# The fractal dynamics of self-esteem and physical self

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# The Fractal Dynamics of Self-Esteem and Physical Self
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Abstract

The aim of this paper was to determine whether fractal processes underlie the dynamics of self-esteem and physical self. Twice a day for 512 consecutive days, four adults completed a brief inventory measuring six subjective dimensions: global self-esteem, physical self-worth, physical condition, sport competence, attractive body, and physical strength. The obtained series were submitted to spectral analysis, which allowed their classification as fractional Brownian motions. Three fractal analysis methods (Rescaled Range analysis, Dispersional analysis, and Scaled Windowed Variance analysis) were then applied on the series. These analyses yielded convergent results and evidenced long-range correlation in the series. The self-esteem and physical self series appeared as anti-persistent fractional Brownian motions, with a mean Hurst exponent of about 0.21. These results reinforce the conception of self-perception as the emergent product of a dynamical system composed of multiple interacting elements.

Key words: Self-esteem, physical self, time series analysis, fractal processes.

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Self-esteem has classically been considered to be a personality trait, a stable quality that characterizes and differentiates individuals across time and situations (Cheek & Hogan, 1983; Coopersmith, 1967; Mischel, 1969). A number of authors advocated this conception of self-esteem, especially in adults, and the observed fluctuations in repeated assessments were attributed to meaningless errors in measurement rather than to an inherent instability (Epstein, 1979). From this point of view, fluctuations had to be removed by averaging to obtain an accurate assessment of dispositional self-esteem. Rosenberg (1986), however, suggested the presence of meaningful short-term instabilities in self-esteem, tied to specific life events such as professional success or failure. Kernis (1993) went further and stated that self-esteem variability, defined as the magnitude of fluctuations in contextually based self-esteem, was a dispositional quality: People differ in self-esteem level, but also in the extent to which they exhibit short-term fluctuations in self-esteem. In a series of studies, Kernis and his collaborators showed how self-esteem level and self-esteem variability interact so that cognitive, emotional or behavioral reactions to events may be predicted (Greenier, Kernis, McNamara, Waschull, Berry, Herlocker & Abend, 1999; Kernis, Cornell, Sun, Berry & Harlow, 1993; Kernis, Grannemann & Mathis, 1991; Kernis & Waschull, 1995).

Typically, Kernis and his collaborators measured self-esteem variability by asking participants to rate themselves several times a day for several days and then by using the individual standard deviation as an index of self-esteem variability. Unfortunately, this approach of focusing only on the magnitude of variability gives quite a poor image of the true nature of self-esteem fluctuations. Self-esteem varies over time on a moment-by-moment basis, and one may assume that the current assessment, albeit partly determined by recent events, is also closely tied to the previous assessment. The successive measures cannot be considered as mutually independent (or uncorrelated), and each of them has to be conceived of as embedded in a historical process. A full characterization of variability requires going beyond the basic assessment of its magnitude and proceeding to an analysis of its dynamic structure (see Slifkin & Newell, 1998).

This perspective on variability analysis is obviously tied to the dynamical conceptions of the self recently emphasized by Nowak, Vallacher, Tesser and Borkowski (2000), Vallacher, Nowak, Froehlich and Rockloff (2002) and Marks-Tarlow (1999, 2002). These authors consider self-esteem to be the emergent property of a dynamical system and have tried to rise above the traditional debate between dispositionalist theories (focused on trait stability) and situationalist theories (focused on states cross-situational inconsistency). Self-esteem is viewed as a continuous flow beyond contextual, social and cultural factors, and the analysis of its historical evolution is essential to completely understand it (Marks-Tarlow, 1999).

In fact, these dynamical conceptions have a long tradition in self-concept research. James (1890) conceived of self-esteem as a "barometer" that continuously fluctuates as a function of one's aspirations and achievements. Cooley (1902) and Mead (1934) emphasized the role of social and interpersonal processes in the variation in self-regard. Morse and Gergen (1970) argued that the self-concept is highly mutable and that its instability could reflect an aspect of personality. More recently, the hierarchical models of self-concept (Fox & Corbin, 1989; Marsh & Shavelson, 1985) have offered an interesting framework to understand how daily events influence self-esteem. According to these models, global self-esteem constitutes the apex of a hierarchical system that is composed of several domain-specific self-concepts (e.g., social, physical, cognitive). Each domain can be further differentiated into sub-domains more specifically tied to individual experiences. Information is supposed to diffuse in such models following top-down, bottom–up, reciprocal and horizontal flows (Marsh & Yeung, 1998).

From this point of view, self-esteem should be conceived as the dynamical product of the history of a complex system composed of a number of interconnected elements.

Despite these theoretical foundations for a dynamical appraisal of self-esteem, few attempts have been made to really analyze its time-evolutionary properties. Most studies focusing on the contextual determinants of self-esteem fluctuations have been performed within a static rather than temporal framework. A notable exception was a study by Savin-Williams and Demo (1983), which applied an autoregressive model to ordered self-ratings collected over a one-week period. Despite some methodological limitations, this study suggested the presence of different dynamics in individual self-feelings (stable, oscillating, or unpredictable). Kernis et al. (1993) recognized that self-esteem might exhibit specific patterns of fluctuation that qualitatively differ across individuals and situations. They argued, nevertheless, that there was no apparent rationale for making such a claim and no adequate means for statistically differentiating among different types of fluctuation. We believe, on the contrary, that such a rationale is offered by the recent dynamical perspectives on self-concept, and that an approach based on time series analysis would allow a meaningful characterization of self-esteem fluctuations (Ninot, Fortes & Delignières, 2001).

A time series is a collection of observations equally spaced in time, ordered and considered sequentially. Time series analyses are generally based on the assumption that the dynamics of the series is explained in terms of the current value's dependence on past values. A classic method for analyzing such time series is offered by the *autoregressive integrated moving average* (ARIMA) models (Box & Jenkins, 1976). Theses statistical methods aim at modeling time series and predicting some future value as a parametric linear function of the current and past values. They are widely used, for example, in econometry for forecasting purposes. They can also offer fruitful insights into the dynamics of the series under study and its underlying processes. Their use in psychology thus opens an interesting window for the analysis of time-dependent behavior (Delcor, Cadopi, Delignières & Mesure, 2003; Spray & Newell, 1986).

Applying these ARIMA procedures to individual self-esteem and physical self time series (ranging from 50 to 168 observations), Ninot et al. (2001) and Fortes, Delignières and Ninot (2003) showed that a differenced first-order moving average model represented the best fit in all cases. This kind of model can be written as:

$$y_t = y_{t-1} - \theta \varepsilon_{t-1} + \varepsilon_t \qquad (1)$$

where $y_t$ is the response at time $t$, $\varepsilon_t$ is a random disturbance at time $t$, and $\theta$ is the moving average coefficient ($0 < \theta < 1$). This model (also called the *simple exponential smoothing model*) is typical of times series that exhibit noisy fluctuations around a slowly varying mean.

