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ABSTRACT

Ten good outcome and ten poor outcome psychotherapy cases were compared to investigate whether or not the temporal stability and flexibility of their process variables can predict their outcomes. Each participant was monitored daily using the Therapy Process Questionnaire (TPQ), which has 43 items and seven sub-scales, and responses over time were analyzed in terms of correlation robustness and correlation variability across the TPQ sub-scales. "Correlation robustness" and "correlation variability" are two basic characteristics of any correlation matrix: the first is calculated as the sum of the absolute values of Pearson correlation coefficients, the second as the standard deviation of Pearson correlation coefficients. The results demonstrated that the patients within the poor outcome group had lower values on both variables, suggesting lower stability and flexibility. Furthermore, a higher number of cycles of increase and decrease in correlation robustness and variability of the TPQ sub-scales was observed within good outcome psychotherapies, suggesting that, these cycles can be considered as process-markers of good-outcomes. These results provide support for the validity of these quantitative process-parameters, correlation robustness and variability, in predicting psychotherapeutic outcomes. Moreover, the results lend support to the common clinical experience of alternating periods of flexibility and integration being beneficial to good psychotherapeutic processes.

1. Introduction

Identifying processes that are associated with better outcomes is a critical goal within psychotherapy research. A better understanding of good process would assist with clinician training, psychotherapy integration, real-time monitoring of treatment, and ultimately better outcomes for more patients. The necessity of optimizing psychotherapy research, bridging it more closely to actual clinical practice, has become increasingly evident over the past decade (Cuijpers et al., 2018; Lambert, 2013; Shedler, 2018). Growing out of the tradition of common factors research, the "contextual model" (Wampold & Imel, 2015), has provided strong evidence for the importance of the myriad factors comprising the therapeutic alliance in explaining outcomes (e.g., goal consensus and collaboration, empathy, positive regard/affirmation, congruence/genuineness). However, based on a systematic literature review, de Felice, Giuliani, et al. (2019) showed that common factors (i.e., relational and non-specific) and specific factors (e.g., techniques) are not independent. As a result, conceptual and statistical approaches that assume the mutual independence of variables (e.g., standard linear regression and ANOVA based models) are fundamentally limited in their predictive validity, with multiplicative models providing a more appropriate alternative (e.g. Malkina-Pykh, 2018; Schiepek et al., 2017). This suggestion is consistent with the longstanding problem in trying to predict psychotherapy outcomes using combinations of independent predictors (Wampold, 2015). As Wampold et al. (2017) suggest: any intervention "…only becomes real when it unfolds during the course of time.…the most constrained and manualized treatments unfold differently in each instance, due to characteristics of the therapist and the

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client" (pp. 24).

Following this line of research, predictors are usually operationalized as specific patterns of process variables rather than as single variables considered in isolation. For example, sudden gains research has generally demonstrated that patterns of disorganization and reorganization of process variables are common in psychotherapy process (Lutz et al., 2013; Olthof et al., 2019) despite approach (Tang et al., 2002), and are predictive of long-term gains (Kelly et al., 2009). A disorganized pattern of process variables may be characterized by their high variability, their complexity, and their low correlation with one another. Disorganization may be a stage of psychotherapy that can be observed across different clinical situations; among other explanations, it may occur when there is an alternation of old dysfunctional patterns of thinking, feeling, or coping and new and more functional patterns. Conversely, an organized pattern of process variables may be characterized by their low variability and complexity and their high intercorrelation. Like disorganization, an organized stage of therapy process may be observed in different clinical situations as well. Among others, it may be clinically identified by the emergence of the patient's core internal theme.

Additionally, cycles of disorganization-reorganization may be interpreted as consecutive increases in the patient's internal flexibility followed by a re-integration of those adaptations (e.g. Baranger & Baranger, 1961; Bion, 1963; Gonçalves et al., 2011; Caro Gabalda & Stiles, 2013). For example, in experiential therapy for depression, measures of correlation robustness, variability, and complexity among process variables have been shown to be reliable descriptors of therapeutic processes (de Felice, Orsucci, et al., 2019). Stabilization and destabilization of process variables have also been observed in the unfolding process of psychodynamic play therapy (Halfon et al., 2016, 2019) and in brief solution-focused therapy (Kowalik et al., 1997). Furthermore, the oscillation between stabilization and destabilization in the therapeutic alliance of adult psychotherapy has been shown to be associated with good outcomes (de Felice & Andreassi, 2014; Gumz et al., 2010, 2012; Haken & Schiepek, 2006; Schiepek et al., 2014). These results support the hypothesis that alternations between stable and unstable patterns of process variables tend to occur more often in successful psychotherapy, as well as providing support for analyzing therapeutic process unfolding in time, rather than through static summary measures (de Felice et al., 2020; de Felice, Giuliani, et al., 2019; de Felice, Orsucci, et al., 2019; Schiepek, Gelo, et al., 2020; Schöller et al., 2018; Giuliani, 2015).

