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Self-organized criticality and the predictability of human behavior

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ABSTRACT

The behavior of normal individuals and psychiatric patients vary in a similar way following power laws. The presence of identical patterns of behavioral variation occurring in individuals with different levels of activity is suggestive of self-similarity phenomena. Based on these findings, we propose that the human behavior in social context can constitute a system exhibiting self-organized criticality (SOC). The introduction of SOC concept in psychological theories can help to approach the question of behavior predictability by taking into consideration their intrinsic stochastic character. Also, the *ceteris paribus* generalizations characteristic of psychological laws can be seen as a consequence of individual level description of a more complex collective phenomena. Although limited, this study suggests that, if an adequate level of description is adopted, the complexity of human behavior can be more easily approached and their individual and social components can be more realistically modeled.

1. Complexity and human behavior

Human behavior is a dynamic phenomenon subject to biological, social, cultural, and cognitive influences (Vallacher, Read, & Nowak, 2002). Although psychological theories in general are not seen as

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a unified and coherent set of hypothesis, the idea that the behavior of one individual is the final result of the interaction of these factors is ubiquitous. Biologic models, for example, are more adequate to explain the occurrence of physiological reactions that accompany emotions while sociological models are essential to figure out how the symbolic value of a given situation evokes innate defense mechanisms. Any attempt to apply a closer examination to factors that modulate individual human behavior usually lead to the emergence of more and more details, and it becomes harder to identify the constituting elements and the basic laws involved in psychological explanations.

Despite an enormous variety of conceptual approaches, there are general characteristics common to almost all psychological theories. Independently from their psychodynamic, biologic, or social emphasis, psychological models usually provide some degree of explanatory power to past events. On the other hand, these theories have a limited capability to predict future human behavior. This limitation is clearly a consequence of the intricate interactions among the elements above mentioned; however, at least two theoretical principles could explain this fact. The first possibility is simply to admit that we have not, at least up to now, enough computational power to determine the value of all relevant variables and to deduce their future states using defined rules. According to this view, the prediction of individual's behavior is possible in principle, but the task would be extremely problematic due to the massive amount of information that should be computed to obtain a reliable result.

Alternatively, human behavior can be conceptualized not as a merely complicated event but as being a complex system (Chialvo, 2008; Garzón, Laakso, & Gomila, 2008; Port & Van Gelder, 1995). According to this approach, individual behavior is the final result of simpler elements interacting through defined rules, leading to the emergence of new and unexpected states. As pointed out by Kantz, Kurths, and Mayer-Kress (1998, p. 1): "Complexity has to do with intricate structures emerging from a system which itself is much simpler than its dynamics. In contrast, a system can be composed of several parts but without the emergence of new properties it can be more properly considered complicated but not complex".

In the context of dynamic systems theory, the emergence of intricate global patterns is a natural consequence of local interactions independently of any central or intentional control. In psychological context, it can be interpreted as the understanding of individual behavior is possible only when considered in relation to the entire context of social interactions (Shoda, LeeTiernan, & Mischel, 2002; Simon & Holyoak, 2002; Vallacher et al., 2002).

This article aims to discuss the empirical evidence suggesting that human behavior is a complex system exhibiting self-organized criticality (SOC). We start by presenting the concept of SOC that was initially proposed to explain the behavior of some physical systems. We argue that, despite the risks of applying this kind of reasoning to human sciences, there is reasonable evidence supporting its relevance in psychological phenomena. This argument is based in our own published results in psychiatric patients (Piqueira et al., 1999) complemented with additional observations of normal controls. We proceed by discussing the implications of this hypothesis in understanding the limitations of psychological theories in predicting future individual states.