The first implication of these results is that these time series are not stationary over time. They cannot be considered as white noise fluctuations around a stable value, such as a personality trait. This model instead suggests that the combination of two opposite processes underlies the dynamics of self-esteem: a *preservation* process, which tends to restore the previous value after a disturbance, and an *adaptation* process, which tends to inflect the series in the direction of the perturbation.

As can be seen in Equation 1, the assessment at time $t$ is characterized by an error term ($\varepsilon_t$), mathematically considered as a random disturbance. More precisely, this error term represents the distance between the expected value (determined on the basis on the preceding

assessment) and the obtained value. Psychologically, this disturbance should be considered as the resultant of all the recent (good or bad) events likely to have affected the assessed dimension. The expected value at time $t$ is modeled as the preceding observed value ($y_{t-1}$) minus a fraction of its own disturbance ($\theta\varepsilon_{t-1}$). In other words, the expected value at time $t$ tends to absorb the preceding disturbance, in order to restore the previously expected value. The amplitude of the correction is given by $\theta$, and the restoration should be complete with a $\theta$ value close to 1. This correction underlies the preservation process, which limits the influence of the perturbations and ensures the stability of the series.

Nevertheless, $\theta$ is generally far from 1. Fortes et al. (2003) reported values ranging from 0.42 to 0.86, indicating that a residual fraction of the previous disturbance remained in the current expected value. In other words, each disturbance tends to leave a persistent trace in the dynamics of the series. This adaptation process could account for the frequently reported effect of daily events on self-esteem (e.g., Butler, Hokanson & Flynn, 1994; Nezlek & Plesko, 2001; Rosenberg, 1986). The moving average coefficient $\theta$ determines the balance between these two opposite processes. Fortes et al. (2003) evidenced a high consistency between the coefficients obtained for the different time series of a given participant. This suggested a kind of individual disposition related to the stability of self-esteem and its resistance to the influence of daily events. As previously stated, the combined effects of these two processes lead to a slow evolution in the local mean of the series. The dynamics of the series seem organized around a locally stable reference value, a kind of *transient trait* that evolves progressively under the influence of life events.

Application of the ARIMA procedures provides interesting statistical results and a quite reasonable model of the psychological processes underlying the dynamics of self-esteem. Nevertheless, this approach tends to focus on short-term correlations in the series and is unable to reveal more complex dynamics like, for example, longer-term time dependencies.

Several theoretical and empirical arguments led us to hypothesize the presence of chaotic or fractal processes underlying self-esteem time series. As previously mentioned, most of the contemporary models of self-esteem consider this construct as multidimensional (e.g., Harter, 1982), and this multidimensionality has been reinforced by the introduction of the hierarchical models (Marsh & Shavelson, 1985). Marks-Tarlow (1999; 2002) argued that each level of the self is formed through interactions and complex feedback loops occurring at various physiological, psychological, and social levels. Each level possesses an emerging dynamics and is embedded in the next, giving rise to fractal properties such as self-similarity. In the same vein, Nowak et al. (2000) considered self-esteem as an emergent property of a complex dynamical system, composed of a myriad of specific and interconnected self-thoughts. From this point of view, the emergence of the self as a coherent structure and its maintenance in the face of incongruent elements can be understood as the result of a process of self-organization on the basis of multiple interactions acting within the system. The macroscopic behavior of such complex dynamical systems has frequently been proven to exhibit fractal properties (Bak & Chen, 1991; Gilden, 2001; West & Shlesinger, 1990). One should also note that in previous studies (Fortes et al., 2003; Ninot et al., 2001), the examination of the autocorrelation functions of self-esteem series revealed the persistence of significant autocorrelation over a wide range of lags (up to 100 lags in some occasions), suggesting the presence of long-term time dependencies in the series.

Another argument relates to the inherent stability of such fractal processes. A number of biological and psychological time series were recently proven to possess fractal properties.

Recent research evidenced this type of result in continuous uni-manual tapping (Chen, Ding & Kelso, 2001), the trajectory of the center of pressure during postural sway (Collins & De Luca, 1993; Delignières, Deschamps, Legros & Caillou, 2003), serial reaction time (Gilden, Thomton & Mallon, 1995), step duration series during locomotion (Hausdorff, Mitchell, Firtion, Peng, Cudkowicz, Wei & Goldberger, 1997) and heartbeat time series (Peng, Mietus, Hausdorff, Havlin, Stanley & Goldberger, 1993). When obtained from young and healthy organisms, these time series exhibit a very special case of fractal behavior, called $1/f$ or *pink* noise. '$1/f$ noise' signifies that when the power spectrum of these time series is considered, each frequency has power proportional to its period of oscillation. As such, power is distributed across the entire spectrum and not concentrated at a certain portion. Consequently, fluctuations at one time scale are only loosely correlated with those of another time scale. This relative independence of the underlying processes acting at different time scales suggests that a localized perturbation at one time scale will not necessarily alter the stability of the global system. In other words, $1/f$ noise renders the system more stable and more adaptive to internal and external perturbations (West & Shlesinger, 1990). One can easily understand why fractal behavior constitutes an appealing hypothesis for modeling the dynamics of self-esteem time series.

In order to ensure better understanding of the following parts of this article, a deeper and more theoretical presentation of fractal processes seems necessary. A good starting point for this presentation is Brownian motion, a well-known stochastic process that can be represented as the random movement of a single particle along a straight line. Mathematically, Brownian motion is the integration of a white Gaussian noise. As such, the most important property of Brownian motion is that its successive increments are uncorrelated: each displacement is independent of the former, in direction as well as amplitude. Einstein (1905) showed that, on average, this kind of motion moves a particle from its origin by a distance that is proportional to the square root of the time.

Mandelbrot and van Ness (1968) defined a family of processes they called *fractional Brownian motions* (fBm). The main difference with ordinary Brownian motion is that in an fBm successive increments are correlated. A positive correlation signifies that an increasing trend in the past is likely to be followed by an increasing trend in the future. The series is said to be persistent. Conversely, a negative correlation signifies that an increasing trend in the past is likely to be followed by a decreasing trend. The series is then said to be anti-persistent.

Mathematically, an fBm is characterized by the following scaling law:

$$<\Delta x> \propto \Delta t^H \tag{2}$$

which signifies that the expected displacement $<\Delta x>$ is a power function of the time interval ($\Delta t$) over which this displacement is observed. $H$ represents the typical scaling exponent of the series and can be any real number in the range $0 < H < 1$. The aims of fractal analysis are to check whether this scaling law holds for experimental series and to estimate the scaling exponent. Ordinary Brownian motion corresponds to the special case $H = 0.5$ and constitutes the frontier between anti-persistent ($H < 0.5$) and persistent fBms ($H > 0.5$).

