synchrony for the therapist-client dyad, $\bar{Z}_{abs}$ (Fig.2). Expressed formally, $\bar{Z}_{abs} = \left[\sum_{1}^{n} \left(\sum_{-L_{\max}}^{L_{\max}} |Z_L| \Big/ m \right) \right] \Big/ n$. Here, *m* is the number of cross-correlations in the window, whereas *n* is the number of segments in the whole session.

The reason for taking the absolutes of correlations is that systematic negative correlation can also be a sign of ('anti-phase') synchrony, e.g. one person's HR may be consistently high when the other person's HR is low. We however also compute $\bar{Z}_{noabs}$, an aggregated synchrony measure of positive and negative cross-correlations, which helps differentiating in-phase from anti-phase coupling.

---Fig.2. here---

The second step in SUSY consists of surrogate tests (Ramseyer & Tschacher, 2010; Moulder et al., 2018). Surrogate time series constitute the control condition for the $\bar{Z}_{abs}$ and $\bar{Z}_{noabs}$ values. We generate surrogate time series by randomly shuffling the sequence of all segments of a session. From a dyadic time series with *n* segments, *n*(*n*-1) surrogates can be produced, each of which contains therapist and client pseudo data, as their sequence is falsely arranged, whereas the means, distributions, autocorrelations and trends of the time series are preserved. When time series are quite long and of varying lengths, as in the present dataset, using all *n*(*n*-1) surrogates is not advisable, and the number of surrogates should be restricted to a constant. This was done in the analysis of respiration and ECG data. Alternatively, the time series may be truncated to identical lengths as realized in most experimental applications (e.g. Tschacher, Rees & Ramseyer, 2014; Lozza et al., 2018). Naturalistic data with different durations may be cut into equal segments and results later aggregated (e.g. Coutinho et al., 2018).

The surrogate step generates two more signatures of synchrony, namely the effect sizes ES_{abs} and ES_{noabs}, for absolute and non-absolute *Z* cross-correlations, respectively. Hence, $ES_{abs} = \left(\bar{Z}_{abs} - \bar{Z}_{abs-pseudo} \right) \Big/ SD(\bar{Z}_{abs-pseudo})$, and accordingly $ES_{noabs} = \left(\bar{Z}_{noabs} - \bar{Z}_{noabs-pseudo} \right) \Big/ SD(\bar{Z}_{noabs-pseudo})$.

Please note that these effect sizes *ES* are effect sizes of real synchrony $\bar{Z}_{abs}$ and $\bar{Z}_{noabs}$ against the surrogates of the respective session. They are therefore not identical to Cohen's *d*, which provides an overall effect size for a sample of sessions. To define Cohen's *d* of e.g. $\bar{Z}_{abs}$ of all *N* sessions of the database, we compute the mean $\bar{Z}_{abs}$ of all *N* sessions, the mean $\bar{Z}_{abs-pseudo}$ of all *N* sessions, and standardize their difference by the standard deviation of the $\bar{Z}_{abs-pseudo}$. Thus the two effect sizes *ES* and *d* are distinguished by their control conditions, so that *ES* is an effect size at the level of the single session, whereas *d* is an effect size at the level of the sample of all *N* sessions. The rationale for the two effect size measures is that one may use *ES* for idiographic purposes, and *d* for generalization.

As a further algorithm to compute signatures of synchrony, the concordance (SUCO for "Surrogate Concordance", cf. www.embodiment.ch) was coded. Rather than on the cross-correlation function, SUCO is based on the correlations of local slopes of the dyad's time series. The concordance approach was previously developed to assess physiological synchrony by Marci & Orr (2006). We adopted the Marci & Orr approach, which we extended in several respects.

The slopes are determined in windows (e.g., window size 2s) of the time series, and the time series are again partitioned in segments (of e.g. 30s duration). The linear slopes are computed by least-squares regression inside the first window of segment *i*, the window is then shifted by an increment of 1 second and the slopes are again computed, until all windows in segment *i* are considered. The slopes in segment *i* of therapist time series are correlated with those of the same segment of the client. The principle of this approach is illustrated in Fig.3. The result is a Pearson correlation r_i that denotes the relation between therapist's and client's slopes in this segment *i* of their session.

The procedure of correlating window-wise slopes is repeated until all *n* segments of the session are finished. These correlations r_i then undergo Fisher's *Z* transforms yielding Z_i , which allows arriving at the mean absolute and non-absolute correlations of a session, $\bar{Z}'_{abs}$ and $\bar{Z}'_{noabs}$. Thus, $\bar{Z}'_{abs} = \sum_{i=1}^{n} |Z_i| \Big/ n$ and $\bar{Z}'_{noabs} = \sum_{i=1}^{n} Z_i \Big/ n$. The segment-wise shuffling used to create surrogate time series are performed in analogy to the computational method described above for SUSY, yielding ES'_{abs} and ES'_{noabs}. For instance, $ES'_{abs} = \left(\bar{Z}'_{abs} - \bar{Z}'_{abs-pseudo}\right) \Big/ SD(\bar{Z}'_{abs-pseudo})$. The difference to the SUSY approach is that in SUCO there is only one step of aggregation – owing to the absence of cross-correlations, each segment is represented by just one correlation Z_i.

The concordance index *CO* across all segments of the client-therapist interaction is finally defined by the natural logarithm of the sum of all positive correlations divided by the absolute value of the sum of all negative correlations. Using segment shuffling and surrogate analysis, an effect size $ES(CO)$ is computed by standardizing the concordance index by the mean and standard deviation of the concordance indexes of surrogate data: $ES(CO) = \left(CO - \overline{CO}_{pseudo}\right) \Big/ SD(CO_{pseudo})$.

We have based our method on the ideas of Marci & Orr (2006) but extended and refined their approach, e.g. by using Fisher's *Z* instead of merely Pearson correlations. We also estimate the slopes by linear regression inside windows of a size that may be freely chosen (Marci & Orr chose a constant window of 5s). As in Marci & Orr, the windows are allowed to overlap, and increments are fixed at 1s. Whereas we amended the method by distinguishing absolute and non-absolute mean Fisher's *Z*, and by introducing surrogate testing to define effect sizes *ES*, we computed the concordance index itself as prescribed by Marci & Orr.

For each physiological signal, respiration, ECG, heart rate, and heart rate variability, we provide descriptive statistics of the sample's synchrony signatures, $\bar{Z}_{abs}$ and $\bar{Z}_{noabs}$ of SUSY, and $\bar{Z}'_{abs}$ and $\bar{Z}'_{noabs}$ of the SUCO approach. For all effect sizes ES and the concordance index CO, we additionally conducted one-sample t-tests against the null hypothesis that ES and CO are not different from zero. All signatures are further characterized by their sample effect sizes using Cohen's *d*.

---Fig.3. here---

Association of synchrony with session reports

We determined the association between the synchrony of a session and the post-session reports by multivariate regression models in JMP Pro 11 statistical software

(SAS Institute Inc., 2013). The signatures of synchrony ES_{abs}, ES_{noabs} and the concordance index CO were used as the dependent variables of these models, and the six scales of self-reports (Alliance_th, Cooperation_th, Progress_th, Alliance_cl, Well-being_cl, Progress_cl) and 'Session number' as the fixed effects. As the dataset is hierarchical (session reports were available in the vreni and vreme therapies), we conducted mixed-effects regression with 'client' as a random effect. To assess model fit, Akaike's Information Criterion (AIC) is reported. Due to the unbalanced dataset, mixed-effects regression may not lead to convergent models. In these cases, we added the client variable as a categorical fixed effect to the multivariate regression models.