2. Self-organized criticality

The concept of self-organized criticality was proposed by Bak, Tang, and Wiesenfeld (1987) to explain why spatial fractal and fractal time series, known as "*1/f* fluctuations" are so ubiquitous in nature (Jensen, 1998, p. 5). Power laws, scaling laws, *1/f* fluctuations, or Zipf's law refer to the nonrandom variation of a given event over space or time. The intensity of earthquakes in a certain geographic region, for example, vary along time with stronger earthquakes (i.e. those releasing greatest amounts of energy) being less frequent than the weak ones. When a temporal series of seismic activity is ordered according their ranking, the relationship between the frequencies of occurrence and the intensity of earthquakes assume the aspect showed in Fig. 1. In a general form, the relationship between the rank of an occurrence (n) and its frequency (G) follows a power law like:

$$G = \frac{A}{(n)^{\lambda}} \tag{1}$$

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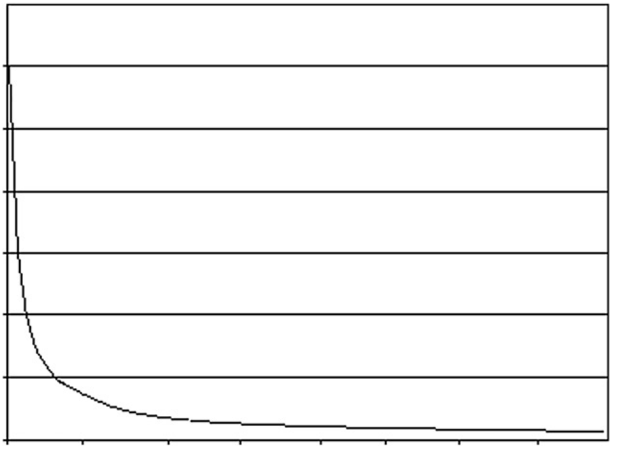

Fig. 1. This figure illustrates, in linear scale, the general aspect of a power law for a generic variable. Examples of power laws include the relation between intensity and frequency of earthquakes (Gutenberg-Richter law), the relation between metabolic rate and animal's mass (Kleiber's law), and the structural self-similarity of fractals.

where A and λ are empirical constants. In addition to the variation in the magnitude of earthquakes, power laws have been reported in the description of several phenomena like variations on stock prices, large and small biological extinction events, intensity of pulsar emissions, and fluctuations in the auditory frequency of music (Bak, 1994; Bak et al., 1987; Correll, 2008).

Bak et al. (1987) proposed that the most basic physical system exhibiting this phenomenon is constituted by a sand pile when new grains are added. Sand piles have a conic form with a defined slope. As described by (Gell-Mann, 1994), "as pile builds up, its sides can become steeper, but only until the slope attains a critical value". Once that critical slope is reached, the addition of more sand starts to produce avalanches that reduce the height of the pile. If the slope is greater than the critical value, an unstable situation results, in which avalanches of sand occur very readily and reduce the slope until it reverts to the critical value. Thus the sand piles are naturally "attracted" to the critical value of the slope, without any special external adjustment being necessary (hence "self-organized criticality") (pp. 97–98).

In the critically self-organized state, after the addition of a single grain we can observe small avalanches, big avalanches, or no movement at all. In this state, it is impossible to predict what will happen to the system after each single grain addition. "For a critical system, the same perturbation applied at different position or at the same position at different times can lead to a response of any size. The average may not be a useful measure of the response; in fact, the average might not even exist." (Jensen, 1998, p. 7).

Although one cannot predict the consequence of adding a single grain, the behavior of the entire pile can be completely described in statistical terms. Small avalanches are more frequent than big ones and the relative frequency among them follows an exponential relationship, a power law. According to Jensen (1998, p. 1) "The systems are complex in the sense that no single characteristic even size exists: there is not just one time and one length scale that controls the temporal evolution of these systems. Although the dynamical response of the systems is complex, the simplifying aspect is that the statistical properties are described by simple power laws".

Another characteristic of systems presenting self-organized criticality is the presence of self-similarity. An object is considered self-similar if it has the same aspect on any scale, i.e., if it is a geometric object made up of smaller copies of itself (Serrano, Krioukov, & Boguna, 2008). The lack of an absolute scale and self-similar appearance can also be found in certain geometric objects, such as fractals.