*Fractional Gaussian noise* (fGn) represents another family of fractal processes, defined as the series of successive increments in an fBm. Note that fGn and fBm are interconvertible: when an fGn is cumulatively summed, the resultant series constitutes an fBm. Each fBm is then related to a specific fGn, and both are characterized by the same $H$ exponent. These two processes possess fundamentally different properties: fBm is non-stationary with time-

dependent variance, while fGn is a stationary process with a constant expected mean value and constant variance over time. Examples of fBm and fGn corresponding to three values of *H* are presented in Figure 1. The *H* exponent can be assessed from an fBm series as well as from the corresponding fGn, but because of the different properties of these processes, the methods of estimation are necessarily different. Thus the determination of the actual nature (fBm or fGn) of the time series obtained in a given experiment constitutes a crucial step in fractal analysis.

<div align="center">Fractional Brownian motions</div>



| $H = 0.25$ | $H = 0.50$ | $H = 0.75$ |

<div align="center">Fractional Gaussian noises</div>
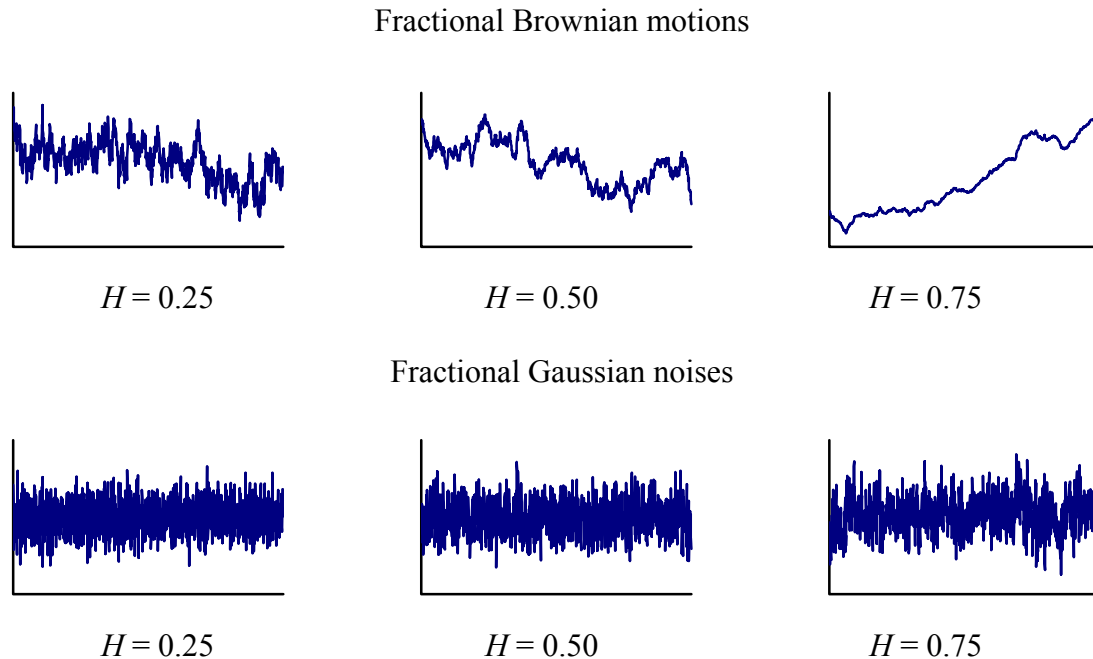


| $H = 0.25$ | $H = 0.50$ | $H = 0.75$ |

*Figure 1: Graphical examples of fractal time series. The upper graphs represent fractional Brownian motions (fBm) and the lower graphs, the corresponding fractional Gaussian noises (fGn), for three typical values of the scaling exponent. The upper median graph shows an ordinary Brownian motion (H=0.5) with its differenced series (white noise) just below. The right and left columns show respectively an anti-persistent fBm (H=0.25) and a persistent fBm (H=0.75) and their corresponding fGns.*

The main purpose of the present work was to apply methods of fractal analysis to self-esteem and physical self time series in order to detect the presence of fractal processes underlying their dynamics. We strictly adhered to the methodological principles recently developed by Eke et al. (2000), which will be presented in the following section. These analyses required the collection of longer time series than those used in previous investigations. ARIMA modeling was also performed in order to confirm Fortes et al.'s results with longer series and to analyze the relationships between the scaling exponents estimated by fractal analyses and the coefficients of ARIMA models.

<div align="center">**Method**</div>

*Participants*

Four adults (2 males and 2 females; mean age = 30.5 years, *SD* = 8.5) volunteered for this study. All were employed and came from middle-class backgrounds. None had pharmacologically treated psychiatric disorders or severe medical illnesses and none had recently undergone major negative life events that would have affected psychological function

over the testing period. All gave informed written consent to participate. They were not paid for their participation.

*Questionnaire*

We used the *Physical-Self Inventory* (PSI-6), a six-item questionnaire especially devoted to repeated measurements, developed and validated by Ninot, Fortes and Delignières (2001). The PSI-6 is a short version of a previously validated questionnaire, the PSI-25 (Ninot, Delignières & Fortes, 2000), adapted from the *Physical Self-Perception Profile* (PSPP; Fox & Corbin, 1989; Page, Ashford, Fox & Biddle, 1993; Sonstroem, Speliotis & Fava, 1992). PSI-6 contains one item for global self-esteem (GSE), one item for physical self-worth (PSW), and one item for each of the four sub-domains identified by Fox and Corbin (1989): physical condition (PC), sport competence (SC), attractive body (AB) and physical strength (PS). This questionnaire was proven to reproduce the factorial structure of the corresponding multi-items inventories (Fox & Corbin, 1989; Ninot et al., 2000) and to possess the same hierarchical properties. Each item is a simple declarative statement, to which participants respond using an analog visual scale. The use of such a scale, rather than a traditional Likert scale, was motivated by the need to avoid learning effects with repeated measurements and to allow the expression of potential variability in the self-assessments (Ninot et al., 2001).

*Procedure*

Each participant completed the questionnaire using specific software twice a day for 512 consecutive days, between 7:00 and 9:00 for the first assessment and between 19:00 and 21:00 for the second. Participants were told to make sure that they could access their computers during these temporal windows for the entire experiment including weekends and holidays. All participants were able to satisfy this requirement, generally by using a laptop computer on holidays. The two temporal windows were defined in order to ensure a quasi-constant time interval between successive assessments (12 hours). Participants were told to systematize their assessment schedule as much as possible (e.g., just before breakfast and just before dinner). The software recorded the exact time and date of each assessment, which allowed for a posteriori checking of assessment regularity. Deviations from the fixed temporal windows remained exceptional and very limited in duration, and were considered as negligible with regard to the length of the obtained series. The four participants involved in the present study never forgot to complete the questionnaire and provided complete series.