Results

Respiratory synchrony

55 sessions with recordings of client's and therapist's respiration were available. We chose lags $-5s \le L \le 5s$, segment size 30s, and restricted the number of surrogates to 1000. Mean synchrony was $\bar{Z}_{abs}$=.167 (SD=.014; Cohen's *d*=-0.30) and, for the non-absolute correlations, $\bar{Z}_{noabs}$=.0041 (SD=.013; Cohen's *d*=0.96). The synchrony effect sizes across all sessions ES_{abs} were significant and negative (mean ES_{abs}=-0.56, SD=1.20; p<.01), whereas ES_{noabs} were positive (mean ES_{noabs}=0.85, SD=3.12; p<.05). With decreasing maximum lags ($|L| = 1,2,3,4,5$), Cohen's *d* of ES_{noabs} increased. ES_{abs} became insignificant for $|L| = 1,2,3$. As insignificant ES_{abs} and positive ES_{noabs} point to in-phase synchrony, we tested whether in-phase correlations exceeded anti-phase correlations (both expressed by Fisher's *Z*), which was significant in a paired *t*-test (*t*(54)=2.85, *p*<.01). In sum, this was in support of hypothesis 1 ('synchrony is present') for ES_{noabs} suggesting in-phase synchrony.

We calculated the concordance index (CO) of synchronized breathing, again using 1000 surrogates and segment size 30s. As a breathing cycle lasts about 5s, we assessed window sizes between 1s and 7s. Fixing window size at 3s, and shifting windows by increments of 1s (i.e. windows were overlapping), we found a mean CO of 0.19 (SD=0.35; Cohen's *d*=7.51). Mean $ES(CO)$ against surrogates was 0.76 (SD=1.25; *p*<.0001). At this window size, insignificant mean ES'_{abs} (mean ES'_{abs}= -.08, SD=.91; Cohen's *d*=.19) and highly significant positive mean ES'_{noabs} were encountered (mean ES'_{noabs}=.74, SD=1.23; Cohen's *d*=7.31). The same picture was found for all considered window sizes. This again supported hypothesis 1. SUSY and SUCO findings were consistent in favoring in-phase synchrony.

Assessing hypothesis 2, we explored the associations of significant in-phase respiratory synchrony (of both synchrony methods) with post-session reports and session number, using multivariate regression models (Table 1). As session reports were filled out at two client levels, we considered 'client' as a random effect. In ES_{abs} the hierarchical model failed to converge and therefore 'client' was inserted as a fixed effect in ordinary regression. No associations between ES_{abs} and session reports were found. The cross-correlational indicator ES_{noabs} was positively linked to the client's alliance and the therapist's progress ratings of a session. 'Client' contributed substantially to whole-model variance in ES_{noabs} and in CO. The concordance index CO was not significantly linked with self-report variables and there was an increase in the course of therapies (i.e.

the fixed effect 'session number' was significant) and a marked difference between the client levels. The concordance index was significantly higher in the vreme sessions than in vreni sessions.

---Table 1 here---

Cardiac synchrony: Electrocardiogram (ECG)

In 55 sessions, the ECG was recorded of both client and therapist. We examined the synchrony of raw ECG signals. The ECG is an oscillatory times series with a period of 1s (heart rate 60/minute) or less. We thus chose maximum lags *L* of 0.25s, 0.5s and 1s to estimate ECG synchrony, always with a segment size of 60s and the number of surrogates set to 400. Results for different maximum lags were similar, thus we report only findings for $-1s \le L \le 1s$. Mean synchrony across all sessions was $\bar{Z}_{abs}$ =0.0156 (SD=0.003; Cohen's *d*=-0.12) and, for the non-absolute correlations, $\bar{Z}_{noabs}$ =0.00037 (SD=0.0013; Cohen's *d*=1.06). Thus, the averages were about one order of magnitude lower than for respiration synchrony, and in themselves not statistically different from zero in a one-sample *t*-test (even in high Cohen's *d*). The cardiac synchrony effect sizes across all 55 sessions ES_{abs} differed significantly from zero (mean ES_{abs} = 0.46, SD=1.49; *p*<.05), whereas ES_{noabs} did not (mean ES_{noabs} = 0.31, SD=1.37; *n.s.*). With increasing maximum lags ($|L| = 0.25;0.5;1$), Cohen's *d* of ES_{noabs} increased but remained insignificant. ES_{abs} was insignificant at maximum lag $|L| = 0.25$, but significantly higher than zero at lags $|L| = 0.5;1$.

We estimated the concordance index (CO) for ECG synchrony choosing window sizes 0.25s and 0.5s to detect slopes of the ECG signal with its period of 1s or smaller. In the application to ECG, we used increments of 0.25s and 0.5s, so that the slopes covered the time series without overlap. Like in SUSY, segment size was 60s, and number of surrogates set to 400. Across 55 sessions, we found mean CO of -0.03 for window size 0.25s and -0.01 for window size 0.5s (both SD=0.41; Cohen's *d*=-0.25 and -0.05), and mean $ES(CO)$ against surrogates of -0.06 and -0.01 (both SD=1.06). For window size 0.25s, 0.5s, mean ES'_{abs} =-0.20, -0.28 (SD=0.96, 1.05; Cohen's *d*=-0.18, 0.29) and mean ES'_{noabs} =-0.03, 0.04 (SD=1.05, 1.10; Cohen's *d*=-0.07, -0.21) were encountered. All means were insignificant in t-tests against the null hypothesis.

Due to the very small *Z* values of synchrony, hypothesis 1 was not supported for ECG synchrony. No significant synchronies were found with the SUCO approach. We do not report associations with session reports. Exploratory calculations however showed that neither the ES_{abs} nor ES_{noabs} of the SUSY algorithm were significantly linked to session report scales.

Cardiac synchrony: Heart rate (HR)

In 51 sessions client's and therapist's HR was assessed in consecutive 15s periods, i.e. quarter minutes. Thus HR time series concern a time scale different from that of ECG and respiration because synchrony here characterizes the synchronization within minutes (not seconds) of the therapy process. Clients' mean HR was 79.0 beats per minute (SD=10.6) across all sessions, the therapist's 85.8 (SD=5.4). We chose maximum lags *L* of 0.5, 1, and 2 minutes to estimate HR synchrony. Segment size was set at 4 minutes, and as the number *n* of surrogates we used the maximum number possible in each session (range, 30<*n*<210). At $|L| = 0.5$ minutes, i.e. with a window size of 1 minute, the mean HR synchrony across all sessions was $\bar{Z}_{abs}$=0.247 (SD=0.029; Cohen's *d*=1.52) and, for the non-absolute correlations, $\bar{Z}_{noabs}$=-0.011 (SD=0.071; Cohen's *d*=-0.91). The HR synchrony effect sizes across all 51 sessions ES_{abs} differed significantly from zero in a one-sample t-test (mean ES_{abs} = 1.34, SD=1.84; *p*<.0001), and the mean ES_{noabs} were significantly negative (mean ES_{noabs} = -1.53, SD=5.16; *p*<.05). A subsequent paired *t*-test of in-phase versus anti-phase correlations (correlations expressed as Fisher's *Z*) was however insignificant (*t*(44)=0.34, *n.s.*). The findings at higher lags ($|L| = 1;2$ minutes) showed again significantly positive mean ES_{abs} (mean ES_{abs} = 0.71; 0.24; both *p*<.0001; Cohen's *d*=1.39; 0.93). Mean ES_{noabs} were not significantly different from zero at these lags. This supported hypothesis 1 for ES_{abs}, with some indications of anti-phase synchrony.

