What Differentiates Poor and Good Outcome Psychotherapy?
A Statistical-Mechanics-Inspired Approach to Psychotherapy Research

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Abstract: *Statistical mechanics investigates how emergent properties of macroscopic systems (such as temperature and pressure) relate to microscopic state fluctuations. The underlying idea is that global statistical descriptors of order and variability can monitor the relevant dynamics of the whole system at hand. Here we test the possibility of extending such an approach to psychotherapy research investigating the possibility of predicting the outcome of psychotherapy on the sole basis of coarse-grained empirical macro-parameters.*
Four good-outcome and four poor-outcome brief psychotherapies were recorded, and their transcripts coded in terms of standard psychological categories (abstract, positive emotional and negative emotional language pertaining to patient and therapist). Each patient-therapist interaction is considered as a discrete multivariate time series made of subsequent word-blocks of 150-word length, defined in terms of the above categories.
Static analysis (Principal Component Analysis) highlighted a substantial difference between good-outcome and poor-outcome cases in terms of mutual correlations among those descriptors. In the former, the patient's use of abstract language correlated with therapist's emotional negative language, while in the latter it co-varied with therapist's emotional positive language, thus showing the different judgment of the therapists regarding the same variable (abstract language) in poor and good outcome cases.
On the other hand, the dynamic analysis, based on five coarse-grained descriptors related to variability, degree of order and complexity of the series, demonstrated a relevant case-specific effect, pointing to the possibility of deriving a consistent picture of any single psychotherapeutic process. Overall, the results showed that the systemic approach to psychotherapy (an old tenet of psychology) is mature to shift from a metaphorical to a fully quantitative status.

Key Words: Psychotherapy, Complex Systems, Statistical Mechanics, Process of Change, Nonlinear Dynamics.

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INTRODUCTION

In the literature there have been many examples aimed at finding coarse-grained descriptors able to explain the behaviour of complex systems composed of several different elements. Statistical thermodynamics has emphasised the importance of focusing on the dynamics of the degree of order of a system [1]. This approach can be extended to any scientific field, posited that we get a sensible measure of system autocorrelation [2],[3], [4].

In econometrics, Gorban and colleagues [2], showed that a market's change occurs after a critical period (tipping point) in which both the internal correlation and variability of the system reach a peak value. In biology, many studies[5],[6],[7] showed the usefulness of looking at biological systems from the perspective of statistical mechanics, that is, focusing on the mutual correlations among system descriptors. This scientific stance takes the name of "middle-out" approach since it focuses on a mesoscopic level maximising the correlations among system descriptors. In other words, this approach lies 'in the middle' between pure 'bottom-up' (the causally relevant layer is the microscopic one) and 'top-down' (the causally relevant layers is where general laws are defined) [8].[9].

Along these lines of thought, in the psychotherapy research literature Schiepek and colleagues [10] formulated an empirical dynamic descriptor that predicts the therapeutic change and correlates with a good outcome. It is obtained by the multiplication of the distribution and fluctuation of a given signal (for a detailed description, see [10]), and can be intended as a measure of system variability (for a review, see [11]. Analogously to what expected [2],[3], a peak of dynamic complexity was usually found to precede a therapeutic change or restructuring. Clinically, this behavior corresponds to the observation of something new in the patient's in-session narratives or in some of his/her behavioral traits outside the clinical room before the occurrence of an important insight [12].

Despite that, an empirical proof of the possibility to predict the evolution of psychotherapy by means of macro-parameters of order, variability and complexity has never been obtained. This prompted us to undergo the present research work mainly based on the two following questions: 1) Which are the macro-parameters relevant for describing psychotherapy and how do they interact? 2) Are these macro-parameters able to differentiate good and poor outcome psychotherapy?

The present work represents the first empirical effort to provide an answer to these questions by applying a statistical mechanics-inspired approach to psychotherapy.