The six items were presented successively in random order, and the participants had to move a cursor with the mouse along a 15-cm line, anchored by the labels "not at all" at the left extremity and "absolutely" at the right. The software then converted the response to a score ranging between 0.0 and 10.0 that was proportional to the distance between the cursor and the left extremity of the line. Participants were not informed of these numerical scores and were not allowed to consult their previous responses. We finally obtained 1024-point time series for each dimension and each participant. The duration of the experiment was determined in order to optimize the spectral analyses, which work on the basis of series with lengths that are powers of 2.

*Descriptive statistics*

In order to provide a global overview of our data, we computed the mean, range, and standard deviation of each series. In addition, to assess the mean local variability of the series, we also computed the mean absolute difference between successive values: The series was differenced, transformed into absolute values, and the mean of this new series was calculated.

*ARIMA modeling*

Each individual series was modeled by means of ARIMA procedures (Box & Jenkins, 1976). A detailed step-by-step presentation of this method can be found in Fortes et al. (2003).

*Fractal analyses*

Eke et al. (2001) proposed a very strict and complete procedure for assessing the fractal correlation structure in time series. As a first step, they recommended the use of *spectral analysis* to distinguish between fGn and fBm. Spectral analysis works on the basis of the periodogram obtained by Fourier analysis. The relation of Mandelbrot and van Ness (1968) can be expressed as follows in the frequency domain:

$$S(f) \propto 1/f^{\beta} \qquad\qquad (4)$$

where $f$ is the frequency and $S(f)$ the correspondent squared amplitude. ß is estimated by calculating the negative slope (-ß) of the line relating log ($S(f)$) to log $f$. Obtaining a well-defined linear fit in the double logarithmic plot is an important indication of the presence of long-range correlation in the original series. fGn corresponds to ß exponents ranging from –1 to +1, and fBm to exponents from +1 to +3.

In the present paper spectral analysis was applied on each individual series. As suggested by Chen et al. (2001), each spectrum was calculated after removing the mean of the series and normalizing by the standard deviation. Finally the series were linearly detrended before spectral analysis.

A number of methods have been proposed for assessing the scaling exponent of fractal series (Eke et al., 2000; Scheppers, van Beek & Bassingthwaighte, 1992). As they work on different statistics and exploit different properties of the time series, these methods sometimes lead to inconsistent results and the use of a unique method may therefore entail misleading interpretations (Rangarajan & Ding, 2000). We decided to apply three different methods on our series. Some of these methods were specifically designed for the analysis of fGns, and the others for fBms. Following the characterization of our series as fGn or fBm with spectral analysis, our strategy was to apply the relevant methods on the original series and to convert these series (from fBm to fGn, or inversely) before the application of the other methods (Cannon, Percival, Caccia, Raymond & Bassingthwaighte, 1997). We thus had the opportunity to obtain three assessments of the scaling exponent, whatever the nature of the original series. The three methods are explained in detail in the methodological appendix of this article.

The first method we used was *Rescaled Range Analysis* (R/S analysis), proposed by Hurst (1965) in his work on the annual discharge of the Nile River. R/S analysis is a classic and commonly used method (Rangarajan & Ding, 2000) designed for the analysis of fGn. This analysis is based on the estimation of the mean range covered by a cumulated version of the original series during a given time interval. For a fractal series, this range is a power function, with exponent $H$, of interval length.

Our second method was *Dispersional Analysis*, introduced by Bassingthwaighte (1988) and applicable only on fGn signals. This method is based on the estimation of the variability

of the mean, calculated on non-overlapping intervals of equal length. For a fractal series, this variability is a power function, with exponent *H*-1, of interval length.

Finally, we used the *Scaled Windowed Variance Method,* designed to work on fBm signals (Cannon, Percival, Caccia, Raymond & Bassingthwaighte, 1997). This method is based on the estimation of the standard deviation of the series in non-overlapping intervals of equal length. For fractal series, this standard deviation (averaged over all intervals of equal length) is a power function, with exponent *H*, of interval length.

For all these methods, the fractality of the series is graphically attested to by a linear regression in a double-logarithmic plot of the estimated variable (range, variability of the mean, or standard deviation) against interval length. The exponent *H* is estimated from the slope of this linear regression.

**Results**

Two representative time series (Participant 1, GSE, and Participant 3, PSW) are presented in Figure 2. As can be seen, the series appeared generally non-stationary, with marked evolutions of the local mean. They were characterized by a kind of roughness, revealing the local variability of the successive assessments, and they followed local increasing or decreasing trends at diverse and interpenetrated time scales.

The descriptive statistics are reported in Table 1. Our participants appeared to be a quite homogeneous sample, with reasonably high mean levels of self-esteem, except Participant 4 who presented a lower mean level, just above the middle of the response scale. The means of the physical self dimensions were generally slightly lower, but remained in the upper part of the scale, expect for Participant 4 who presented quite low mean levels on the PSW, PC and PS subscales. Range values indicated that the assessment was not bounded within narrow limits, but could present quite distant extreme values. The highest ranges were reported for Participant 4, with a maximum of 8.46 for the SC subscale. The analysis of standard deviations suggests, nevertheless, that these high ranges were more related to the exceptional use of extreme values, rather than to the effective use of a broad bandwidth.

These data revealed no indication of a relationship between the variability of a series and the hierarchical level of the corresponding dimension in the model. A one-way analysis of variance with repeated measures revealed no significant difference in standard deviation among scales ($F_{5,15} = 2.46$, $p>0.05$). Standard deviation values appeared quite consistent over the six scales for each participant: Participant 4 presented the highest variabilities and Participant 1 the lowest. Finally, the mean absolute difference values obtained for the first three participants were quite similar, between participants and among scales, but were higher for Participant 4. Here also, the results did not suggest any effect of the level of the dimension in the model on self-assessment variability.