The identification of power laws and SOC in a given system, however, is not self evident. There are no consensual mathematical procedures to detect its presence in experimental data. Even the simplest physical system constituted by a sand pile can have its behavior described by alternative ways. Jensen (1998) points out that, if grains of sand are slowly dropped onto the pile at random positions, avalanche activity can be observed on the slope of the pile. If the pile is large enough, no important interference between individual avalanches takes place. In this situation, the instantaneous activity of the pile can be statically described by considering a random linear superposition of individual avalanches. The power spectrum of the total activity can then be calculated as the appropriately weighted sum of power spectra of the individual avalanches. Although the power spectra generated by this approach is found to be numerically indistinguishable from that generated by a SOC exhibiting system, "it is not clear how much sense it makes to develop models and theories of strong correlated processes and then to describe them as a linear superposition of independent events" (Jensen, 1998, p. 10).

A similar discussion is found in the experimental psychology field. Van Orden, Holden, and Turvey (2003) reported two experiments that examined background noise across responses in tasks involving reaction time and speeded up word naming times. According to the authors, the finding of $1/f^{\alpha}$ noise (pink noise) is the same as predicted by self-organized criticality model. "Pink noise appears as an inverse relation between the frequency of the composite waves (obtained from time series of response times) and their amplitude (power) on log scales. Slowly meandering lower frequencies are associated with greater amplitudes, intermediate frequencies are associated with intermediate amplitudes, and jittery high frequencies are associated with smaller amplitudes in a statistically self-similar fractal pattern" (p. 338). Van Orden et al. (2003) suggest that "Self-organized criticality supplies the first plausible metaphor for self-control. Near critical points, interaction-dominant dynamics coordinate activity across the multiple time scales of embodied fluctuations. Context sensitivity near critical points situates behavior within the flow of circumstances" (p. 347).

In contrast, Wagenmakers et al. (2005) argue that the results reported by Van Orden et al. could also be explained by other mathematical formalism like autoregressive moving average (ARMA) in which the behavior of a given system at time t is related to behavior in time $t-k$ via a procedure similar to linear regression (p. 121). According to Wagenmakers et al. (2005), "the immediate problem is that there is no statistical test to determine whether $1/f$ noise is present. Although fitting a regression line to a log-log power spectrum may yield a negative slope, this does not imply that the data follow a straight line. The reader is left to judge, by eye, whether he or she believes the straight line produces an accurate fit". Moreover, "the difference between a persistent $1/f\alpha$ noise process and a transient ARMA process is not in the absolute value of serial correlations but in the rate of decay of these serial correlations with increasing lag".

Although there are no formal procedures to detect power laws, its identification is an indispensable condition before any further theoretical speculation can be done. Power laws and spontaneous scale invariance are essential for the empirical demonstration of SOC as organizational principle in any natural (Joshi & Selvam, 1999) or living system (Adami, 1995).

Although used to explain a diversity of phenomena, the entire idea of self-organized criticality should not be considered as a comprehensive theory at the same level of thermodynamics, for example. Perhaps SOC must be seem as a group of models that are connected to each other by formal analogy, i.e., models that "bear no similarity other than that of both being interpretations of the same mathematical calculus" (Frigg, 2003).

The idea of self-organized criticality is attractive due to its proposal of simplification and unification of general principles but its use outside physical systems requires a distinction between simple metaphor and heuristic hypothesis based in empirical evidence. In relation to human behavior, some empirical findings were reported by Piqueira et al. (1999) who found that power laws described behavioral changes in individuals with different psychiatric disorders. In the next section, we will further review this data and expand it with additional unpublished information collected from normal volunteers.

3. Power laws in human behavior: empirical evidence

In this section, we demonstrate the heuristic value of applying the concept of SOC in the analysis of a set of empirical data. This strategy results in a simplified but comprehensive view of both individual and social phenomena. The demonstration of the possible presence of SOC is based in the observations that the behavioral variations observed in individuals during social interaction fits a power law and that this phenomena is observed in groups of individuals with different mental disorders and, consequently, with very distinctive behavioral patterns. This recurrent pattern, we will argue, is compatible with the hypothesis of scale invariance or self-similarity.

In a previous study (Piqueira et al., 1999), we collected data from 40 individuals (19 individuals with major depression, 11 with mania, and 10 with schizophrenia) consecutively admitted into a female psychiatric unit for acute patients. Individual behavior was evaluated during 60 days through two simple scales scored daily by an observer, who averaged the patient's individual behavior regarding psychomotor activity and social interaction on the preceding 24 h. Scales reliability was previously tested in 10 individuals independently evaluated by two psychiatrists during 10 days. The rating scales were.