MATERIAL AND METHODS

Sample

The sample analysed was drawn from the York Depression Study I, a randomised clinical trial to assess the efficacy of brief experiential therapy (client-centered therapy [CCT] and emotion-focused therapy [EFT]) for depression [13]). The original sample was comprised of 17 CCT and 17 EFT. Hence, for the present study, we focused on these cases including their transcripts. Initially, we selected the six best-outcome cases (CCT = 3; EFT = 3) and the six worst-outcome cases (CCT = 3; EFT = 3) based on the Reliable

Change Index (i.e. RCI; [14]) of the Beck Depression Inventory (BDI; [15]). Further, four cases (3 = CCT and 1 = EFT) were excluded due to some missing sessions. In so doing, our final sample was comprised of four good-outcome (1 = CCT and 3 = EFT) and four poor-outcome (2 = CCT and 2 = EFT) cases, for a total of N = 8 treatments. For the good outcome cases, the BDI pre-post change was from 30 to 5, from 25 to 3, from 35 to 4, and from 21 to 12. For the poor outcome cases, it was from 23 to 22, from 15 to 13, from 19 to 19, and from 13 to 9 (for more details, see also [16]).

Patients. Patients were one man and seven women with a mean age of 37.08 years who met the criteria for major depressive disorder (MDD) on the Structured Clinical Interview for DSM-III-R (SCID; [17]).

Therapists. Therapists were seven women and one man with an average of approximatively 5.5 years of therapeutic experience and 24 weeks of training in experiential psychotherapy [18]. All therapists were monitored for adherence through video recordings and weekly supervisions.

Treatments. CCT, emphasises empathy, positive regards and congruence [18], EFT, integrates CCT with “process-directive gestalt and experiential interventions” for the resolution of dysfunctional cognitive-affective processing [13]. The treatment length was between 15 and 20 sessions (mean = 17.62, st.dev. = 1.38), for a total of 141 sessions.

Measures

The semantic production of the eight brief psychotherapies was coded according to Mergenthaler’s Therapeutic Cycle Model (TCM; [19],[20],[21], a computer-assisted deductive content analytic tool which breaks the transcript down into chunks of 150 word-blocks and then analyses them according to three different dictionaries: a) positive emotional tone (POS), b) negative emotional tone (NEG) and c) abstraction (AB). The first two contain adjectives, verbs, or adverbs with a positive or negative valence (e.g. happy, sad; agree, disagree; hug, abandon; incredible, astonished). The third contains abstract words (e.g. year, hour, accident, soul, wedding). All sessions were transcribed according to the international standards [21]. The TCM automatically assesses the relative frequency of the three dictionaries per each word-block.

In short, the dataset has 6 variables– the relative frequencies of the three vocabularies pertaining to patient and therapist of each therapy (i.e. 8 different therapeutic couples, no therapist carried out more than one therapy) – and as statistical units the word-blocks in temporal order.

Data Analysis

We investigated the correlation structure of the data set by Principal Component Analysis (PCA, [22].[23]). The strategy of analysis stems from the hypothesis that good and poor outcome cases corresponded to two different correlation structures imposed on the 6 descriptors (i.e. variables). This is consistent with the fact that the same descriptor takes a different meaning (and consequently a different pattern of correlation with other descriptors) in good and poor outcome contexts. Thus, given the extracted components are eigenvectors of the correlation matrix [22], we expect the distinct PCA solutions pertaining to poor-outcome cases, good-outcome cases and good-and-poor-outcome cases taken together not to be super-imposable, for the changes in the correlation structure linked to different outcomes [23]. Moreover, given that the principal components of a specific dataset are each other orthogonal by construction, the discovery of mutual correlations between components of those three solutions allows us to highlight ‘hidden variables’ which have the same latent meaning even if

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endowed with a different loading structure. The actual steps of the analysis were scheduled as follows following the scheme set forth in [23]:

1) Three independent PCAs are performed: a) PCA of poor-outcome cases (variables); b) PCA of good-outcome cases (6 variables); and c) PCA of good-and-poor-outcome cases taken together with 12 (6+6) variables.
2) The component scores of the 24 variable case (i.e. 12 + 6 + 6) are scrutinised by means of mutual Pearson correlations with the scores of the poor and good outcome analyses. This procedure allows to gather two crucial information. On the one hand, the component scores pertaining to a) or b) (subset) cases that scale with the same component scores of c) (whole set) point to latent factors common to good and poor outcome cases. On the other hand, the component scores pertaining to c) that scale only with one of the a) and b) subsets are peculiar to either poor or good outcome cases.

These results can be helpful in understanding the differences and analogies pertaining to good and poor outcome datasets. However, as they depict the latent dimensions of a given data matrix, with no explicit reference to time course, they produce static results.

In order to understand the dynamics pertaining to good and poor outcome cases as well as their possible differences and analogies, we need to go back and study the original data, recovering their temporal dimension, changing our level of analysis from the aggregation of cases to single patient-therapist dynamics. Building upon the widely recognised link between the onset of transitions and the increase in autocorrelation of the system at hand [2], we computed different statistical indexes of temporal correlation on the psychotherapy time series.

We divided the original data matrix of each patient (i.e. 6 linguistic variables as columns and consecutive word-blocks as rows) into sub-matrices: one sub-matrix for each psychotherapeutic session. The sub-matrices were the input for the computation of five different statistical indices, widely used to forecast transitions in temporal series:

a) Canonical Correlation Coefficient; b) Percentage of variance explained by the first principal component; c) Sum of Pearson correlation coefficients higher than |0.25|; d) Standard deviation of Pearson coefficients and e) Shannon Entropy on Eigenvalues.

The usefulness of these indexes in anticipating critical transitions was assessed in many different fields spanning from economics to biology and chemistry [2], consistently with the universal character of statistical mechanics. The rationale behind these measures (see appendix) is the existence of common dynamics relating to both the correlation and variability of a system approaching a critical transition [3].

The “canonical correlation coefficient” corresponds to the highest canonical correlation between patient (X variable subset) and therapist (Y variable subset) descriptors and thus monitors the strength of the interaction between therapist and patient along the process.

The “percentage of variance explained by the first principal component” is a measure of the degree of correlation for all the variables (both therapist and patient related). A very similar interpretation holds for the “sum of Pearson correlation coefficients higher than |0.25|”, but in this case, the estimation of the amount of correlation is limited to middle-to-high correlations.

The “standard deviation of Pearson correlation coefficients” points to another feature of correlation dynamics: its variation in time, and, thus, it is supposed to be more sensitive to the presence of ‘transitions’ along the process. The last index, “Shannon entropy of eigenvalues” focuses on the dimensionality of the time series on the phase space: a high entropy points to the lack of any dominant correlation flux.

A routine in Matlab was developed to compute such variability and correlation indices on each single case with a time window corresponding to one session. Then, the extracted measures were examined by a Principal Component Analysis to understand their latent dimensions. Eventually, their component scores were included as dependent variables of three General Linear Models to check the existence of peculiar case-specific correlation dynamics (section "Dynamic Analyses"). The discovery of such relations would be the proof that the above formalisation grasps the uniqueness of each psychotherapeutic process, thus constituting its sensible quantitative description.

RESULTS

Static Analyses

From the correlation matrix of the original dataset made of both good- and poor-outcome cases it was not possible to obtain any significant information. The pairwise Pearson coefficients the variables AB (abstract language), POS (positive language) and NEG (negative language) of therapist and patient were near to zero and thus apparently linear independent.
The PCA confirmed this observation displaying a flat eigenvalues distribution (Table 1) so pointing to the lack of a relevant shared correlation structure at this level of analysis. This implies the adopted dictionary is made of largely independent categories, in other words AB, POS and NEG as such are well-defined not overlapping concepts.