ARIMA modeling showed that a differenced first-order moving average model adequately captured the dynamics of each series. These models were similar to those found in previous studies (Fortes et al., 2003; Ninot et al., 2001). The differentiation constant was never significant, and the models could thus be expressed following Equation 1. The estimated moving average coefficients (θ) are reported in Table 2. The results revealed a high consistency in the coefficients obtained for each participant. Participants 1, 3, and 4 were characterized by rather high coefficients, ranging from 0.56 to 0.75 and denoting the

prevalence of the preservation process in all series. The coefficients were smaller for Participant 2, and especially for GSE. This result seemed to indicate for this participant a higher sensitivity to disturbance, and particularly at the most global level.
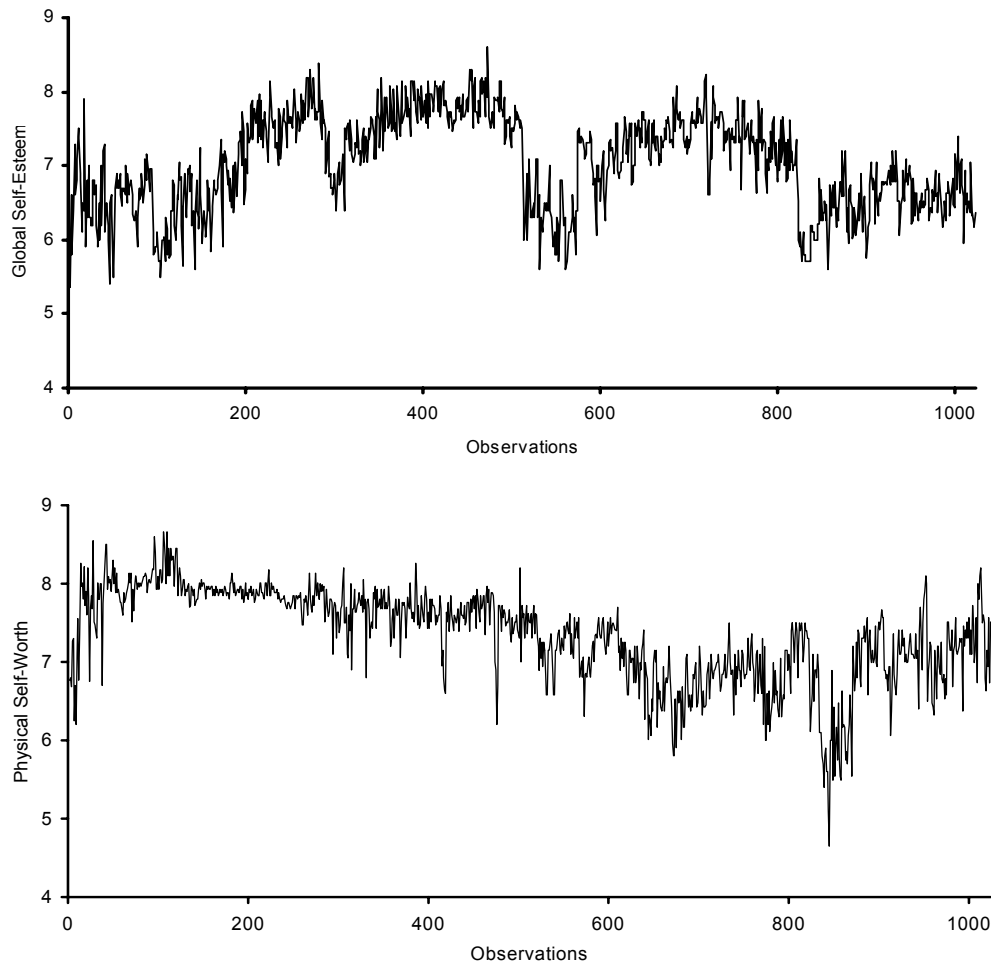


*Figure 2: Two representative examples of experimental time series (upper panel: Participant 1, Global Self-Esteem, lower panel: Participant 3, Physical Self-Worth).*

Spectral analysis revealed for each series a straight line in the double logarithmic plot of power against frequency (Figure 3), allowing a valid assessment of the ß exponent. We found no traces of flattening of the plot in the low-frequency region, as expected for short-memory processes (Pressing & Jolley-Rogers, 1997; Chen et al., 2001). These characteristic shapes suggest the presence of long-term memory processes underlying the time series. The obtained ß exponents are reported in Table 3 and appeared quite similar within and between participants. More precisely, ß values appeared close to 1.0 (from 0.95 to 1.39), suggesting that the series behaved like 1/*f* noise. The exponent was in most cases above 1.0, and it seemed reasonable to process all series in subsequent analyses as fBms (Eke et al., 2000).

R/S analysis was then performed on the differenced series and in all cases provided a well-defined linear relationship in the double logarithmic plot of rescaled range against interval length (Figure 4). This graphical result confirmed, in the time domain, the presence of long-term correlation in the series. We found no traces of the crossover phenomenon (i.e., a flattening of the slope for long intervals), which is generally considered as indicative of a

bounding effect in the series (Delignières et al., 2003; Liebovitch & Yang, 1997). The present data would have been biased by this kind of effect, as responses were constrained in amplitude by the length of the analog scale. R/S analysis results showed that this was not the case.

| | Participant | GSE | PSW | PC | SC | APP | PS |
|---|---|---|---|---|---|---|---|
| Mean | 1 | 7.04 | 6.75 | 6.24 | 6.36 | 7.09 | 6.13 |
| | 2 | 7.30 | 6.28 | 5.88 | 6.01 | 6.26 | 5.90 |
| | 3 | 7.55 | 7.35 | 6.74 | 7.14 | 7.38 | 6.82 |
| | 4 | 5.44 | 3.43 | 3.30 | 6.27 | 5.73 | 3.24 |
| Range | 1 | 3.25 | 3.03 | 2.77 | 2.47 | 2.94 | 2.70 |
| | 2 | 5.24 | 4.24 | 4.72 | 4.47 | 3.49 | 4.15 |
| | 3 | 3.80 | 4.01 | 4.80 | 3.85 | 3.96 | 3.50 |
| | 4 | 5.83 | 7.15 | 7.98 | 8.46 | 6.65 | 6.97 |
| Standard Deviation | 1 | 0.64 | 0.59 | 0.52 | 0.49 | 0.52 | 0.54 |
| | 2 | 0.56 | 0.79 | 0.94 | 0.76 | 0.68 | 0.80 |
| | 3 | 0.54 | 0.59 | 0.76 | 0.70 | 0.59 | 0.63 |
| | 4 | 0.86 | 1.40 | 1.36 | 1.17 | 0.83 | 1.35 |
| Mean Absolute Difference | 1 | 0.27 | 0.26 | 0.28 | 0.24 | 0.25 | 0.26 |
| | 2 | 0.22 | 0.22 | 0.23 | 0.20 | 0.21 | 0.23 |
| | 3 | 0.24 | 0.24 | 0.36 | 0.26 | 0.24 | 0.31 |
| | 4 | 0.57 | 0.44 | 0.42 | 0.55 | 0.49 | 0.40 |

*Table 1: Mean, range, standard deviation, and mean absolute difference of each time series. GSE: global self-esteem scale, PSW: physical self-worth, PC: physical condition, SC: sport competence, AB: attractive body, and PS: physical strength.*

| Participant | GSE | PSW | PC | SC | APP | PS |
|---|---|---|---|---|---|---|
| 1 | 0.58 | 0.65 | 0.70 | 0.66 | 0.63 | 0.69 |
| 2 | 0.35 | 0.46 | 0.48 | 0.50 | 0.45 | 0.46 |
| 3 | 0.58 | 0.65 | 0.75 | 0.63 | 0.56 | 0.68 |
| 4 | 0.66 | 0.56 | 0.60 | 0.59 | 0.64 | 0.53 |