The present study aims to identify whether fluctuations of stable and unstable patterns of intercorrelation among seven daily measures of psychotherapeutic process can discriminate between good and poor outcome among twenty cases of psychotherapy. Based on prior theory and empirical research, it is expected (hypothesis 1 of the present work) that good outcome cases will demonstrate greater stability overall and (hypothesis 2) also more oscillations between stable and unstable patterns of process variables. Greater stability overall may be interpreted as reflecting greater connectivity or integration among the various aspects of the patient's experience. While the oscillations between flexibility and stability of process variables over the course of therapy may represent a healthy process of openness (i.e., to novelty) and then re-integration (i.e., re-introjection).

2. Methods and materials

2.1. Sample

The 20 patients of this study were treated at two psychotherapy centers, the Department of In-patient Psychotherapy at the University Hospital of Psychiatry, Psychotherapy, and Psychosomatics (Paracelsus Medical University Salzburg, Austria) and the Department of Psychotraumatology at the Clinic St. Irmingard (Prien am Chiemsee, Germany). The diagnostics were done by experienced psychiatrists, based on the ICD-10 F-categories. The first order diagnosis of most of the patients was Adjustment to Severe Stress and Adjustment Disorder (F43: 11 cases). The characteristics of the patients are shown in Table 1, for the full sample and separated for 'good' and 'poor' outcome cases. The descriptive statistics shows a clear difference between the 'good' and the 'poor' cases in terms of the mean effect sizes of the outcome criterion, the ICD-10 Symptom Rating (ISR-10: Tritt, 2015; Tritt et al., 2008) (1.96 [SD: 0.19] vs. -1.09 [SD: 0.49]). The difference is statistically highly significant (Mann–Whitney *U* test, $p < 0.0001$). All the other differences in the descriptive statistics were not significant.

The 10 'good' and 10 'poor' cases were included based on a criterion of less than 10% missing data in the time series of the process measure (Therapy Process Questionnaire, see below). The mean number of missing data in the full sample was 2.3 days (= measurement points; SD: 2.3), which corresponds to a compliance rate of 96.6%. The mean time series length was 68.4 days (SD: 22.6). The inclusion criterion of less than 10% missing data is due to the necessity of having time series with high variability (missing data produce straight lines in the process) to get a realistic picture of the dynamics and to get valid inter-factor correlations.

2.2. Outcome and process measures

The outcome of the inpatient treatments was assessed by the ICD-based Symptom Rating (ISR; Fischer et al., 2009, 2010, 2011; Tritt, 2015; Tritt et al., 2008). The ISR is a first-order outcome measure, it assesses symptom severity and corresponds to the criteria of the diagnostic F-clusters of the ICD-10. The subscales of the ISR are "depression", "anxiety", "obsessive-compulsive disorder", "somatoform disorder", "eating disorder", and an additional scale with problems not related to the other subscales. The total score of the ISR averages all subscales by a weight of 1, except for the additional scale which is weighted by 2. For all patients, ISR-based assessments at the beginning of the hospital stay (pre) and at the release (post) were available.

The process was assessed by the Therapy Process Questionnaire (TPQ) which was developed for routine process monitoring with an equidistant time sampling rate of once per day (Schiepek, Aichhorn, et al., 2016). The TPQ is a multidimensional self-rating scale for the high-frequency monitoring of psychotherapeutic processes. The factor structure and the statistical properties were published in Schiepek et al. (2019). The 7 factors are "well-being and positive emotions" (WPE), "relationship with fellow patients" (RFP), "therapeutic alliance and clinical setting" (TAS), "emotional and problem intensity" (EPI), "insight/confidence/therapeutic progress" (ICP), "motivation for change" (MOT), and "mindfulness/self-care" (MSC). All 43 items are

Table 1

Patients' characteristics. AM: arithmetic mean, SD: standard deviation, ES: effect size, ISR: ICD 10-based Symptom Rating. The differences across the two groups are non-significant except the effect size based on ISR total score (Mann-Whitney *U* test, $p < 0.0001$). F43: Reaction to severe stress and adjustment disorders; F41: Other anxiety disorders; F44: Dissociative disorders; F31: Bipolar affective disorder; F32: Depressive episode; F33: recurrent depressive disorder; F60.3: Emotionally unstable personality disorder.