The concordance (SUCO) of synchronized HR was estimated using a window size of 1 minute, with increments of 1 min (i.e. we used non-overlapping windows for slope computations). The segment size was varied between 4 and 8 minutes, which again determined the number of surrogates. At segment size 4, the mean CO was -0.45 and differed from zero in a one-sample t-test (SD=1.06; *p*<.01), with mean $ES(CO)$ against surrogates of -0.75 (SD=1.64; *p*<.01). At this segment size, we found significant mean ES'_{abs} (mean ES'_{abs} = 0.43, SD=1.24; *p*<.05; Cohen's *d*=1.29) and significant mean ES'_{noabs} (mean ES'_{noabs} = -0.56, SD=1.49; *p*<.05; Cohen's *d*=-1.49). The results with higher segment sizes of 5 to 8 minutes were consistent with this, as Cohen's *d* of the CO and ES'_{noabs} were generally high and negative, whereas they remained positive for ES'_{abs}. The SUCO findings are consistent with anti-phase synchrony of HR (supporting hypothesis 1).

We estimated the associations of HR synchrony with self-reports and session number, using multivariate regression models and a maximum lag *L* of 0.5 minute, i.e. a window size of 1 minute (Table 2). The cross-correlational synchrony indicator ES_{abs} was not associated with self-reports, whereas ES_{noabs} was associated with the therapist's progress ratings of a session, and negatively with her cooperation ratings (hypothesis 2). The concordance index was significantly linked with clients' ratings of well-being and alliance quality, and (negatively) with clients' ratings of progress. It was evident that CO differed markedly in vreni and vreme therapies. Thus, this is in support of hypothesis 2 for the concordance index.

---Table2 here---

Cardiac synchrony: Heart rate variability (HRV)

In 51 sessions, clients' and therapist's HRV was assessed by the mean standard deviations of interbeat intervals (SDNN) in consecutive 15s periods, i.e. quarter minutes. Clients' mean SDNN was 33.5 ms (SD=19.1) across all sessions, the therapist's 41.8 ms (SD=8.6). SDNN time series represent approximations to phasic (high-frequency) HRV, and we studied the possible synchrony of these processes in the sessions. As in HR, we again chose maximum lags *L* of 0.5, 1, and 2 minutes to estimate SDNN synchrony. Segment size was set at 4 minutes, and as the number *n* of surrogates we used the maximum number possible in each session (range, 20<*n*<210). At $|L| = 0.5$ minutes, the mean SDNN synchrony across all sessions was $\bar{Z}_{abs}$=0.216 (SD=0.026; Cohen's *d*=0.64) and, for the non-absolute correlations, $\bar{Z}_{noabs}$=0.006 (SD=0.041; Cohen's *d*=0.20). The

SDNN synchrony effect sizes across all 51 sessions, ES_{abs}, differed significantly from zero in a one-sample t-test (mean ES_{abs} =0.95, SD=3.33; *p*<.05), whereas the mean ES_{noabs} did not (mean ES_{noabs} = -0.06, SD=2.60; *n.s.*). The findings at higher lags $|L| = 1;2$ minutes showed again significantly positive mean ES_{abs} for $|L| = 1$ (mean ES_{abs} = 0.26; *p*<.05; Cohen's *d*=0.55), but insignificant mean ES_{abs} for $|L| = 2$. Mean ES_{noabs} were not significantly different from zero at these lags. Hypothesis 1 was supported for HRV synchrony, in-phase and anti-phase synchrony apparently canceled each other out.

The concordance (SUCO) of SDNN time series was estimated using a window size of 1 minute, with increments of windows by 1 min (i.e. we again used non-overlapping windows). The segment size was varied between 4 and 8 minutes, determining the number of surrogates. At segment size 4, the mean of concordance indices was -0.13 and not statistically different from the null hypothesis that it was zero (SD=0.84; *n.s.*), with mean $ES(CO)$ against surrogates of -0.55 (*n*=48; SD=1.98; *n.s.*; Cohen's *d*=-1.06). At this segment size, we found insignificant mean ES'_{abs} (mean ES'_{abs} =0.26, SD=1.15; *n.s.*; Cohen's *d*=0.51) and insignificant mean ES'_{noabs} (mean ES'_{noabs} = -0.23, SD=1.48; *n.s.*; Cohen's *d*=-0.49). The results with higher segment sizes of 5 to 8 minutes were consistent with these insignificant SUCO findings of SDNN. Hypothesis 1 for HRV synchrony using SUCO was rejected.

We estimated the associations of SDNN synchrony with post-session reports and session number by multivariate regression (Table 3), using maximum lag *L* of 0.5 minute as in HR. Mixed regression models were computed where possible; in all but one model, however, convergence failed so that ordinary multiple regressions were performed, entailed by stepwise backward regression. The cross-correlational synchrony indicator ES_{abs} was not significantly associated with self-reports. ES_{noabs} was positively related to the therapist's estimation of the alliance quality of sessions. Thus, hypothesis 2 was accepted for SUSY. The CO was negatively linked with the therapist's cooperation ratings. Thus, negative CO was associated with higher cooperation. Session number was unrelated with SDNN synchrony, and the concordance index was smaller in vreme sessions.

---Table3 here---

Concerning hypothesis 3 ('signatures measure different aspects of synchrony'), Table 4 provides the intercorrelations of the synchrony signatures ES_{abs}, ES_{noabs} (of the SUSY approach) and the concordance index CO of the SUCO approach, at the parameter settings displayed in Tables 1 to 3, respectively. For the respiration data, the signatures were not significantly correlated in Table 4, favoring hypothesis 3. In the same sense, ES_{abs} and ES_{noabs} were not significantly correlated with each other throughout, and in the cardiac synchronies, the concordance index CO was even negatively correlated with ES_{abs}. Thus, intercorrelations of synchrony signatures supported hypothesis 3 with one exception, the positive correlation between ES_{noabs} and the concordance index in heart rate.

---Table4 here---

Discussion

Four physiological signals, respiration activity, electrocardiogram (ECG), heart rate (HR) and heart rate variability (HRV), were recorded simultaneously from a therapist and her client in naturalistic psychotherapy sessions, and analyzed for signs of physiological synchrony. The entire durations of 55 sessions were monitored. Synchrony analyses were conducted using two methodological approaches, computation of cross-correlations (Surrogate synchrony [SUSY], Tschacher & Haken, 2019) and of window-wise slopes (Surrogate concordance [SUCO], based on Marci & Orr, 2006). We wished to attain proof-of-principle, i.e. explore whether computing physiological synchrony in psychotherapy session is feasible, whether synchrony is present, and potentially linked to therapist's or client's self-report assessments, and we believe that these conclusions can be tentatively drawn on the basis of the data.

Our present study is one of the very few that have addressed physiological signals in real psychotherapy sessions, and to our knowledge the first study exploring respiration, ECG, HR and HRV synchronies using the approaches of windowed cross-correlation with surrogate tests (SUSY) and the concordance method with surrogate tests (SUCO).