*Table 2: Individual moving average coefficients (θ) obtained through ARIMA modeling.*
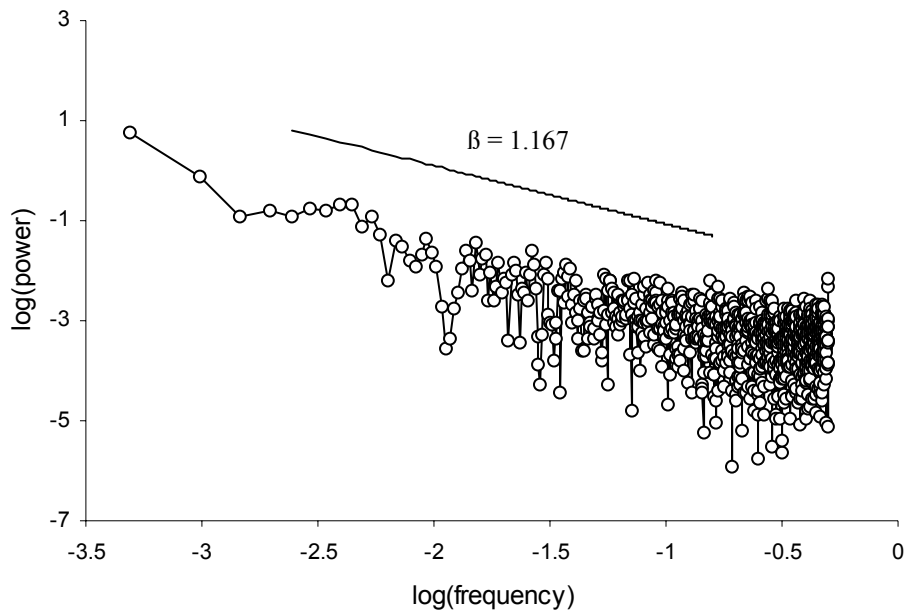
*Figure 3: Example graphical result of the spectral analysis: double logarithmic plot of power against frequency (Participant 1, Global Self-Esteem; see Figure 2, upper panel).*

| Participant | GSE | PSW | PC | SC | APP | PS |
|---|---|---|---|---|---|---|
| 1 | 1.17 | 1.15 | 0.95 | 1.00 | 1.15 | 0.95 |
| 2 | 1.13 | 1.39 | 1.36 | 1.24 | 1.27 | 1.23 |
| 3 | 1.09 | 1.05 | 0.96 | 1.34 | 1.12 | 1.11 |
| 4 | 0.96 | 1.14 | 1.02 | 1.18 | 0.95 | 1.05 |

*Table 3: Individual ß exponents obtained with spectral analysis.*

The individual estimates of $H$ obtained by R/S analysis are reported in Table 4. All these values were located in a quite narrow range, between 0.18 and 0.40, with a mean of about 0.31, suggesting that the series were underlain by an anti-persistent long-range correlation process. Nevertheless, this first estimation should be considered with caution, as R/S analysis was shown to overestimate the scaling exponent for $H < 0.7$ (Caccia, Percival, Cannon, Raymond & Bassingthwaigthe, 1997). A deeper examination of the exponents revealed their homogeneity among scales within each participant. As can be seen, the six exponents for a given participant were closely grouped around a mean value (Participant 1: 0.27 +/- 0.04; Participant 2: 0.37 +/- 0.02; Participant 3: 0.31 +/- 0.05; Participant 4: 0.28 +/- 0.07). These results suggested that the six series shared common fractal properties and that each participant was characterized by a specific level of fractality.

Dispersional analysis was also applied on the differenced series. Well-defined linear slopes were obtained for each double logarithmic plot of standard deviation against interval length. A plot example is shown in Figure 4. These graphical results confirmed those obtained by R/S analysis and evidenced the presence of long-range correlation in the time series. The estimates of $H$ obtained by Dispersional analysis are reported in Table 4. These exponents were

generally slightly lower than those obtained with R/S analysis (Participant 1: 0.19 +/- 0.04; Participant 2: 0.29 +/- 0.14; Participant 3: 0.20 +/- 0.08; Participant 4: 0.11 +/- 0.05). Note, however, that for the five physical self series of Participant 2 we obtained estimates similar to those from R/S analysis (0.35 +/- 0.04): Dispersional analysis gave a very low estimate for GSE (0.02 vs 0.34 for R/S analysis) but similar results for the remaining dimensions. The overestimation with R/S analysis is stronger for low values of $H$ (Caccia et al., 1997), and one could suppose that in the present case R/S analysis overestimated the exponents of Participants 1, 3 and 4, but not those of Participant 2.

| Method | Participant | GSE | PSW | PC | SC | APP | PS |
|---|---|---|---|---|---|---|---|
| R/S analysis | 1 | 0.33 | 0.27 | 0.21 | 0.26 | 0.29 | 0.26 |
|  | 2 | 0.34 | 0.36 | 0.38 | 0.38 | 0.36 | 0.40 |
|  | 3 | 0.28 | 0.28 | 0.31 | 0.36 | 0.38 | 0.25 |
|  | 4 | 0.18 | 0.28 | 0.33 | 0.36 | 0.24 | 0.31 |
| Disp analysis | 1 | 0.26 | 0.25 | 0.14 | 0.15 | 0.25 | 0.12 |
|  | 2 | 0.02 | 0.34 | 0.38 | 0.36 | 0.28 | 0.36 |
|  | 3 | 0.19 | 0.15 | 0.18 | 0.36 | 0.12 | 0.21 |
|  | 4 | 0.11 | 0.14 | 0.11 | 0.17 | 0.02 | 0.10 |
| ldSWV | 1 | 0.22 | 0.21 | 0.16 | 0.19 | 0.20 | 0.19 |
|  | 2 | 0.16 | 0.35 | 0.39 | 0.36 | 0.30 | 0.36 |
|  | 3 | 0.10 | 0.10 | 0.11 | 0.13 | 0.13 | 0.12 |
|  | 4 | 0.10 | 0.15 | 0.15 | 0.20 | 0.15 | 0.16 |

*Table 4: Individual H exponents obtained with R/S analysis, Dispersional analysis (Disp) and the linear detrended Scaled Windowed Variance method (ldSWV).*

The Scaled Windowed Variance method was applied on the raw series. The double logarithmic plot of mean standard deviation against interval length gave acceptable linear fits. An example plot is shown in Figure 4. The obtained estimates of $H$ are reported in Table 4. As can be seen, these exponents were close to those obtained with Dispersional analysis (Participant 1: 0.19 +/- 0.02; Participant 2: 0.32 +/- 0.08; Participant 3: 0.11 +/- 0.02; Participant 4: 0.15 +/- 0.03). The exponent obtained for the GSE series of Participant 2 (0.16) was higher than that of Dispersional analysis, but lower than that of R/S analysis. For the five remaining dimensions, the results of the preceding analyses were confirmed, with similar standard deviation (0.35 +/- 0.02). One should also note that the exponents of Participant 3 were lower than those obtained with Dispersional analysis (mean value 0.11 vs 0.20).