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Component	**PCA good-outcome cases. Eigenvalues, % of variance explained.**	**PCA poor-outcome cases. Eigenvalues, % of variance explained.**
1	23.192	20.742
2	18.112	18.303
3	17.114	16.896
4	15.707	15.752
5	14.393	15.360
6	11.482	12.947

Table 1. PCA of good and poor outcome cases. Percentages of variance explained by each component for good-outcome and poor-outcome cases

In order to grasp the potential differences in the correlation structures of good- and poor-outcome cases, we deepened their study by performing three different principal component analyses at different definition levels: (a) PCA of poor-outcome cases, (b) PCA of good-outcome cases (6 variables) and (c) PCA of poor-and-good-outcome cases taken together. Then, the component scores obtained were scrutinised by a Pearson correlation matrix to identify (see Methods, section Data Analysis) "mixed" and "pure" components across good and poor-outcome cases. The latter components, peculiar to either good or poor-outcome cases, will show the idiosyncrasies of patient-therapist interaction in the two outcome classes. Components 1, 5 and 6 of good-outcome and poor-outcome cases pertain to this latter category, while components 2, 3 and 4 to the former (Table 2).

Components PCA c)	**Good-comp1**	Good-comp2	Good-comp3	Good-comp4	**Good-comp5**	**Good-comp6**	**Poor-comp1**	Poor-comp2	Poor-comp3	Poor-comp4	**Poor-comp5**	**Poor-comp6**
1	**.991****	.008	.003	.004	.012	.004	.088**	.127**	-.015	.025	-.010	.081**
2	.075**	-.029	-.010	.045**	-.008	-.051**	**.995****	.020	-.006	.014	-.006	.015
3	-.070**	**.710****	.015	.055**	.058**	-.011	.013	**.694****	.143**	-.137**	.063**	-.024
4	-.076**	**-.568****	-.194**	.201**	.067**	-.012	-.033*	**.658****	-.341**	.200**	-.051**	.023
5	-.015	-.254**	**.800****	.062**	-.047**	-.030	-.005	.177**	**.495****	.139**	-.085**	.049**
6	-.001	.170**	**.560****	.047**	.077**	.023	.007	-.064**	**-.779****	-.103**	.027	.020
7	-.018	.241**	-.044**	**.708****	-.134**	-.047**	-.025	-.163**	-.011	**.630****	-.047**	.131**
8	.010	-.058**	.030	-.001	.302**	.079**	.006	-.017	.051**	.158**	**.940****	-.025
9	-.001	.119**	.026	**-.642****	-.154**	-.021	.017	.063**	-.102**	**.683****	-.058**	-.174**
10	.015	.037*	-.021	-.002	**.914****	-.030	.005	-.068**	.058**	.144**	-.307**	-.130**
11	-.042*	.024	-.027	-.174**	.103**	-.274**	-.006	.005	-.008	.037*	.004	**.933****
12	-.005	.002	-.010	-.047**	.030	**.953****	.027	.011	.016	.042*	-.069**	.238**

Table 2. Pearson Correlation Matrix between the three PCAs' component scores (here, for the sake of simplicity, only the area in which some significant correlations appeared is shown). The components that scale with only one component of PCA c) (e.g. only Good-comp1 scales with component 1) are given in bold on a red background. They represent peculiar features of either good or poor-outcome cases. The other components are coupled (e.g. both Good-comp2 and Poor-comp2 scale with the same component) and scale with more than one component of PCA c). They don't represent specific features of either good or poor outcome cases
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

Good and poor principal component solutions are substantially different: when we merged the two groups of descriptors by performing a global PCA with 12-variables, some of their peculiarities (i.e. "pure" good- or poor-outcome components) do emerge (i.e. shown in bold and on a red background, Table 2). Metaphorically, if our outcome groups had been fluids, we would have been able to observe the behaviour of something like oil and water, or a very poor vodka Martini: even if we keep shaking it, there will always be some unstirred components (i.e. components 1, 5 and 6) (see [23]).
Now, in order to maximise the differences between good-outcome and poor-outcome cases, we performed the Pearson correlation matrices partialising the effect of the "stirred" components: 2, 3 and 4. Table 3 shows the main differences between poor and good outcome cases.