Results suggest that clients' and therapist's respiration activity showed significant signatures of in-phase synchrony using both approaches. In-phase SUSY synchrony, but not the concordance index, was associated with client's alliance and therapist's progress ratings.

Clients' and therapist's ECG time series, however, were found synchronized only at few parameter settings of the SUSY approach, with values much lower than of other signals. Local slopes (SUCO approach) were not synchronized. We therefore rejected hypothesis 1 (physiological synchrony is present) for ECG synchrony. ECG synchrony values were not systematically tested for associations.

HR synchrony was significant for absolute and anti-phase cross-correlations (SUSY), and the concordance index was significantly negative, thus slopes were coupled in anti-phase. Anti-phase HR synchrony signatures were associated with therapist's alliance ratings, in-phase synchrony with progress ratings. The HR concordance index was strongly linked with clients' well-being and alliance ratings, negative (anti-phase) concordance with client's progress.

Clients' and therapist's HRV was also synchronized using the cross-correlational approach of SUSY, but synchrony was not significant using the SUCO. In-phase HRV synchrony signatures were associated with therapist's alliance, which is not necessarily in contradiction with the finding that in-phase synchrony was not significantly different from zero across the sample of sessions. Negative (anti-phase) concordance index was linked with therapist's cooperation ratings. We thus found in HRV that synchrony signatures for whom H1 was rejected were nevertheless linked with self-report.

It is not possible to generalize the findings because they may be restricted to the present dataset. Nevertheless, we found signs of physiological synchrony in respiration, HR and HRV in support of hypothesis 1. Physiological synchrony was also connected to session reports in various ways, thus hypothesis 2 was likewise supported in this proof-of-principle study in all signals except ECG. As Table 5 shows in overview, alliance rated by the client or therapist was positively associated with physiological synchrony, and this was also true for therapist's cooperation assessment, a further aspect of alliance.

No associations with self-reports were found however for synchrony based on absolute values of cross-correlations (ES_{abs}), even when these were significantly present. It may also be noted that several associations with self-report measures are negative. This points to the necessity that in-phase and anti-phase synchrony should be specifically considered when addressing physiological signals. Negative associations may be interpreted to indicate that anti-phase synchronization (SUSY) or anti-phase slopes (SUCO) were linked with better assessments. For example, in heart rate (HR) synchronization, client-rated progress was higher in those therapy sessions where client's HR acceleration met therapist's HR deceleration (anti-phase slopes), but at the same time client's well-being and alliance ratings were seemingly linked with in-phase slopes. It is obvious that the significances of the regression models cannot be generalized due to short-comings of this dataset that allows proof-of-principle but not generalization (for a discussion of limitations see below).

---Table5 here---

We hypothesized in addition that cross-correlational SUSY and SUCO would give different results (hypothesis 3). As is seen in Table 4, with one exception, the signatures of synchrony were not positively correlated. This was endorsed when evaluating synchronies and their associations to self-report, where there was little overlap between the associations of the different synchrony measures. Thus SUSY and SUCO likely adhere to different facets of sociophysiological coupling, they may not be convergent attributes and rather complement each other (Schönherr et al., 2018).

As for the exploratory hypothesis, ECGs of clients and therapist were not synchronized. ECG synchrony was however not plausible from the beginning, as the specific waveform of cardiac activity is a highly defined process that is at the same time unobservable to participants in psychotherapy, and inaccessible even to self-monitoring. It is thus not likely that the precise ECG dynamics can become synchronized, and hypotheses such as the 'heart beat coalitions' assumed to arise in group psychotherapy (Enke, 1983) are probably insubstantial. Breathing however can be observed, even if interacting people are commonly unaware of it. HR and HRV cannot be observed directly either, yet they concern a different time scale, as these measures were defined at quarter-minute units. HR and HRV are closely linked with general activation and relaxation, which is communicated on many verbal and nonverbal levels in the therapeutic setting.

A number of limitations must be considered. We are aware that the synchrony concept is based on an aggregated statistical measure that exceeds by far the range of statistics that psychotherapy research commonly applies. Any mean value, e.g. of session reports, may merge the information of a few items measured in 55 sessions. Yet, for instance, the values of therapist's and client's respiration throughout these 55 sessions comprise approximately 5 million single measurements (we are dealing with time series of a 16 Hz signal), and the SUSY synchrony value of respiration accordingly derives from the aggregation of hundreds of thousands of cross-correlations. For ES values, this number must even be multiplied by the number of surrogates. In other words, we should be aware of the complexity of the data underlying synchrony, and of the dramatic compression of this complexity into a single measure. Therefore, decisions on the choice of parameters may have great effects on the results of computation. The field of synchrony in psychotherapy is in need of further efforts to validate its statistical measures.

Other limitations pertain to the present dataset specifically and are quite straightforward: Although we considered 55 single sessions of psychotherapy, the sample of sessions is obviously not representative – the inclusion of only four clients treated by a single therapist as well as the unbalanced contribution of data by clients preclude any generalization of findings. Many tests without alpha adjustment were done due to the exploratory nature of this study, and the regression models were derived from dependent data of two clients' therapy courses. In this observational case study, we were therefore merely aiming at proof of principle.

Proof of principle however was considered successful – we developed a prototype for synchrony assessments of physiological data in psychotherapy, which was feasible for describing the therapy sessions. Furthermore, we found tentative associations of these signatures of synchrony in the two clients with documented self-report scales. Future research may implement this methodological prototype and should aim at generating datasets that yield generalizable results, by recruiting a random sample of therapists and clients, or at least inclusion of a cohort in a (larger) treatment facility. The effect sizes documented here may be used to estimate the necessary sample size. As for monitoring devices, technological progress is advancing rapidly, and a wide range of commercial hardware has become available for data acquisition. The physiological measures may be respiration, heart rate and heart rate variability (as in this study), and in addition electrodermal activity. Cardiac measures may be retrieved using photoplethysmography, i.e. optical LEDs with sensors, which measure the blood flow by the light reflected through the skin. Photoplethysmography is less intrusive compared to electrocardiography based on electrodes. Further physiological measures can be central-nervous signals such as provided by near-infrared spectroscopy (NIRS) or by electroencephalography (EEG) to study interbrain coupling (Koole & Tschacher, 2016). Yet NIRS and especially EEG, due to its sensitivity for motion artifacts, are still hard to manage in naturalistic psychotherapy settings. The time has however arrived to realize a study on the synchrony of peripheral physiology – respiration, cardiac, and electrodermal data – in naturalistic therapy environments with random or cohort samples.

Acknowledgement

The authors thank David Leander Tschacher who coded the SUSY and SUCO applications. Nikolai Philipp Tschacher has programmed the web interfaces to run these apps on www.embodiment.ch

References

Bachrach, A., Fontbonne, Y., Joufflineau, C., & Ulloa, J. L. (2015). Audience entrainment during live contemporary dance per- formance: Physiological and cognitive measures. *Frontiers in Human Neuroscience*, *9*, 179.

Birbaumer, N., & Schmidt, R. F. (2010). Biologische Psychologie (7 ed.). Berlin: Springer.