Finally, Table 5 shows the correlation matrix between the coefficients and exponents obtained in the preceding analyses. All estimates of $H$ presented significant correlations with ß. The three estimates of $H$ were obviously highly intercorrelated. Finally, the moving average coefficients θ, obtained through ARIMA procedures, presented significant negative correlations with ß and the $H$ estimates obtained from R/S analysis and the Scaled Windowed Variance method.

| | β | H(R/S) | H(Disp) | H(ldSWV) |
|---|---|---|---|---|
| θ | -.64** | -.67** | -.25 NS | -.60** |
| β | | .75** | .81** | .69** |
| H (R/S) | | | .56** | .61** |
| H (Disp) | | | | .71** |

($^{NS}$: non-significant; *: p<.05; ** p<.01)

*Table 5: Correlation matrix between the moving average coefficients θ, the ß exponents and the H estimates obtained with R/S analysis, Dispersional analysis (Disp), and the linear detrended Scaled Windowed Variance method (ldSWV).*
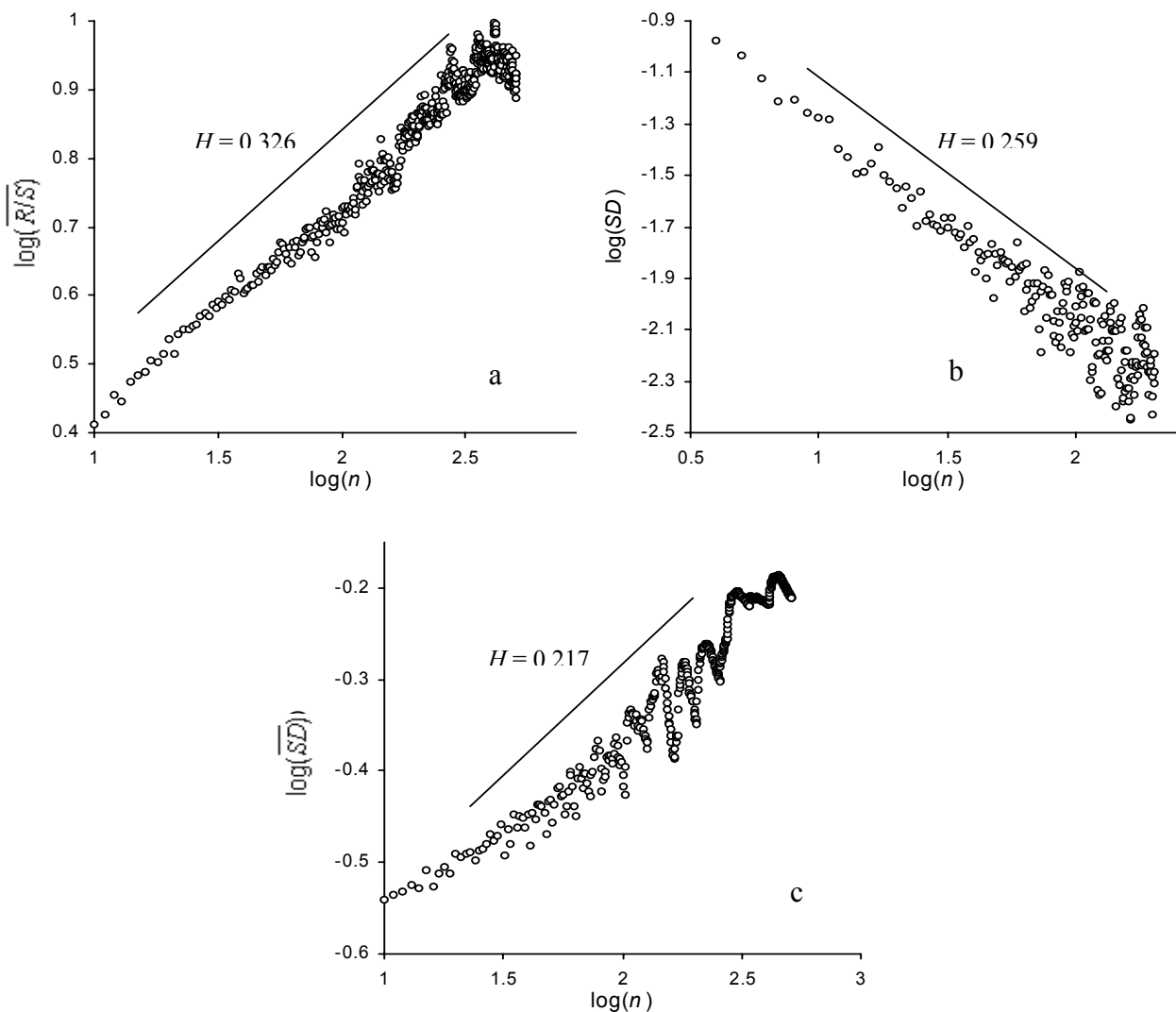


*Figure 4: Example graphical results. Panel a: R/S analysis, double logarithmic plot of averaged rescaled range against interval length; panel b: Dispersional analysis, double logarithmic plot of the standard deviation of mean estimates against interval length; panel c: linear detrended Scaled Windowed Variance method: double logarithmic plot of the averaged standard deviation against interval length. Data from Participant 1, Global Self-Esteem (see Figure 2, upper panel).*

**Discussion**

The aim of this paper was to study the dynamics of individual self-esteem and physical self time series in adults. We analyzed a unique set of data obtained through repeated self-assessments over a period of 512 consecutive days, with two assessments per day. Our main goals were to apply fractal analyses to these series in order to go beyond the classic Gaussian approaches and to assess the temporal structure of their variability.

We are aware that our approach may appear intriguing for most social psychologists. Self-esteem and similar constructs are generally approached through nomothetic perspectives, in the attempt to infer general models of psychological functioning from the average behavior of a number of individuals in selected situations. The present work was based on only four participants and one might well wonder if general knowledge can be obtained from such a restricted sample. The use of time series and the associated analysis methods opens a new window on psychological functioning and constitutes an innovative means of understanding its dynamics. Nevertheless, the collection of such extended series represents a difficult challenge. Because these series are processed individually, their quality and genuineness are essential. The aim of such a dynamical approach is less to derive an epistemic model by averaging a number of observed behaviors than to evidence that individual behaviors share common dynamics, despite superficial differences. From this perspective, the richness of the individual data sets that can reveal the dynamics is more crucial than the number of participants involved in the experiment. Researchers in many fields, for example in the dynamical approach to motor control and learning, have also adopted this experimental strategy (e.g., Nourrit, Delignières, Caillou, Deschamps & Lauriot, 2003; Sparrow & Irizarry-Lopez, 1987; Zanone & Kelso, 1992).