	Descriptive statistics of the sample	
	Good-outcome	Poor-outcome
N	10	10
m/f	2/8	1/9
Age AM (SD)	40.5 (9.7)	38.7 (11.4)
Time series length (days) AM (SD)	75.2 (18.0)	61.5 (25.6)
Missing data AM (SD)	3.2 (5.4)	1.3 (2.5)
Compliance Rate AM% (SD%)	95.6 (7.5%)	97.5 (5.5)
ES (SD) based on ISR total score	1.96 (0.19)	−1.09 (0.49)
Diagnoses	F43: 3	F43: 8
	F41: 1	F41: -
	F44: 1	F44: -
	F31/32/33: 4	F31/32/33: 2
	F60.3: 1	F60.3: -

rated on Visual Analog Scales. Both questionnaires, the TPQ and the ISR, were administered by an internet- and app-based monitoring system, the Synergetic Navigation System (SNS), which was developed for the assessment and analysis of processes and outcome in naturalistic settings (Schiepek, Aichhorn, et al., 2016; Schiepek et al., 2018; Schiepek, Schöller, et al., 2020; Schiepek, Stöger-Schmidinger, et al., 2016).

2.3. Statistical procedures

2.3.1. Dynamical descriptors

Each patient filled in the TPQ daily. Thus, the dataset comprised seven variables for each time point (daily assessment, rows), corresponding to the seven TPQ subscales (columns). For each patient these seven scores were analyzed in terms of four macro-parameters quantifying the amount of stability and flexibility of the process variables (and, thus, of the psychotherapeutic system) at hand. Each macro-parameter was calculated over a moving window of 7 + 2 time points (i.e., considering the time points from 1 to 7 then from 3 to 9, from 5 to 11 and so on) for each patient. Hence, for each macro-parameter a single time point was represented by a matrix with the seven subscales as columns and the seven temporal points as rows. The four macro-parameters were as follows: 1) The sum of Pearson correlation coefficients above |0.25|, (CORR) (Gorban et al., 2010; Gorban et al., 2021; Schiepek et al., 2018; Schiepek, Stöger-Schmidinger, et al., 2016). It is a measure of correlation robustness, or connectivity, that has been broadly used to quantify the order of a dynamic system with multiple interactive agents in different scientific domains. 2) The standard deviation of Pearson correlation coefficients (STDEV), a measure that must be interpreted with CORR. Whenever a sample has a restricted range of scores, the correlations among scores will be reduced (i.e., Range Restriction Effect). STDEV together with CORR measure how much a given matrix of the seven TPQ subscale values is ordered and robust in terms of intercorrelations. 3) The percentage of variance explained by the first principal component (VARIANCE), another widely used measure of order in dynamical systems. The more variance explained by the first principal component of the seven TPQ subscales, the more ordered is the patient's system of ratings within that seven-day time-window. By contrast, the less variance explained by the first principal component, the flatter the scree plot, and the higher the complexity of the system at hand. 4) Finally, the Shannon Entropy applied on the eigenvalues of each matrix of the seven TPQ subscales values (SHANNON), a widely used measure of complexity of a dynamical system (Pincus & Metten, 2010; Shannon, 1948). SHANNON is as a measure of richness of information, novelty or dispersion among the eigenvalues of a given matrix. In some respects, SHANNON is the opposite of VARIANCE, and the lower VARIANCE, the higher the complexity of the system at hand. However, VARIANCE only considers the eigenvalue of the first PCA component, while SHANNON is computed across the entire spectrum of principal components (de Felice, Orsucci, et al., 2019). For a random variable X the Shannon (1948) entropy $H(X)$ quantifies the "level of predictability" of the corresponding distribution $p(X)$, and is formally defined as:

$$H(X) = -\sum p(X) log_2(p(X))$$

The higher the entropy, the more unpredictable is each drawing from the distribution $p(X)$. For a review of all these indices and their applications see Gorban et al., 2021.

2.3.2. Inferential analysis

As a first step we wanted to know if those macro-parameters were able to describe a significant aspect of the twenty psychotherapeutic processes of the sample. This issue was investigated by a general linear model approach (i.e. linear regressions) with the different patients as a source of variation and each descriptor as dependent variable: the higher the F-value of the general linear model, the higher the ability of the macro-parameter to describe the peculiarities of the different psychotherapeutic processes. This is a crucial step in order to ascertain the ability of the four parameters to significantly describe each therapeutic process. As a second step we quantitatively tested if those macro-parameters were statistically significant in discriminating between good- and poor-outcome cases. In order to avoid overpowered results, we calculated the mean of each macro-parameter for each patient. Then, we performed the Student t over them. Finally, cycles of stability and flexibility of process variables over time were investigated to test whether they can be considered as process-markers of good-outcome psychotherapies.