Coutinho, J., Oliveira-Silva, P., Fernandes, E., Goncalves, O., Correia, D., Perrone McGovern, K., & Tschacher, W. (2018, online). Psychophysiological synchrony during verbal interaction in romantic relationships. *Family Process*. doi: 10.1111/famp.12371

Di Mascio, A., Boyd, R. W., and Greenblatt, M. (1957). Physiological correlates of tension and antagonism during psychotherapy; a study of interpersonal physiology. *Psychosomatic Medicine*, 19, 99–104.

Di Mascio, A., Boyd, R. W., Greenblatt, M., and Solomon, H. C. (1955). The psychiatric interview: a sociophysiologic study. *Dis. Nerv. Syst*. 16:4.

Enke, H. (1983). Soziophysiologie. In H. Enke, V. Tschuschke & W. Volk (Eds.), *Psychotherapeutisches Handeln* (pp. 101-118). Stuttgart: Kohlhammer.

Ferrer, E., & Helm, J. L. (2013). Dynamical systems modeling of physiological coregulation in dyadic interactions. *International Journal of Psychophysiology*, *88*, 296-308.

Flückiger, C., Regli, D., Zwahlen, D., Hostettler, S., & Caspar, F. (2010). Der Berner Patienten- und Therapeutenstundenbogen 2000. *Zeitschrift für Klinische Psychologie und Psychotherapie: Forschung und Praxis*, 39, 71-79.

Geller, S. M., & Porges, S. W. (2014). Therapeutic presence: Neurophysiological mechanisms mediating feeling safe in therapeutic relationships. *Journal of Psychotherapy Integration, 24*, 178-192.

Gates, K.M., Gatzke-Kopp, L.M., Sandsten, M., & Blandon, A.Y. (2015). Estimating time-varying RSA to examine psychophysiological linkage of marital dyads. *Psychophysiology*, *52*, 1059-1065.

Graham, F. K. & Clifton, R. K. (1966). Heart-rate change as a component of the orienting response. *Psychological Bulletin*, 65, 305-320.

Grammer, K., Kruck, K. B., & Magnusson, M. S. (1998). The courtship dance: Patterns of nonverbal synchronization in opposite-sex encounters. *Journal of Nonverbal Behavior, 22*, 3-29.

Grawe, K., & Braun, U. (1994). Qualitätskontrolle in der Psychotherapiepraxis. *Zeitschrift für Klinische Psychologie*, 23, 242-267.

Helm, J. L., Sbarra, D. A., & Ferrer, E. (2014). Coregulation of respiratory sinus arrhythmia in adult romantic partners. *Emotion*, *14*, 522-531.

Imel, Z.E., Barco, J.S., Brown, H.J., Baucom, B.R., Baer, J.S., Kircher, J.C., et al. (2014). The association of therapist empathy and synchrony in vocally encoded arousal. *Journal of Counseling Psychology*, 61, 146-153.

Jain, A., Gehde, E., Feist, A., & Alfer, D. (2003). Bedienungshandbuch VARIOGRAF (Version 4.0). Karlsruhe: BECKER MEDITEC.

Karvonen, A., Kykyri, V.-L., Kaartinen, J., Penttonen, M., & Seikkula, J. (2016). Sympathetic nervous system synchrony in couple therapy. *Journal of Marital and Family Therapy*, 42, 383-395.

Kleinbub, J.R. (2017). State of the art of interpersonal physiology in psychotherapy: A systematic review. *Frontiers in Psychology*, 2053.

Kodama, K., Tanaka, S., Shimizu, D., Hori, K., & Matsui, H. (2018). Heart rate synchrony in psychological counseling: A case study. *Psychology*, 9, 1858-1874.

Konvalinka, I., Xygalatas, D., Bulbulia, J., Schjødt, U., Jegindø, E. M., Wallot, S., & Roepstorff, A. (2011). Synchronized arousal between performers and related spectators in a fire-walking ritual. *Proceedings of the National Academy of Sciences*, *108*, 8514-8519.

Koole, S.L. & Tschacher, W. (2016). Synchrony in psychotherapy: A review and an integrative framework for the therapeutic alliance. *Frontiers in Psychology*, 7, 862.

Kop, W. J., Synowski, S. J., Newell, M. E., Schmidt, L. A., Waldstein, S. R., & Fox, N. A. (2011). Autonomic nervous system reactivity to positive and negative mood induction: The role of acute psychological responses and frontal electrocortical activity. *Biological Psychology*, *86*, 230-238.

Lozza, N., Spoerri, C., Ehlert, U., Kesselring, M., Hubmann, P., Tschacher, W., & La Marca, R. (2018). Nonverbal Synchrony and Complementarity in Unacquainted Same-Sex Dyads: A Comparison in a Competitive Context. *Journal of Nonverbal Behavior*, 42, 179-197.

Marci, C.D., Ham, J., Moran, E., and Orr, S.P. (2007). Physiologic correlates of perceived therapist empathy and social-emotional process during psychotherapy. *Journal of Nervous and Mental Disease*, 195, 103–111.

Marci, C.D. & Orr, S.P. (2006). The effect of emotional distance on psychophysiologic concordance and perceived empathy between patient and interviewer. *Applied Psychophysiology and Biofeedback*, 31, 115-128.

Moulder, R.G., Boker, S.M., Ramseyer, F., & Tschacher ,W. (2018, online). Determining synchrony between behavioral time series: An application of surrogate data generation for establishing falsifiable null-hypotheses. *Psychological Methods*. doi: 10.1037/met0000172

Mutz, G. & Becker, K. (2006). Ambulante physiologische Meßgeräte – Entwicklung und stand der Technik am Beispiel von Vitaport und Varioport. In U.W. Ebenr-Priemer (Ed.) Ambulantes psychophysiologisches Monitoring – neue Perspektiven und Anwendungen (137-147). Frankfurt: Peter Lang

Ode, S., Hilmert, C. J., Zielke, D. J., & Robinson, M. D. (2010). Neuroticism's importance in understanding the daily life correlates of heart rate variability. *Emotion*, *10*, 536-543.

Palmieri, A., Kleinbub, J. R., Benelli, E., Messina, I., Sambin, M., and Voci, A. (2018). Attachment security prime effect on skin conductance synchronization in psychotherapists: an empirical study. *Journal of Counseling Psychology*, 56, 490-499.

Palumbo, R. V., Marraccini, M. E., Weyandt, L. L., Wilder-Smith, O., McGee, H. A., Liu, S., & Goodwin, M. S. (2017). Interpersonal autonomic physiology: A systematic review of the literature. *Personality and Social Psychology Review, 21*, 99-141.

Paulick, J., Deisenhofer, A.-K., Ramseyer, F., Tschacher, W., Rubel, J., & Lutz, W. (2018). Nonverbal Synchrony: A new approach to understand psychotherapeutic processes and drop-out. *Journal of Psychotherapy Integration*, 28, 367-384.

Pocock, G., Richards, C. D., & Richards, D. A. (2013). *Human physiology*. Oxford: Oxford University Press.

Ramseyer, F. & Tschacher, W. (2010). Nonverbal synchrony or random coincidence? How to tell the difference. In: Esposito A, Campbell N, Vogel C, Hussain A, & Nijholt A (eds.) Development of Multimodal Interfaces: Active Listening and Synchrony (pp. 182-196). Berlin: Springer.

Ramseyer, F. & Tschacher, W. (2011). Nonverbal synchrony in psychotherapy: Coordinated body-movement reflects relationship quality and outcome. *Journal of Consulting and Clinical Psychology*, 79, 284-295.