Control Variables (Good-comp2, 3 and 4)	AB therapist (good cases)	POS therapist (good cases)	NEG therapist (good cases)	AB patient (good cases)	POS patient (good cases)	NEG patient (good cases)
AB therapist	1.000	-.259**	-.460**	-.463**	-.114**	.780**
POS therapist		1.000	-.541**	**-.714****	**-.183****	**-.583****
NEG therapist			1.000	**.918****	-.346**	.186**
AB patient				1.000	**.046****	**.078****
POS patient					1.000	-.473**
NEG patient						1.000
Control Variables (Poor-comp2, 3 and 4)	AB therapist (poor cases)	POS therapist (poor cases)	NEG therapist (poor cases)	AB patient (poor cases)	POS patient (poor cases)	NEG patient (poor cases)
AB therapist	1.000	-.170**	-.064**	-.637**	-.323**	.977**
POS therapist		1.000	-.424**	**.831****	**-.559****	**-.296****
NEG therapist			1.000	**-.072****	-.343**	.148**
AB patient				1.000	**-.418****	**-.680****
POS patient					1.000	-.354**
NEG patient						1.000

Table 3. Partial Correlations of good (top) and poor (bottom) outcome cases. Their main differences are given in bold and on a red background.
**. Correlation is significant at the 0.01 level (2-tailed). *. Correlation is significant at the 0.05 level (2-tailed).

The differences (in bold on a red background) in the correlation matrices between good-outcome and poor-outcome cases are now evident. The most obvious one concerns the dynamics in which the patient makes use of abstract language (AB), interpreted by the therapist very positively in poor-outcome cases and very negatively in good-outcome cases (see the opposite sign of correlation of AB with POS and NEG therapist variables in the two subsets). In the latter, the use of an abstract language is probably considered as a patient's defense mechanism to address. On the contrary, in the poor-outcome cases the therapist (already conscious of the difficulty of the case), intends the use of an abstract language by the patient as a positive sign of critical assessment of his/her pathological status.

This interpretation is consistent with the use of positive and negative emotional languages that results to be inversely proportional to abstraction only in poor-outcome patients.

The defense mechanism of rationalisation is a way to protect the mind from painful feelings using an abstract, intellectual and often concrete attitude in dealing with them. The good-outcome therapists seem to respond promptly to that by addressing the emotional content lying under the surface of the psychotherapeutic field (i.e. use of the therapist's negative emotional language). In the poor-outcome cases the therapists seem less able to address the dynamic of rationalisation or, on the other hand, the poor-outcome patients make an extreme use of it impeding their own clinical progress.

Dynamic Analyses

We divided the original data matrix of each patient (i.e. 6 linguistic variables as columns and consecutive word-blocks as rows, around 800 word-blocks per patient) into sub-matrices: one sub-matrix for each psychotherapeutic session. Then we computed, from the above sub-matrices, five different indices used as possible transition signatures: a) Canonical Correlation Coefficients; b) Percentage of explained variance by the first component; c) Sum of Pearson correlation coefficients higher than |0.25|; d) Standard deviation of Pearson coefficients and e) Shannon Entropy on Eigenvalues. A routine in Matlab was developed to compute the aforementioned statistical indices on each single case with a time window corresponding to one session. Then, these results were examined by a PCA in order to investigate their latent dimensions (Table 4).