3. Results

Here below we included the descriptive statistics and correlation structure of the four macro-parameters. The original dataset comprises 1244 rows (statistical units, corresponding to the daily administration of the TPQ) and 7 columns (seven TPQ subscales scores). The calculation of the macro-parameters has been performed over a moving time window of 7 + 2 (i.e. considering from time point 1 to time point 7 as first window, from time point 3 to time point 9 as second window, from time point 5 to time point 11 as third window and so on); this produces 566 time points per macro-parameter (see Table 2).

The correlation structure is consistent with the literature (e.g. de Felice, Orsucci, et al., 2019). As expected, the Shannon Entropy is almost exactly the inverse of the variance explained by the first principal component (VARIANCE). The higher the percentage explained by the first component, the more the matrix is ordered and less complex. On the other hand, the standard deviation and the sum of the Pearson correlation coefficients above |0.25| (i.e. STDEV and CORR) are strongly positively related, demonstrating that they can be considered as two complementary bits of information. The positive correlation between VARIANCE and CORR is also expected, given that they are two different measures of order of the system at hand.

The four macro-parameters were able to capture the unique features of the twenty psychotherapeutic processes across the sample, as evidenced by large and significant F-values for each parameter (see Table 3).

Consistent with the literature, all the four macro-parameters significantly describe the evolution of the psychotherapeutic processes of our sample, demonstrating the usefulness of abstracting general quantitative indices from the process variables at hand without losing the finer-grained information therein embedded.

Next, the four macro-parameters were examined for their ability to differentiate poor- and good-outcome cases. In order to avoid an inflated result of the Student t, we calculated the arithmetic average of each of

Table 2
Descriptive Statistics of the four macro-parameters performed over the original dataset and their correlation structure. In bold the correlations above 0.6.

Descriptive statistics of the macro-parameters

Variable	N	Mean	SD	Sum	Min	Max
STDEV	566	0.569	0.092	322.424	0.294	0.890
SHANNON	566	1.332	0.345	754.010	0.197	2.086
CORR	566	24.838	5.479	14,058	11.805	44.342
VARIANCE	566	66.178	12.614	37,457	38.552	97.557

Pearson correlation coefficients, $N = 566$

	STDEV	SHANNON	CORR	VARIANCE
STDEV		−0.58102	**0.78568**	0.53476
		<0.0001	**<0.0001**	<0.0001
SHANNON			−0.58951	**−0.94069**
			<0.0001	**<0.0001**
CORR				0.54775
				<0.0001

Table 3
Results of the general linear models of the four macro-parameters with the twenty patients as a source of variations.

GENERAL LINEAR MODELS		
MACRO-PARAMETER	F-VALUE	p
STDEV	6.61	**<.0001**
SHANNON	7.59	**<.0001**
CORR	7.13	**<.0001**
VARIANCE	5.88	**<.0001**

macro-parameter for each patient. Then, we performed the *t*-tests over them. Furthermore, in addition to the four quantitative indices described above, we performed a Principal Component Analysis (PCA) over the macro-parameters extracting the first principal component (PC) as a general index of order of the system at hand. Here below the results of the PCA (Table 4).

The first PC explained the majority of the variance of the dataset, 81%. Hence, PC1 can be considered as a global score of order or stability of the system. In fact, as it is possible to observe in the loading pattern, it scales almost perfectly with CORR, VARIANCE and STDEV, and negatively with SHANNON. The higher PC1, the more stable the system at that point in time. Here below the results of *t*-tests statistics for the four macro-parameters and PC1 (Table 5).

The results of the inferential analyses show the strong discrimination power of CORR ($p = 0.0008$, t-value = 4.01), outperforming the other macro-parameters, and followed by STDEV ($p = 0.011$, t-value = 2.82) and the composite index PC1 ($p = 0.014$, t-value = 2.71). The poor outcome cases have a less organized therapeutic process evidenced by a smaller range of TPQ subscale correlations across their therapy sessions along with poorer correlation robustness over time. In other words, the connections among the seven TPQ subscales are lesser within poor-outcome cases than within the good-outcome cases. This is also evident by looking at the mean scores of PC1 within the good- and poor-outcome cases (good = 0.524, poor = −0.524).

Finally, considering the trajectories of the psychotherapeutic processes, cycles of stability and flexibility of process variables over time were investigated. Given that there is an almost perfect inverse correlation between SHANNON and VARIANCE ($r = -0.941$) we excluded, for the sake of simplicity, this latest index from the figures (Figs. 1 and 2 in Appendix A). By looking at the figures it is possible to observe cycles of increase and decrease in the correlation robustness of the process variables at hand. We defined a cycle as a pattern of at least two consecutive time points in which the values of correlation robustness (i.e. connectivity, measured by STDEV and CORR) were at least two standard deviations above or below the complexity score (SHANNON). In so doing, it was possible to highlight 25 cycles in the processes of good-outcome cases and 6 cycles within the poor-outcome trajectories ($p = 0.025$, odds ratio = 4.167).