Ramseyer, F. & Tschacher, W. (2016). Movement coordination in psychotherapy: Synchrony of hand movements is associated with session outcome. A single-case study. *Nonlinear Dynamics, Psychology, and Life Sciences*, 20, 145-166.

Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-Time Monitoring of Psychotherapeutic Processes: Concept and Compliance. *Frontiers in Psychology, 7* , 604.

Schönherr, D., ., J., Worrack, S., Strauss, B., Rubel, J., Schwartz, B., Deisenhofer, A.-K., Stangier, U., Altmann, U. (2018, online). Quantification of nonverbal synchrony using linear time series analysis methods: Lack of convergent validity and evidence for facets of synchrony. *Behavior Research Methods*.

Sequeira, H., Hot, P., Silvert, L., & Delplanque, S. (2009). Electrical autonomic correlates of emotion. *International Journal of Psychophysiology*, *71*, 50-56.

Thayer, J. F., Hansen, A. L., Saus-Rose, E., & Johnsen, B. H. (2009). Heart rate variability, prefrontal neural function, and cognitive performance: The neurovisceral integration perspective on self-regulation, adaptation, and health. *Annals of Behavioral Medicine*, *37*, 141-153.

Tschacher, W. (1997). *Prozessgestalten – Die Anwendung der Selbstorganisationstheorie und der Theorie dynamischer Systeme auf Probleme der Psychologie*. [Processual gestalts – the application of self-organization theory and dynamical systems theory to fields of psychology]. Göttingen: Hogrefe.

Tschacher, W. & Bergomi, C. (eds.) (2011). The implications of embodiment: Cognition and communication. Exeter: Imprint Academic.

Tschacher, W. & Haken, H. (2019). The process of psychotherapy: Causation and chance. Berlin: Springer.

Tschacher, W. & Scheier, C. (1997). Complex psychological systems: Synergetics and chaos. In: Masterpasqua F. & Perna P. (eds.), The Psychological Meaning of Chaos: Translating Theory into Practice, (pp. 273-298). Washington DC: American Psychological Association Press.

Tschacher, W., Greenwood, S., Kirchberg, V., Wintzerith, S., van den Berg, K., & Tröndle, M. (2012). Physiological correlates of aesthetic perception of artworks in a museum. *Psychology of Aesthetics, Creativity and the Arts*, 6, 96-103.

Tschacher, W. & Ramseyer, F. (2017). Nonverbal synchrony. In Wetzel A (ed). *The SAGE Encyclopedia of Abnormal and Clinical Psychology* (p. 2297-2298). Thousand Oaks, SAGE Publications.

Tschacher, W., Ramseyer, F., & Koole, S. L. (2018). Sharing the now in the social present: Duration of nonverbal synchrony is linked with personality. *Journal of Personality, 86*, 129-138.

Tschacher, W., Rees, G.M. & Ramseyer, F. (2014). Nonverbal synchrony and affect in dyadic interactions. *Frontiers in Psychology*, 5, 1323.

Upham, F., Egermann, H. W., & McAdams, S. (in press). Audience's Breath: Collective Respiratory Coordination in Response to Music. Abstract from International Conference of Music Perception and Cognition, Graz, Austria

Vickhoff, B., Malmgren, H., Åström, R., Nyberg, G., Ekström, S. R., Engwall, M., & Jörnsten, R. (2013). Music structure determines heart rate variability of singers. *Frontiers in Psychology*, *4*, 334.

Williams, P. G., Rau, H. K., Cribbet, M. R., & Gunn, H. E. (2009). Openness to experience and stress regulation. *Journal of Research in Personality*, *43*, 777-784.

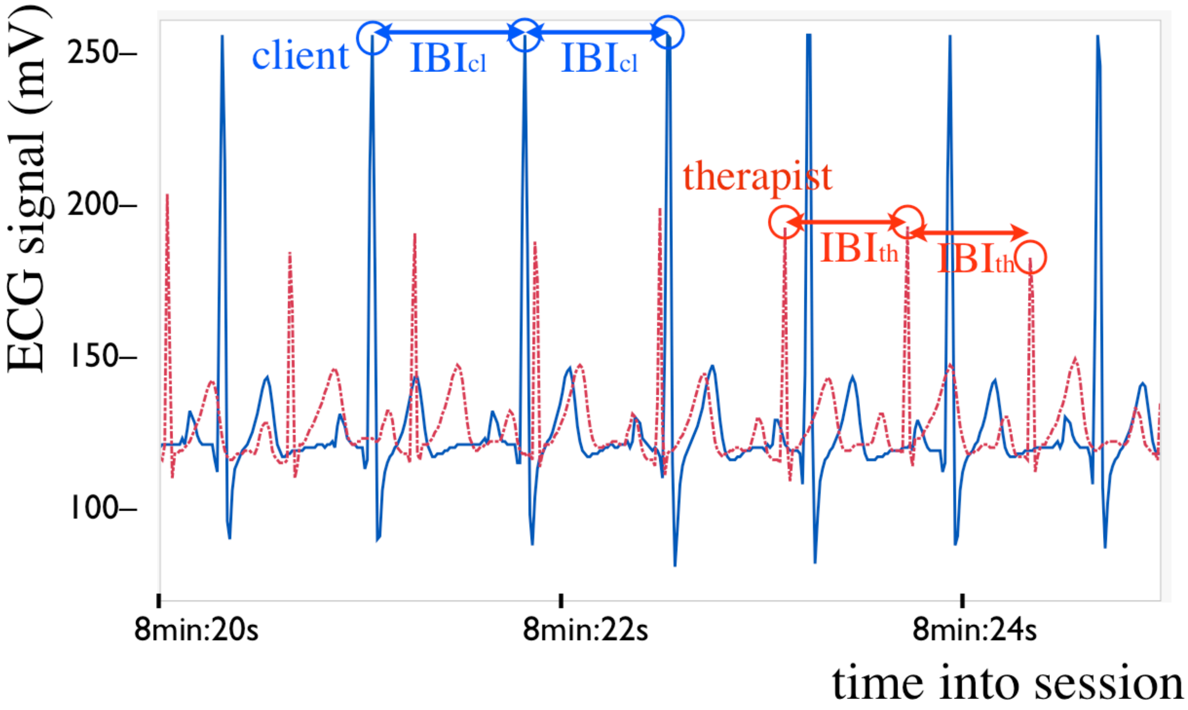

Fig.1. Example of electrocardiograms (ECG, session chran2) of therapist (red, dotted) and client (blue). Interbeat intervals (IBI_{th} and IBI_{cl}) are the temporal distances between consecutive peaks of cardiac activity. From the IBI data, heart rate and heart rate variability are computed