Component	Eigenvalue	Difference	Proportion	Cumulative
1	**2.36**	**0.73**	**0.47**	**0.47**
2	**1.62**	**1.11**	**0.32**	**0.79**
3	**0.50**	**0.21**	**0.10**	**0.89**
4	0.29	0.08	0.05	0.95
5	0.21		0.04	1.00
Components' Loadings				
	Component 1	Component 2	Component 3	
Canonical Correlation	**0.77**	0.46	-0.31	
Shannon Entropy	-0.30	**0.86**	0.11	
Gorban's G	**0.86**	0.29	-0.18	
Standard Deviation	**0.79**	0.05	**0.60**	
Variance I Component	0.52	**-0.75**	-0.08	

Table 4. Principal Component Analysis of the five dynamic indices after their application on the eight single cases. Three components (in bold) were retained by the scree test criterion. The most important descriptors of each component are given in bold (see "Components' Loadings").

Component 1 appears to be strictly linked with the Pearson correlation standard deviation, average amount of correlation and canonical correlation of a given matrix. This component allows for a clinical interpretation, being a proxy of those periods of time in which a patient does something new *prior* to a proper insight (i.e. often called "second order change"). It can sometimes happen that the patient, especially at the beginning of psychotherapy, opens a "forgotten" drawer to see old pictures of her/himself or her/his family, regaining pleasure in old habits like doing sport or meeting old friends, or travels to places associated with her/his past. In these conditions, his/her behavioral variability increases as well as the correlation robustness of his/her personal history: s/he becomes able to narrativise it and thus his/her personal identity acquires robustness and coherence.

Component 2 appears to be linked with the Shannon Entropy on the eigenvalues and the variance explained by the first component. When the former has a peak, we have a very "flat" scree plot with all the principal components (that can be made to correspond to order parameters) pulling the data matrix into their respective directions, with almost equal strength. Alternatively, when the variance explained by the first component has a peak, the slope of the scree plot increases a great deal, giving rise to a clear organisation in the system. Clinically, this latest picture has often been called "first order change", in which a patient is now able to describe the reasons, e.g., of a relational attitude s/he was aware of but could not explain. In short, the patient's personality does not re-organise itself as in the case of second order changes, but it attains more coherence. That is why we do not observe an increase in its standard deviation here (i.e. the necessary precondition of a personality re-organisation).

Component 3 is linked with the standard deviation of Pearson coefficients independently of the system's degree of order.

Summing up:

Component 1: The higher the component score, the higher the relational consistency between therapist and patient (canonical correlation), its correlation robustness and variability.

Component 2: The higher the component score, the higher the complexity of the system (the more negative the correlation with the amount of variance explained by the first component, the flatter the spectrum of eigenvalues).

Component 3: The higher the component score, the higher the emergence of 'low' and 'high' correlation phases along the process.

Then, the component's scores were included as dependent variables of three General Linear Models with the different therapeutic dyads as source of variation. This allows to investigate if the three components describe the peculiarities of each single psychotherapeutic process or, in the case of lack of significance, if the 8 therapeutic series are not discriminable, and consequently the coarse-grained descriptors chosen aren't their sensible representation. In so doing, we tested the hypothesis to find some macro-parameters that significantly explain the temporal peculiarities of each psychotherapeutic process independently of their different theoretical orientation (Table 5).

The GLM Procedure					
Dependent Variable: Component 1					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	35.47	5.06	**6.45**	**<.0001**
Error	133	104.52	.78		
Corrected Total	140	140			
		R-Square	Coeff. Var.	Root MSE	Mean Component 1
		.25	-5.4E+14	.88	0
Dependent Variable: Component 2					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	17.79	2.54	**2.77**	**.010**
Error	133	122.21	.91		
Corrected Total	140	140			
		R-Square	Coeff. Var.	Root MSE	Mean Component 2
		.12	-4.47E+15	.95	0
Dependent Variable: Component 3					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	7	8.47	1.21	1.22	.29
Error	133	131.53	.99		
Corrected Total	140	140			
		R-Square	Coeff. Var.	Root MSE	Mean Component 3
		.06	-2.85E+15	.99	0

Table 5. The GLM procedure. The variables which are statistically significant in describing each psychotherapeutic process are given in bold.