4. Discussion

The present work investigates the possibility of predicting the outcome of twenty psychotherapies by means of four quantitative macro-parameters reflecting levels of stability and flexibility of psychotherapy process. It was expected (hypothesis 1) that good outcome cases demonstrate greater stability overall and (hypothesis 2) also more oscillations between flexibility and stability of process variables.

All the four macro-parameters describe a significant aspect of the twenty psychotherapeutic processes (all F ratios were $p < 0.0001$). This first analysis (general linear models) demonstrates the possibility of abstracting quantitative indices from the intercorrelations of the seven TPQ subscale values without losing the detailed, fine-grained information embedded therein. Furthermore, two of the macro-parameters, CORR ($p = 0.0008$, t-value = 4.01) and STDEV ($p = 0.011$, t-value = 2.82), and a composite score, PC1 ($p = 0.014$, t-value = 2.71), derived from all four parameters, significantly discriminate between good- and poor-outcome cases. The poor outcome cases have lower values of STDEV and CORR. This may be interpreted as stuckness in the process of poor outcome cases within a relatively unchanging and less organized state. By contrast, the good outcome cases show greater correlation robustness and variability in the inter-correlations among the seven TPQ sub-scales. This may be interpreted as a more integrated experience of psychotherapy process in good-outcome patients.

Interpretation of these differences becomes clearer when one examines the significant difference in trajectories of stability and flexibility over time: the process of good-outcome cases is characterized by cycles of stability and flexibility of the TPQ subscales; while such cycles are relatively rare in the poor outcome cases ($p = 0.025$, odds ratio = 4.167). This result extends prior empirical results examining the role of discontinuous changes within psychotherapy process from the perspective of self-organizing, or complex adaptive systems (e.g., Haken & Schiepek, 2006; Schiepek et al., 2017; Tschacher et al., 1998). In addition to the importance of sudden-gains, and phase transitions, these more subtle and ephemeral cycles of openness and re-integration observed here may be of great importance for understanding the general process by which therapy is successful across different clinicians, patients, and specific approaches. Successful psychotherapy may rely intrinsically on the complementary processes of flexibility and integration (Kashdan & Rottenberg, 2010; Pincus, 2009, 2015, 2016). The present results show that successful therapies had stronger stability over time as well as more cycles of increasing and decreasing stability and flexibility of process variables: hence, both of our hypotheses are

Table 5
Results of the *t*-tests statistics. In bold the significant results.

T-TESTS						
Variable	N	Mean	SD	Student t		
				df	t-value	Pr > |t|
STDEV good cases	10	**0.595**	0.044			
STDEV poor cases	10	**0.543**	0.038	18	**2.82**	**0.011**
SHANNON good cases	10	1.279	0.219			
SHANNON poor cases	10	1.404	0.113	18	−1.60	0.126
CORR good cases	10	**26.970**	2.484			
CORR poor cases	10	**22.791**	2.159	18	**4.01**	**0.0008**
VARIANCE good cases	10	68.139	7.009			
VARIANCE poor cases	10	63.938	3.738	18	1.67	0.111
PC1 good cases	10	**0.524**	1.065			
PC1 poor cases	10	**−0.524**	0.603	18	**2.71**	**0.014**

Table 4
Results of the principal component analysis performed over the four macro-parameters.

PCA over the four macro-parameters					
Component	Eigenvalue	Variance explained	Cumulative variance	Loading Pattern	
				Loading	Component 1
PC1	**3.259**	**0.814**	**0.814**	STDEV	**0.908**
PC2	0.595	0.148	0.963	SHANNON	**−0.917**
PC3	0.127	0.031	0.995	CORR	**0.855**
PC4	0.017	0.004	1.000	VARIANCE	**0.927**

confirmed.

Overall, these results represent an important advancement both in terms of research and integrative practice. Primarily, they make an incremental contribution toward the identification of a meta-model of change in psychotherapy. Instead of using single process variables to predict outcomes, these results, together with the previous literature (e.g. de Felice, Orsucci, et al., 2019; Pincus, 2019) have shown the potential for macro-parameters representing stability and flexibility *among* individual process measures to predict good versus poor outcomes (e.g. Schöller et al., 2018). This evidence suggests the presence of process characteristics that may generally apply to any psychotherapeutic interaction, each a unique self-organizing system through which individual components dynamically interact to allow for new properties to emerge (e.g. Arora et al., 2020).