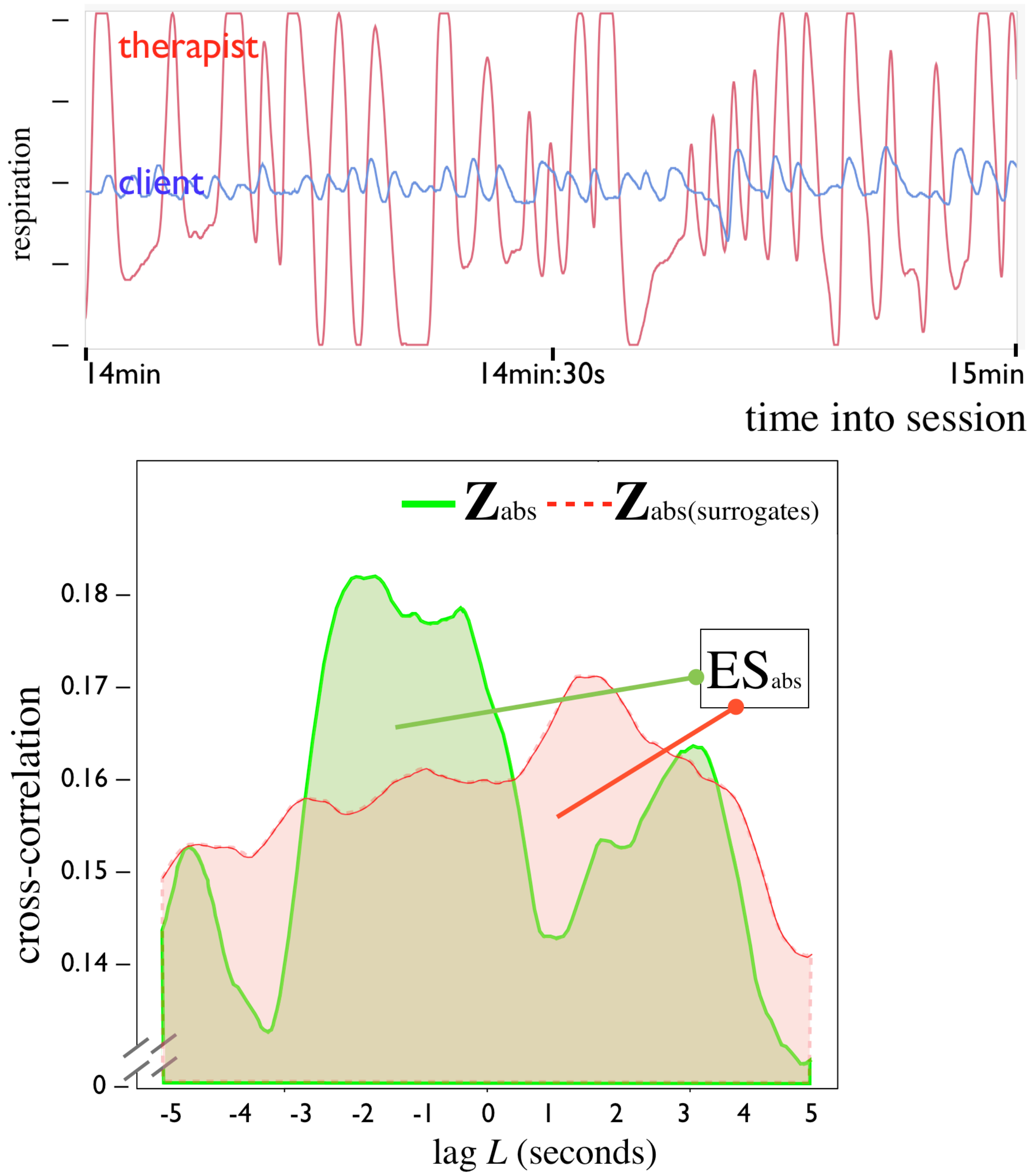

Fig.2. Principle of surrogate synchrony (SUSY), estimated using cross-correlations and surrogate testing. Upper panel: Two respiration time series (therapist data and client data of 1 minute, session vreme11). Lower panel: Absolute cross-correlation *Z*-values per lag *L* of time series aggregated over the complete session (green) and for all surrogates (dotted, red). Effect site (ES) is the area under the green curve minus the area under the red (surrogate) curve, divided by the standard deviations of surrogate *Z*

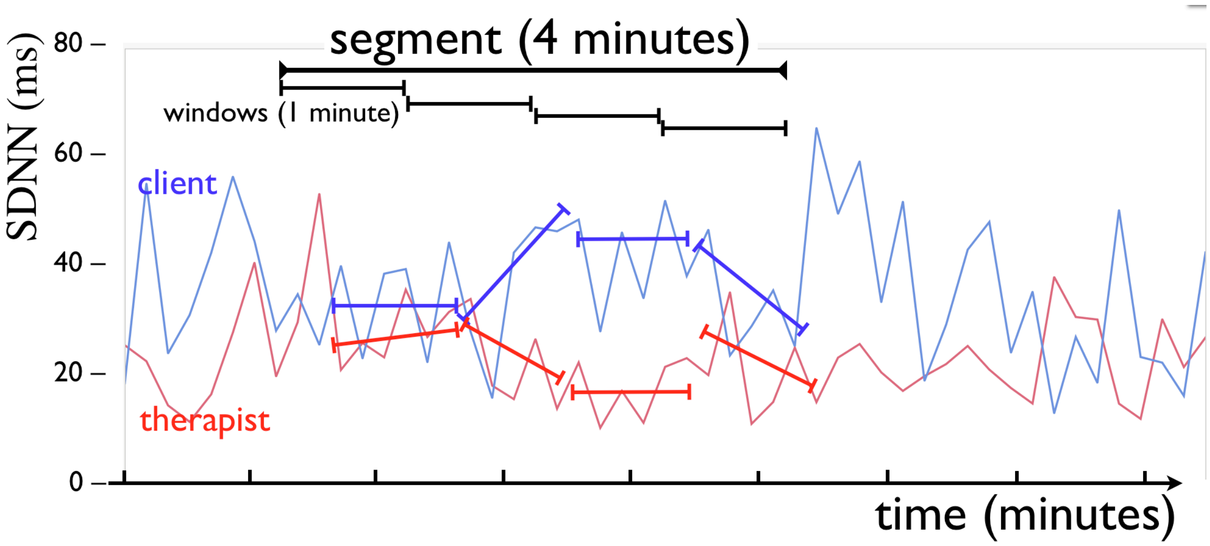

Fig.3. Principle of surrogate concordance (SUCO). In segments of client (blue) and therapist (red) time series (example: heart rate variability (SDNN), session vreni17), the local slopes of regression lines are computed in all windows of the segment. SUCO is based on the correlations of the client with therapist slopes. Please note that windows may also be overlapping as window size may exceed the step size of 1 minute.

Table 1. Respiration (RESP) synchrony predicted by session report scales. Multivariate regression models of N=47 psychotherapy sessions. For each model, fixed effects estimates, random effects variance (where convergence was achieved), whole model variance and AIC are listed (top to bottom).

Dependent Variable	**ES_{abs}**	**ES_{noabs}**	**ES_{noabs}**	**CO**	**CO**	**CO**
sample size	N=47	N=47	N=47	N=47	N=47	N=47
window size	10s	10s	10s	3s	3s	3s
segment size	30s	30s	30s	30s	30s	30s
regression type	ordinary	mixed	backward	mixed	ordinary	backward
number of surrogates	1000	1000	1000	1000	1000	1000
Fixed Effects						
Alliance_cl	t=-0.16	t=2.87**	t=3.71***	t=-0.49	t=-0.42	
Well-Being_cl	t=0.50	t=-1.11		t=0.70	t=0.66	
Progress_cl	t=0.35	t=0.13		t=-1.01	t=-1.19	t=-1.92
Alliance_th	t=-0.08	t=1.05		t=-0.71	t=-0.45	
Cooperation_th	t=-1.18	t=-1.84	t=-1.65	t=0.51	t=0.46	
Progress_th	t=0.36	t=1.71	t=2.38*	t=-0.52	t=-0.49	
Session number	t=-0.06	t=0.17		t=1.49	t=1.86	t=2.82**
Client [vreme]	t=-0.72	–		–	t=1.61	t=3.86***
Random Effect						
Client (% variance)	–	8.98	–	10.04	–	–
r^2 (% variance)	9.44	38.70	31.74	27.75	28.48	26.45
AIC					31.6	18.3

Note. AIC = Akaike's Information Criterion (only provided where comparison between models is meaningful). mixed = mixed regression. backward = backward regression. ordinary = ordinary least squares regression. CO = Concordance Index. – marks that an effect was not entered in the respective model

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

Table 2. Cardiac synchrony (heart rate) predicted by session report scales. Multivariate regression models of N=43 to 41 psychotherapy sessions. For each model, fixed effects estimates, random effects variance (where convergence was achieved), whole model variance and AIC are listed (top to bottom).