The hypothesis is verified for component 1 and 2, that can be viewed as statistically significant descriptors of the psychotherapeutic processes. Their variability is case-specific, (i.e. it is dependent on being a certain therapeutic dyad): and, in so doing, they represent statistically significant macro-parameters of the psychotherapeutic process, independently of the therapeutic approach.

Concerning significant differences in those indices between poor-outcome and good-outcome case, the former showed greater linguistic redundancy (more variance explained by the first principal component, $p = 0.003$) and less variability (less standard deviation of Pearson correlation coefficients, $p = 0.011$). Regarding the differences between psychotherapists and patients, the former showed greater linguistic variability (higher standard deviation of Pearson correlation coefficients, $p < 0.0001$), and less redundancy (less variance explained by the first principal component, p = 0.001).

Going back to the original descriptor the only two variables showing a statistically significant separation between goo- and poor- outcome cases were (Std, as for Component1) and Variance I Component, as for Component 2). Over the 150 blocks for each group the Mean and (Standard deviation) of Std was:

0.525 (0.05) and 0.500 (0.05) for good and poor groups respectively,

while for the Variance I Component the statistics were:

49.62 (7.50) and 52.4 (8.9) for good and poor groups respectively.

Despite the reaching of statistical significance, this is in any case a very weak difference but, given the exploratory nature of the case and the poor numerosity, it can be considered as a promising initial result.

CONCLUSION

By means of "static analyses", we were able to highlight significant differences between good- and poor-outcome cases concerning their latent correlation structures. These results pointed to a shift of meaning of the adopted psychological dictionaries dependent on the two outcome classes. The most evident difference was related to the patient's use of abstract language, interpreted very positively in poor-outcome cases and very negatively in good-outcome cases. This observation is closely associated to the use of positive and negative emotional languages inversely proportional to abstraction only in poor-outcome patients. An open question is whether the poor-outcome patients are more inclined to do so, or, alternatively, the poor-outcome therapists are less able to address it. In the first case we can conceive a more prolonged therapy or an exclusion of such patients from the brief therapy protocols, in the second case it should be highlighted the importance of a clinical, or clinical and empirical (feedback derived from empirical data), supervision
However, the comparison between the three PCA solutions clearly showed that the same observable (i.e. variable) changed its meaning according to its correlation structure with the other variables. This is a classical feature of any proper "system", from chemistry (a hydrogen atom bonded to oxygen in water has different properties when bonded to carbon in a methane molecule) to ecology (the same species that positively contributes to system equilibrium can be a threat to the ecological balance when they are placed in a different environment). Thus, the results stressed the crucial importance of basing our clinical and research investigations on such a systemic view also when dealing with psychotherapy [24], [25], [26], [27].

As for dynamical analysis, it is worth stressing the fact that, while much more cogent for sketching a usable picture of ongoing psychotherapy process with respect to static analysis, the dynamical approach is much more difficult to accomplish. The difficulty arises from many sources as the contingent character of single episodes along the process, the coarse-grain character of the alphabets, and clearly the impossibility to take into consideration potentially crucial 'context variable' like relative empathy established in patient-therapist dyad, oscio-demographic status of the patient and so forth. The observed statistical significance, given the marginal relevance of the effect, can only interpreted as an indication of the interest in pursuing such kind of analysis.

Notwithstanding that, it is worth noting that the empirical dynamical macro-parameters give a quantitative value to concepts often present in the therapist's mind. Are the narratives of a given patient rigid and fixed or are they flexible and adaptable? Is there some new element in them or are they always going around the same anxiety (stationary attractor)? Is the narrative rich or impoverished? Is the patient's thought symbolic or concrete? These are all typical clinical questions implicitly concerning the system's variability, degree of order and complexity or richness of information, and this work represents, to our knowledge, the first successful effort to translate them empirically.
The systemic approach, often widely claimed in psychotherapy, promises to become operational.

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