From this perspective, researchers and clinicians alike may be encouraged to let go of a more reductionist perspective. For researchers, this means letting go of the quest for some final set of process variables placed within a general mediation or moderation model that will account for the most variance of the psychotherapy outcomes across different individuals and contexts. For the clinicians, this perspective means the letting go of the application of specific techniques without carefully considering the context and timing in which they are applied. A very good clinician with whom one of us is familiar, for example, unlocked the defensive structure of one of his patients by reading a poem during a session. This didn't lead him to do it systematically, or to run a randomized clinical trial testing the efficacy of the "poem-based therapy". Instead, a variety of different techniques may be applied within an open, empathic psychotherapy process to gain access to novel experiential information. Once that novel information becomes available, it may be important to weave it together with the patient's broader set of experience (i.e. oscillation between flexibility and re-integration).

A clinical example within the good outcome cases can be the following. One patient suffered greatly from the absence of, and emotional neglect from, her parents. Growing up she became a young woman who complained about her inability to find a loving and caring partner. Her experience was described as having partners who would be very much in love with her initially, but then losing intimacy within a few months. This repetition of unfortunate relationships was based on a cyclical relational process arising from her extreme compliancy and her need for narcissistic affirmations from intimate relations. The greater these latter needs became, the more the relationship would struggle to acquire emotional depth. The patient managed to break this vicious cycle only after having re-integrated in herself the painful emotional experiences coming from the absences and the neglect of her past. This re-integration process helped the patient to acquire greater identity stability, so that she slowly managed to return to having significant and lasting emotional relationships. These more sustainable relationships no longer served the narcissistic demands of the patient, but rather became grounded in her genuine interest in her partner. This change, therefore, implies two phases: a temporary increase in relational flexibility in which a new relational modality can be introduced, and its stabilization and re-integration in the patient's personality.

Applied focus on processes such as flexibility and re-integration (i.e. stability) can be found across the various approaches to psychotherapy, for example in the cognitive-behavioral approaches, where common strategies involve increasing the novelty of rigid cognitive processes and behavioral habits (for reviews, c.f., Batista et al., 2020; Pincus, 2009, 2015, 2016). Also, the clinical psychoanalytic literature has described the process of acquisition of knowledge occurring in psychoanalysis by using theoretical notions similar to stability and flexibility (for example see Bion, 1963 for a comparison with the concept of oscillations PS-D; see Baranger & Baranger, 1961 for a comparison with the concept of the spiral process characterising psychoanalysis).

This alternation between integration (high CORR and STDEV and low SHANNON) and flexibility (high SHANNON and low CORR and STDEV) appears to be a key marker of the learning process acquired within the psychotherapeutic system, while a lack of such oscillations appears to be a hallmark of poor outcomes. That said, some limitations and caveats should be considered. First, the present results are based on the seven subscales of the TPQ. While one would expect similar results from other scales measuring psychotherapeutic process, this remains to be demonstrated in follow-up investigations. Second, although there were far more stability-flexibility cycles in the good outcome cases, there were some exceptions to this rule. Further investigations may shed light on the contextual factors that may be important when interpreting those cycles, such as whether they come earlier or later in therapy or if their characteristics depend on the patient's personality organization (e.g. neurotic, psychotic or borderline). The content around which the cycles emerge may be important as well, such as whether a cycle occurs within the bounds of the therapeutic alliance or as a reaction to an unresolved alliance rupture. Similarly, the definition of a cycle within the present investigation (+/− two standard deviations) may potentially obscure other types of clinically relevant cycling. For example, might a higher number of smaller fluctuations between stability and flexibility of process variables in some cases be as impactful as a few larger cycles?

Fortunately, this study is part of a larger project. One complementary line of investigation that is ongoing is to examine the network dynamics of poor- and good-outcome psychotherapies, and to expand these investigations to larger samples. The present results provide an incremental step, however, toward a more parsimonious paradigm for psychotherapy process research, and a more integrative perspective for empirically grounded psychotherapy practice.

Declaration of competing interest

The authors declare no conflict of interests.

Appendix A

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Fig. 1. Good-outcome cases. In the title of each graph there is the patient's code name and, in parenthesis, the effect size based on the ISR outcome questionnaire. Hence, the cases are ordered from the best to the worst outcome. In this case, the worst case is the closest, in terms of effect size, to the poor-outcome cases. The green

squares highlight the cycles of stability and flexibility of process variables. Each macro-parameter has been standardized.