(a) Psychomotor activity: 1 – calm, adequate; 2 – mild restlessness, noticed only when asked; 3 – clearly uneasy, frequently walking around the ward; 4 – severe agitation, disturbing other patients; 5 – extreme excitation, needing sedation and/or physical restriction.
(b) Social interaction: 1 – active social contact, interacting with the other patients and staff; 2 – mild tendency to socially withdraw, noticed only when asked; 3 – clearly isolated, keeping some social contact with a few people; 4 – severe social inhibition, keeping contact only when stimulated; 5 – absence of verbal and non-verbal communication, catatonia.

Using similar rating scales, we later studied a further set of medical students without mental disorders (unpublished data). The descriptive content of these scales, however, was different than that used for psychiatric patients due to the expected differences between their behavioral spans. Thus, although similar in their format, the scales were designed to detect behavioral variations of different magnitudes. Another important methodological issue was the adoption of self-rating scales for normal controls while patient's behavior was scored by an observer. These different approaches are justified by the severity of cognitive symptoms observed in psychiatric inpatients that could affect the reliability of their answers. Self-rating scales, in contrast, are easily used in normal individuals who are not always available for daily interviews.

Thirty-four medical students without any history of mental disorders agreed to participate in the study. They received a set of questionnaires and answer sheets that should be filled twice a day and that were collected weekly. They were instructed to choose the alternative that best described their state in the past 6 h. Overnight behavioral changes, therefore, were not considered. They were also instructed to not share information with other colleagues also participating in the study and they were assured that all obtained information would be strictly confidential. The scale items were.

(a) Subjective sensation of well being: 1 – moderate sensation of dissatisfaction/restlessness; 2 – mild sensation of dissatisfaction/restlessness; 3 – comfortable, neutral feelings; 4 – mild sensation of satisfaction and well being; 5 – moderate sensation of satisfaction and well being.
(b) Social interaction: 1 – very isolated; 2 – moderate isolation; 3 – usual levels of social interactions; 4 – mild increase in social interactions; 5 – moderate increase in social interactions.

All individuals were instructed about the nature of the experiment and signed an informed consent to participate in the study.

3.1. Data analysis

For the patients groups, daily scores were attributed each individual variables X (psychomotor activity/sensation of well being) and Y (social interaction), preparing the matrixes A_W, A_D, A_B, and A_S of joint incidence of scores for the whole ward, depressive, manic (bipolar), and schizophrenic patients, respectively. Each element $a_{i,j}$ in these matrices represents the percentage of occurrence of the scores i and j ascribed to the variables X and Y simultaneously for the same individual. For example, the element $a_{1,1}$ from the matrix A_w means that 18.41% of all scores obtained from all individuals were 1 in the "Well Being" scale and 1 in the "Social Interaction" scale, simultaneously.

$$A_w = \begin{pmatrix} 18.41 & 17.66 & 14.43 & 7.45 & 1.91 \\ 11.54 & 6.67 & 3.89 & 1.01 & 0.52 \\ 6.86 & 4.48 & 1.41 & 0.52 & 0.61 \\ 0.61 & 0.61 & 0.42 & 0 & 0.02 \\ 0.22 & 0.52 & 0 & 0 & 0 \end{pmatrix} A_D = \begin{pmatrix} 14.53 & 15.22 & 4.59 & 2.21 & 3.09 \\ 16.01 & 8.46 & 5.35 & 0.71 & 0 \\ 13.74 & 9.15 & 3.01 & 0 & 0 \\ 1.52 & 2.21 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_B = \begin{pmatrix} 17.63 & 19.82 & 23.41 & 11.74 & 1.41 \\ 6.11 & 5.36 & 2.68 & 0.91 & 0 \\ 5.39 & 2.29 & 1.41 & 0.41 & 0 \\ 0.41 & 0.41 & 0.22 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} A_S = \begin{pmatrix} 7.35 & 20.41 & 17.72 & 8.04 & 3.31 \\ 12.03 & 6.67 & 7.03 & 1.31 & 0.34 \\ 5.68 & 5.09 & 1.61 & 0.61 & 1.61 \\ 0 & 0.61 & 0 & 0.32 & 0.32 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Using the same data a table was constructed for the absolute value of the variation of X (ΔX) and of the variation of Y (ΔY), between two successive days, preparing the matrixes ΔA_W, ΔA_D, ΔA_B and ΔA_S for the score variation for the whole ward, depressive, bipolar, and schizophrenic patients, respectively. For example, the element $a_{1,1}$ from the matrix $A_{\Delta w}$ means that 32.81% of all scores obtained from all individuals varied in 1 point (score in day $n+1$ minus score in day n) in the "Well Being" scale and 1 point in the "Social Interaction" scale, simultaneously. As the matrices were independently generated by the mathematical modeling process, values as $A_{2,5} = 0.52$ in A_w and $A_{5,4} = 0.01$ in $A_{\Delta w}$ were obtained although the equivalent elements in the other matrices were zero.