Dependent variable	**ES_{abs}**	**ES_{abs}**	**ES_{noabs}**	**ES_{noabs}**	**CO**	**CO**	**CO**	**CO**
sample size	N=43	N=43	N=43	N=43	N=41	N=41	N=41	N=41
window size	1min	1min	1min	1min	1min	1min	1min	1min
segment size	4min	4min	4min	4min	4min	4min	5min	5min
regression type	ordinary	backward	ordinary	backward	ordinary	backward	mixed	backward
number of surrogates	max	max	max	max	max	max	max	max
Fixed Effects								
Alliance_cl	t=0.01		t=-0.80		t=-0.41		t=-1.21	t=2.37*
Well-Being_cl	t=0.03		t=0.03		t=2.63*	t=3.01**	t=4.78****	t=5.73****
Progress_cl	t=1.84		t=-1.63	t=-1.60	t=-1.46	t=-1.69	t=-1.82	t=-2.09*
Alliance_th	t=0.76	t=1.70	t=-0.56	t=-1.63	t=-0.84		t=0.44	
Cooperation_th	t=-0.13		t=-2.00	t=-2.41*	t=-0.96	t=-1.76	t=-0.96	
Progress_th	t=-1.25		t=3.15**	t=3.42**	t=0.63		t=0.98	
Session number	t=-0.79		t=1.84	t=1.88	t=-0.00		t=-0.38	
Client [vreme]	t=-0.37		t=0.17		t=0.90	t=3.94***	–	t=4.65****
Random Effect								
Client (% variance)	–	–	–	–	–	–	29.3	–
r^2 (% variance)	17.7	6.6	33.1	31.7	44.7	55.9	46.0	43.5
AIC	197.2	182.4	274.2	265.4	113.2	122.2		

Note. Heart rate measured in consecutive quarter minutes. AIC = Akaike's Information Criterion (only provided where comparison between adjacent models is meaningful). mixed = mixed regression. backward = backward regression. ordinary = ordinary least squares regression. CO = Concordance Index. ES = effect size. max = the maximum number of surrogates was chosen per dyad. – marks that an effect was not entered in the respective model

* $p < .05$, ** $p < .01$, *** $p < .001$, , **** $p < .0001$

Table 3. Cardiac synchrony (heart rate variability) predicted by session report scales. Multivariate regression models of N=43 to 41 psychotherapy sessions. For each model, fixed effects estimates, random effects variance (where convergence was achieved), whole model variance and AIC are listed (top to bottom).

Dependent variable	**ES_{abs}**	**ES_{abs}**	**ES_{noabs}**	**ES_{noabs}**	**CO**	**CO**	**CO**	**CO**
sample size	N=43	N=43	N=43	N=43	N=41	N=51	N=41	N=41
window size	1min	1min	1min	1min	1min	1min	1min	1min
segment size	4min	4min	4min	4min	4min	4min	5min	5min
regression type	ordinary	backward	ordinary	backward	ordinary	backward	mixed	backward
number of surrogates	max	max	max	max	max	max	max	max
Fixed Effects								
Alliance_cl	t=-0.55		t=-0.62		t=1.20		t=0.80	
Well-Being_cl	t=-0.50		t=-0.87		t=0.34		t=-0.77	
Progress_cl	t=-0.44		t=0.30		t=0.12		t=-0.39	
Alliance_th	t=0.61		t=2.41*	t=3.90***	t=-0.36		t=0.32	
Cooperation_th	t=-1.43	t=-1.70	t=-0.92		t=-0.18		t=-2.13*	t=-2.02*
Progress_th	t=1.20	t=1.86	t=0.32		t=-0.68		t=0.87	
Session number	t=-0.17		t=1.24		t=-0.51		t=0.33	
Client [vreme]	t=0.22		t=0.97		t=-0.93	F=1.63	–	t=-2.54*
Random Effect								
Client (% variance)	–	–	–	–	–	–	4.4	–
r^2 (% variance)	16.0	10.5	35.2	27.1	18.2	9.4	23.1	16.5
AIC	250.7	235.6	216.9	201.7	114.0	114.0		

Note. Heart rate variability measured in consecutive quarter minutes, using SDNN = standard deviation of interbeat intervals. AIC = Akaike's Information Criterion (only provided where comparison between adjacent models is meaningful). mixed = mixed regression. backward = backward regression. ordinary = ordinary least squares regression. CO = Concordance Index. ES = effect size. max = the maximum number of surrogates was chosen per dyad. – marks that an effect was not entered in the respective model

* *p* < .05, ** *p* < .01, *** *p* < .001, , **** *p* < .0001

Table 4. Intercorrelations of synchrony signatures per physiological signal

	RESP		**HR**		**HRV**	
	ES_{abs}	**ES_{noabs}**	**ES_{abs}**	**ES_{noabs}**	**ES_{abs}**	**ES_{noabs}**
ES_{abs}	1		1		1	
ES_{noabs}	0.10	1	-0.20	1	-0.19	1
CO	-0.04	0.06	-0.35*	0.49***	-0.31*	0.26

Note. Parameter settings as in Tables 1-3, respectively
RESP, respiration. HR, heart rate. HRV, heart rate variability. ES_{abs} , ES_{noabs}, effect sizes of synchrony of the SUSY approach. CO, concordance index of the SUCO approach
* *p* < .05, *** *p* < .001

Table 5. Overview of hypothesis 2 (associations of synchrony signatures with self-report variables; session number; client).
+ =significant positive association; **–** =significant negative association

	ES_{abs}(SUSY)	**ES_{noabs}(SUSY)**	**Concordance Index (SUCO)**
Respiration	[synchrony not clearly present] –	[in-phase synchrony] **+**Alliance_cl **+**Progress_th	[in-phase synchrony] **+** Session number **+** client[vreme]
Electrocardiogram	[no synchrony] –	[no synchrony] –	[no synchrony] –
Heart rate	[synchrony] –	[anti-phase synchrony] **–**Cooperation_th **+** Progress_th	[anti-phase synchrony] **+** Alliance_cl **+** Well-being_cl **–** Progress_cl **+** client[vreme]
Heart rate variability	[synchrony] –	[synchrony not clearly present] **+** Alliance_th	[no synchrony] **–** Cooperation_th **–** client[vreme]

note: SUSY = surrogate synchrony method, based on absolute cross-correlation values (ES_{abs}), or based on cross-correlation values (ES_{noabs}). In square brackets, summary of hypothesis 1 'Synchrony present'. SUCO = surrogate concordance method