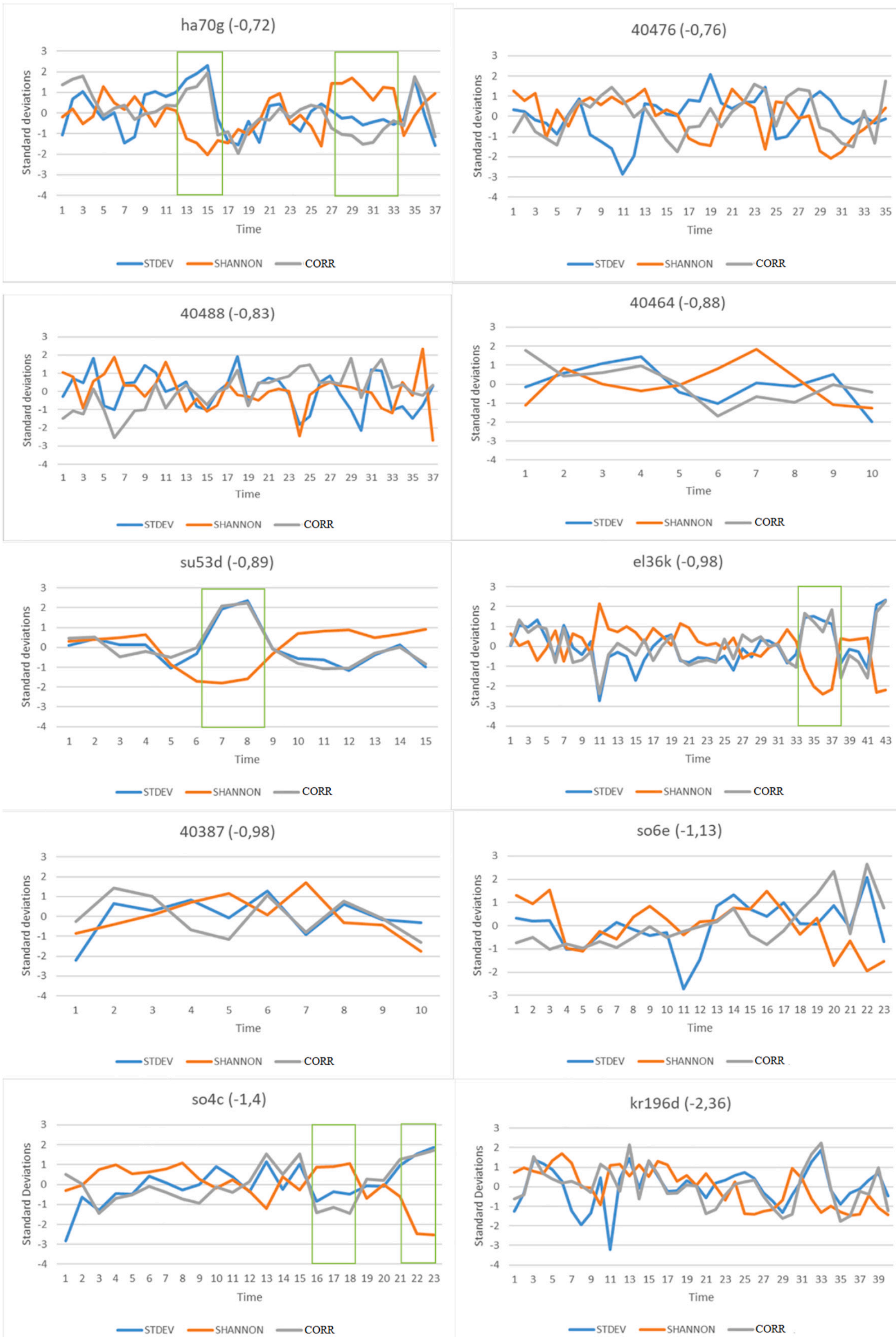

Fig. 2. Poor-outcome cases. In the title of each graph there is the patient's code name and, in parenthesis, the effect size based on the ISR outcome questionnaire. Hence, the cases are ordered from the best to the worst outcome. In this case, the best case is the closest, in terms of effect size, to the good-outcome cases. The green squares highlight the cycles of stability and flexibility of process variables. Each macro-parameter has been standardized.

Furthermore, we deepened the study of the relationships between the four macro-parameters and three more quantitative indices used in psychotherapy research and in complex systems literature. With the same moving time window, and over the same dataset, we calculated the Dynamic Complexity (e.g. Schiepek et al., 2014); the Shape Parameter (e.g. Pincus & Metten, 2010) (i.e. the fit to an exponential relationship between small and large correlations between TPQ subscales); and the autocorrelation at lag-1 (Scheffer et al., 2012). The Dynamic Complexity is defined as the fluctuation multiplied by the distribution of each matrix of the seven TPQ subscales scores. The higher the DC, the higher the fluctuations in the intercorrelations of the TPQ subscales. The Shape Parameter, in this case, is defined by the size of the exponential relationship between large and small correlations among the seven TPQ subscales. The more small correlations relative to large ones, the larger the shape parameter. The more large correlations relative to small ones, the smaller is the shape parameter. The autocorrelation at lag-1 is a broadly used measure of critical slowing downs; an increase in the autocorrelation at lag-1 usually precedes a critical transition. In this case the autocorrelation is defined as the Pearson correlation coefficient between the matrix of the TPQ subscales scores at time t and the matrix at time t-1.