$$A_{\Delta W} = \begin{pmatrix} 32.81 & 25.92 & 5.95 & 1.49 & 0.31 \\ 14.83 & 9.14 & 2.86 & 0.71 & 0.21 \\ 2.67 & 2.08 & 0.61 & 0.21 & 0 \\ 0 & 0.02 & 0 & 0 & 0.01 \\ 0 & 0 & 0 & 0 & 0.01 \end{pmatrix} A_{\Delta D} = \begin{pmatrix} 30.31 & 22.32 & 6.25 & 0 & 0 \\ 18.73 & 13.34 & 2.67 & 0 & 0 \\ 3.56 & 1.78 & 0.89 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

$$A_{\Delta B} = \begin{pmatrix} 32.32 & 39.11 & 3.55 & 0.21 & 0 \\ 13.83 & 4.64 & 1.97 & 0 & 0 \\ 2.16 & 1.68 & 0.59 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix} A_{\Delta S} = \begin{pmatrix} 25.72 & 26.71 & 8.55 & 3.57 & 0.71 \\ 11.43 & 11.04 & 6.06 & 1.48 & 0.71 \\ 1.41 & 1.49 & 0.32 & 0.71 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \end{pmatrix}$$

Similarly, for the normal individuals we have the matrix A_N and ΔA_N for the incidence of absolute scores in both scales and for the relative variation of scores in two successive measures expressed in percentage.

$$A_N = \begin{pmatrix} 2.08 & 1.31 & 0.62 & 0.71 & 0.03 \\ 0.52 & 9.13 & 8.34 & 1.31 & 0.03 \\ 0.42 & 6.97 & 34.19 & 7.56 & 0.02 \\ 0.22 & 1.01 & 8.25 & 14.22 & 0.22 \\ 0.02 & 0 & 0.32 & 1.59 & 0.62 \end{pmatrix} A_{\Delta N} = \begin{pmatrix} 29.66 & 14.61 & 2.08 & 0.12 & 0.02 \\ 15.13 & 24.02 & 3.26 & 0.31 & 0.02 \\ 1.58 & 4.15 & 2.41 & 0.22 & 0 \\ 0.21 & 0.41 & 0.64 & 0.41 & 0 \\ 0.12 & 0.12 & 0.02 & 0.21 & 0 \end{pmatrix}$$

The data appearing on matrices $A_{(N)}$ were organized in a decreasing order of occurrence, from the most to last frequent pairs of scores. Similarly, in matrices $A_{(\Delta N)}$ they were organized from the most to the last frequent variation of scores. Each element of these rankings was associated to an integer number n and fitted using the more general form of Zipf's strategy (Gell-Mann, 1994) given by

$$G = \frac{G_1}{(n+\beta)^{\lambda}} \tag{2}$$

Where parameters G_1, β, and λ are empirical constants adjusted using the f_{mins} function of the MatLab (Hanselman & Littlefield, 1996) to provide the better fitting of data by minimizing the mean square error. The results of the parameters adjustments are shown in Table 1 where σ_1 represents the mean square error, defined as:

$$\sigma_1 = \frac{\sqrt{\sum_{i=1}^{n} (A_i - G_i)^2}}{n} \tag{3}$$

The data shown in matrixes $\Delta A_{(N)}$ were organized following a similar process, associating to the order an integer number n. Power laws described in the former section were adjusted fitting the elements of ΔA to the values of G, given by Eq. (2).

The results of the parameters adjustments are shown in Table 2 where σ_2 represents the mean square error, defined in the same way of σ_1.

Fig. 2 shows that scores variations follow a power laws for each diagnostic group (Piqueira et al., 1999) and Fig. 3 shows the same pattern for normal individuals.

The main result of these experiments was the closer superposition, i.e., the similarity not the difference, of the curves that describe the behavioral variations of individuals with very different characteristics. In other words, our data suggest that, when in social interaction, normal individuals and patients with different psychiatric disorders vary their behavior in a very similar way. Depressed patients are less active than controls that, by their turn, are less active than patients with mania but the relative variation of their states are comparable. The observation of identical patterns of variation in different levels of human activity suggests the presence of self-similarity. This characteristic, and the fact that a power law fit could explain the behavioral variations in our samples, are the empirical basis of our hypothesis that human individuals in social interaction constitute a SOC exhibiting system.

Our observations are limited by two important caveats. First, they are based on a small sample of individuals and one must consider the possibility that the descriptive curves would not fit power laws if the number of individuals studied is increased or if the design of rating scales is changed. Second, there are no formal procedures to identify power laws and to distinguish them from other possible distributions. Using Ezyfit, a curve fitting toolbox for Matlab (http://www.fast.u-psud.fr/ezyfit), we found that each curve could be modeled by a power law in the form$a(x+b)^n$ as well as by an exponential distribution in the form $ae^{bx}+c$ with a confidence interval $R = 0.999$ for both cases. These results do not invalidate our hypothesis because the decision about the presence of power laws in any set of experimental data is ultimately subjective. In this case, admitting the presence of power laws is particularly advantageous from a heuristic point of view.

We emphasize that the groups studied were constituted by individuals subjected to extreme variations of mental states associated to very different levels of susceptibility to social influences. In these conditions, the close superposition among the curves seems a robust phenomenon whose meaning certainly deserves further investigation.

Summarizing, we propose that the compatibility of the patterns of behavioral variation with power laws is supported by the mathematical description of each group of individuals and the compatibility of the entire data set with the presence of self-similarity is suggested by the reproduction of the same pattern at different descriptive levels (the superposition of all curves). Based on these observations, we will now discuss the heuristic value for psychological theories in admitting the presence of SOC as an organizing principle of human behavior.

Table 1
Results of the parameters adjustments for absolute scores.

	$G1$	β	λ	σ_1
Whole ward	2.67×10^{25}	58.03	13.62	0.20
Bipolar	2.25×10^{20}	38.66	11.85	0.32
Depressive	1.08×10^{18}	50.01	9.81	0.38
Schizophrenic	4.28×10^{9}	22.68	6.05	0.24
Normal controls	9.57×10^{13}	19.32	9.55	0.40

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Table 2
Results of the parameters adjustments for the variation of scores.

	*G*1	β	λ	σ_2
Whole ward	1.20×10^{24}	32.64	14.76	0.26
Bipolar	2.28×10^{21}	24.54	14.02	0.97
Depressive	2.16×10^{17}	28.14	10.81	0.63
Schizophrenic	1.49×10^{21}	35.00	12.66	0.49
Normal controls	9.73×10^{20}	31.96	12.84	0.31

4. Self-organized criticality and psychological theories

The innovative characteristic of the presented study was the level of description of human behavior adopted. This approach can not be defined as specifically biologic (because it does not take in consideration neurological details of mental disorders), psychodynamic (concepts like unconsciousness or defense mechanisms are irrelevant to this level of description), nor sociologic (sophisticated social constructs can not be verified from this very simplified kind of data record). We studied human