The descriptive statistics and the Pearson correlation coefficients between these indices and the four macro-parameters are shown in Table I and II.

Table I
Descriptive statistics of the four macro-parameters and three more quantitative indices used in the literature.

Descriptive statistics			
	Mean	Std. deviation	N
STDEV	0,569	0,092	566
SHANNON	1332	0,345	566
CORR	24,838	5479	566
VARIANCE	66,178	12,614	566
AUTOCORRELATION	0,722	0,177	566
SHAPE	−0,119	0,522	566
DYNAMIC COMPLEXITY	0,065	0,031	566

Table II
Pearson correlation coefficients between the four macro-parameters and three more quantitative indices used in the literature.

Correlations								
		St. Dev.	Shannon	Corr	Variance	Auto correlation	Shape	Dynamic complexity
STDEV	Pearson Correlation		−0,581**	0,786**	0,535**	−0,334**	0,639**	0,193**
	Sig. (2-tailed)		0,000	0,000	0,000	0,000	0,000	0,000
SHANNON	Pearson Correlation			−0,590**	−0,941**	0,184**	−0,433**	−0,165**
	Sig. (2-tailed)			0,000	0,000	0,000	0,000	0,000
CORR	Pearson Correlation				0,548**	−0,412**	0,818**	0,229**
	Sig. (2-tailed)				0,000	0,000	0,000	0,000
VARIANCE	Pearson Correlation					−0,147**	0,419**	0,123**
	Sig. (2-tailed)					0,000	0,000	0,003
AUTOCORRELATION	Pearson Correlation						−0,280**	−0,400**
	Sig. (2-tailed)						0,000	0,000
SHAPE	Pearson Correlation							0,124**
	Sig. (2-tailed)							0,003

** Correlation is significant at the 0.01 level (2-tailed).

Finally, by performing a principal component analysis (PCA) over all the macro-parameters we can observe how they can be grouped together in two principal components. The first comprises all the different measures of stability of the process variables at hand, in fact it is strongly inversely correlated with Shannon Entropy. The second, instead, comprises only Dynamic Complexity (positively correlated) and Autocorrelation (negatively correlated). Dynamic complexity is a quantitative index very sensitive to changes and fluctuations of time series. Hence, while the first component identifies the degree of stability the second identifies the degree of fluctuations in the intercorrelation structure of the process variables at hand (e.g. precursor of phase transition). The results are shown in Table III and Fig. 3.

Table III
Principal Component Analysis (PCA) over all the macro-parameters. The first two principal components explain the 71% of variance. In bold the loadings with r > |0,5|.

Principal component analysis[a]		
	Component	
	1	2
STDEV	**0,846**	0,000
SHANNON	**−0,817**	0,365
CORR	**0,904**	0,070
VARIANCE	**0,785**	−0,413
AUTOCORRELATION	−0,462	**−0,691**
SHAPE	**0,778**	0,021
DYNAMIC COMPLEXITY	0,322	**0,692**

Extraction Method: NFACTOR Criterion.

[a] 2 components extracted.

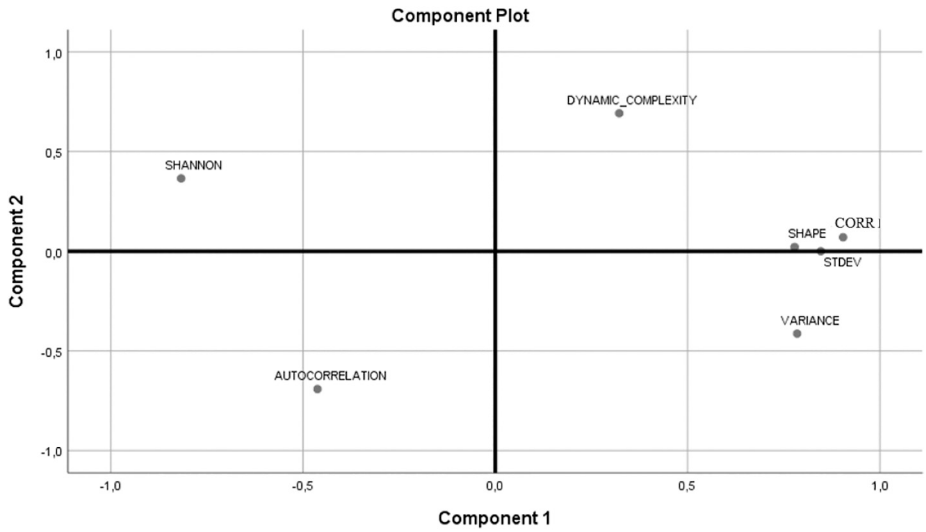

Fig. 3. Visual representation of the loadings within the components' space.

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