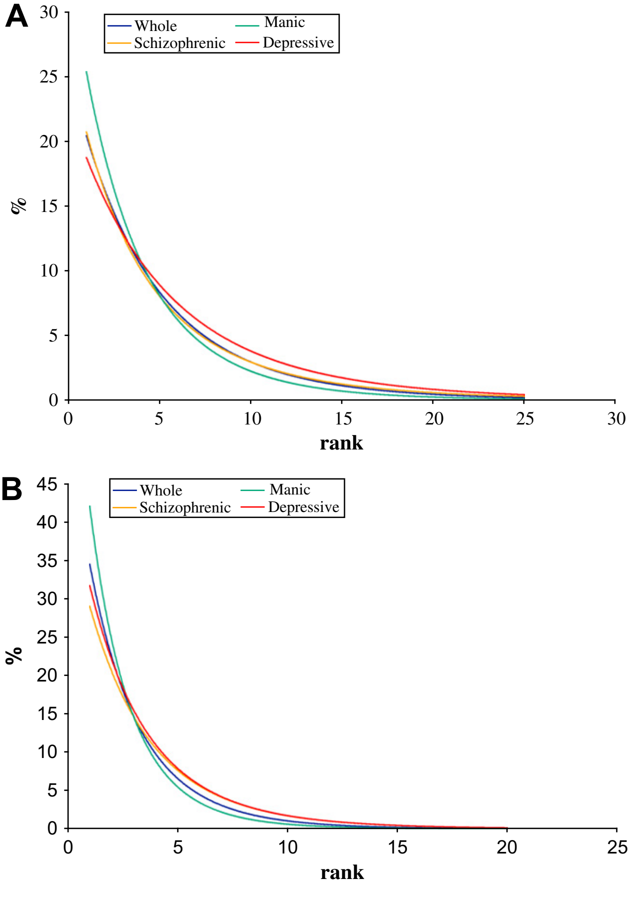

Fig. 2. A – Plotting, in percentage, of the data expressed in matrixes A_W, A_D, A_B, and A_S for the scores frequency, discriminating patients with different diagnosis (mania, depression, and schizophrenia) and the whole ward. B – Frequency of absolute scores variation between two successive days, as presented in matrixes ΔA_W, ΔA_D, ΔA_B and ΔA_S.

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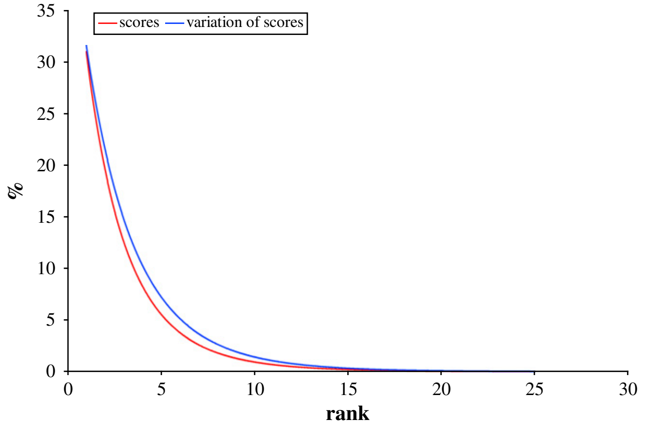

Fig. 3. Plotting of scores frequency and absolute scores variation for normal controls (matrixes A_N and ΔA_N).

behavior at a level between individual psychology and micro-social dynamics not considering psychopathological details. This adjustment of the level of analysis is essential to the identification of complex systems. Gell-Mann (1994, p. 29) points out that "when defining complexity is always necessary to specify a level of detail up to which the system is described, with finer details being ignored. Physicists call that coarse graining". In psychology, it means that a model aiming to describe social interactions will not be adequate to depict details at the molecular or neurobiological levels. Conversely, hypothesis about synaptic events proposed to explain brain mechanisms will not account for sociological phenomena. One type of theory is not better or more complete than other. They only focus at different levels of explanation and make different kinds of predictions.

Our modeling of human behavior is relatively simple but heuristic by revealing the emergence of self-similar patterns impossible to predict from more individually detailed models. By crossing through different descriptive levels, our model ignores details of human nature but, on the other hand, it allows one to more comprehensively model multifactorial aspects of personal behavior. The dissemination of information in social groups, for example, can be easily modeled in this way. Stress transmission, the familiar or social impact of mental disorders, the influence of social variables like tendencies or prejudices over individual behavior, and epidemiologic modeling of psychiatric conditions sensitive to stress are examples of problems that can take advantage from this approach.

Thus, we did not study specific cognitive processes but we statistically described the final result of biological, psychological, and social interactions. This approach differs from that reported by Van Orden et al. (2003) who discussed the possibility of adopting SOC as explanatory principle at a psychophysiological level. Using a more integrative approach, i.e., incorporating the influences of external factors in individual behavior, our findings corroborate the potential applicability of the concept of SOC in psychology (Chialvo, 2008).

Although suggestive, our findings do not imply that complexity, self organization, and critical states are inherent to all levels of human functioning. Quoting Gell-Mann (1994, p. 33): "If complexity is defined in terms of the length of a description, then it is not an intrinsic property of the thing described. …Any definition of complexity is necessarily context-dependent, even subjective". This contextualization reinforces the importance of distinguishing between the metaphoric use of complex systems theory and the empirical demonstration supporting the use of this theoretical approach in psychology. Our findings suggest that adjustments in the descriptive level can facilitate the identification of systemic phenomena and give empirical support in admitting the presence of SOC in human behavior.

Systems exhibiting SOC present another interesting characteristic. Jensen (1998, p. 3) comments that, in order to evolve into a SOC dynamical state, a separation of time scales is required: "The process connected with the external driving of the system needs to be much slower than the internal relaxation processes. In earthquakes, the stress in the earth's crust is built up on the scale of years owing to the motion of the tectonic plates. The stress is subsequently released in a few seconds or minutes. The separation of time scales is intimately connected with the existence of thresholds". The idea of thresholds is widespread in psychological theories, from Freud's theories to contemporary multifactorial models of psychiatric disorders. The concept that chronic stress (accumulation of tensions) is an important risk factor to precipitate depressive and psychotic episodes is an example of this kind of hypothesis (Krabbendam & van Os, 2005; Matheson et al., 2006). Although not directly investigated in this article, individual thresholds for reaction to external influences are both compatible with the presence of SOC and coherent with other psychological models.

Finally, the application of the SOC concept in psychological theories can help us to see the question of predictability of human behavior through a new perspective. In SOC exhibiting systems, the precise prediction of future states of individual components is intrinsically impossible. Even in the situation where the state of all individuals is known (in a computer simulation, for example), isolated stimuli provoke unpredictable systemic responses at different scales. Thus, the description of SOC exhibiting systems is possible only in probabilistic terms. Disciplines that work with SOC exhibiting phenomena, seismology for example, are essentially descriptive or historic, they explain individual or systemic changes only after they had occurred despite their detailed knowledge of the factors involved.

This situation is also observed in psychological explanations. Horgan and Tienson (1996) point out that psychological theories, differently from physical sciences, are based in *ceteris paribus* generalizations (*p* implies *q* when all other things are equal) that, by virtue of their scope and generality, deserve to be considered laws, *soft laws* (p. 107). In psychology, there is a potential relevance of anything to anything (although, we intuitively perceive that near things are more related than distant things (Nijkamp, 2007)) leading to a high degree of holism in the determination of the relevance of psychological processes (p. 113).

This extreme interconnectivity among components makes psychological explanations, i.e., individually based, somewhat vague and opened to exceptions but not necessarily unscientific. The understanding of this feature of psychological theories does not imply in admitting the presence of self-organized criticality. Complicated but not complex systems can show the same characteristic. However, admitting the occurrence of SOC is a heuristic alternative hypothesis that places the problem in the following terms: the prediction of future behaviors of human individuals is impossible not due to our computational limitations but because they are part of a larger system that exhibits self-organized criticality. The identification of this dynamic functioning is possible when we dislocate our point of view to an adequate level of description. As consequence, the use of probabilistic concepts can be the best approach to describe human behavior at all levels, including the psychological level. The vagueness of psychological explanations is the consequence of the use of deterministic language to examine parts of a complex phenomenon that would be better understood in statistical terms. In this sense, psychological theories must be seem as essentially stochastic in relation of their capacity to describe current and future states.

This study aimed to discuss the possible presence of SOC in human social systems based in empirical but limited evidence. Further investigations are naturally necessary but we believe that the use of different levels of description in psychological studies deserve additional exploration due to its clear potential to reveal unexpected details of human behavior.

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