An analysis of the events or experiences that caused the waxing and waning of self-esteem might have been interesting and, indeed, our participants were requested to report the daily events they considered important. Some typical effects were evidenced, such as a systematic devalorization in self-esteem during long periods of vacation (see, for example, in Figure 2, observations 300 to 350 or 520 to 600). Along the same lines, a recent experiment showed the positive impact of a three-week rehabilitation program on self-esteem dynamics in patients suffering from chronic obstructive pulmonary disease (Ninot et al., 2002). The focus of the present work, however, was on the global dynamics of self-esteem and physical self, not on their responses to particular events. These responses can differ in amplitude, according to the importance or the duration of each event, but their nature remains invariant and constitutes the core of the dynamical models derived for the series.

The main result of the present paper was the uncovering of long-range, fractal correlations in self-esteem and physical self time series. The fractal behavior of the series was proven without ambiguity, with consistent results obtained by different methods, one in the frequency domain, and three in the time domain. Rangarajan and Ding (2000) showed how the use of a single method in fractal analysis could lead to misleading results and false interpretations. Here each method gave graphical evidence for one of the typical power functions presented in the method section and detailed in the appendix.

The estimation of scaling exponents gave more inconsistent results. The best agreement between methods was obtained for the highest exponents, and especially for the five dimensions of physical self for Participant 2. R/S analysis, even in its detrended version,

seemed to overestimate the lower exponents and, for example, was unable to differentiate GSE from the other dimensions for Participant 2. All the other methods, including spectral analysis (see Table 3), detected this difference in fractality between the apex level and the other dimensions. Dispersional analysis was selected by Caccia et al. (1997) as the most relevant method for assessing the scaling exponent in fGn. The exponents obtained by this method seemed generally consistent with the ß exponents of spectral analysis. Both methods agreed for detecting a particularly high exponent for the SC dimension of Participant 3, a feature that was ignored by the other methods. The Dispersional analysis estimate for GSE of Participant 2 nevertheless appeared rather low, in relation to its ß counterpart.

The Scaled Windowed Variance method was the most relevant method for our fBm series (Cannon et al., 1997). The results obtained with this method were quite consistent with those of Dispersional analysis, despite some lower values for Participant 3.

These results give a good illustration of the interest of an integrated approach in fractal analysis by the joint use of different methods (Rangarajan & Ding, 2000), not only for detecting the presence of fractal processes, but also for the estimation of the scaling exponents. Working on the basis of different statistics and exploiting distinct facets of fractal theory, these methods can selectively produce inconsistent results. An integrated approach allows a more accurate assessment of the exponents, which is essential for experimental protocols including group means comparisons. We confirm in the present paper the quality of the two methods selected by Eke et al. (2000) for estimating scaling exponents. The results demonstrate the interest of complementary use of these two methods, i.e., applying Dispersional analysis on fGn and the Scaled Windowed Variance method on the corresponding fBm (Cannon et al., 1997).

The ARIMA modeling confirmed previous results (Fortes et al., 2003; Ninot et al., 2001), with the uncovering of moving average models for each individual series. Moreover, the moving average coefficients appeared to be negatively related to $H$ estimates. This suggests that $1/f$ noise and the moving average model possess similar properties, characterized by a subtle balance between the preservation of a reference value and an adaptation to events. The present results show that this balance is not simply achieved over the short term, as suggested by the ARIMA models, but occurs at multiple time scales, in a self-similar way. We assume that the moving average model, which implies a systematic correction of disturbances, mimics over the short term the fractal anti-persistent correlation that underlies the series. In other words, low moving average coefficients should be related to weakly anti-correlated series, close to Brownian motion (with $H$ close to 0.5), and higher coefficients should correspond to series closer to $1/f$ noise, with lower $H$ exponents. This relationship between moving average coefficients and fractal exponents could be of practical importance in applied settings, as ARIMA procedures can work with relatively short series. Note, however, that we failed to demonstrate this relationship with Dispersional analysis exponents. This result is quite disappointing because of the supposed quality of Dispersional analysis estimates.

The uncovering of long-range, fractal correlation in self-esteem and physical self series leads to important theoretical considerations. Such fractal behavior at a systemic level is generally considered to be the expected outcome of a complex, dynamical system, composed of multiple interacting elements (West & Shlesinger, 1990). Recently a number of mechanisms were advocated to explain the emergence of such processes. According to Bak and Chen (1991), long-range correlations constitute the typical signature of complex systems in critical self-organized state. Hausdorff and Peng (1996) showed that multi-scaled

randomness would give rise to such behavior under some conditions. All these propositions share the idea of the presence of many interacting components acting on different time scales. Our results represent an interesting support for the model proposed by Nowak et al. (2000), which considered self-esteem as a self-organized dynamical system.

Interestingly, this fractal behavior was discovered for each dimension in the model with similar scaling exponents. On the basis of the principles underlying the hierarchical model of physical self (Fox & Corbin, 1989), one might conceive of self-esteem as more complex (i.e., integrating a greater number of elements) than the other dimensions. Our results suggest that the sub-domains behave much as the higher and more global levels and should also be considered as complex systems. This result is consistent with the basic principles of self-similarity, with each level in the self appearing to contain similar dynamics while being embedded in the next level (Marks-Tarlow, 1999). It would be interesting, however, to check whether a time series obtained from the self-assessment of perceived competence in a single task exhibits similar long-term memory or presents another kind of temporal structure.

The exponents obtained for each series allowed us to classify them as close to $1/f$ noise. As stated previously, $1/f$ noise represents a compromise between white noise and Brownian motion. More precisely, $1/f$ noise represents a compromise between the absolute preservation of the mean achieved by white noise (which is characterized by a strictly stationary series, with random fluctuations around a stable mean) and the absolute adaptation of Brownian motion (defined as the cumulative sum of a series of random shocks).

These results have important implications concerning the way one conceives of stability and instability in self-esteem. As explained in the introduction, $1/f$ noise possesses an intrinsic stability, due to the relative independence of the underlying processes acting at different time scales. The system is thus more adaptive to endogenous and exogenous perturbations. $1/f$ noise has been discovered in a number of biological systems. This "optimal" fractality appears as the typical signature of young, healthy, and adaptive systems. On the contrary, certain diseases seem associated with a disruption of this "optimal" fractality (West & Shlesinger, 1990). Hausdorff et al. (1997) showed that fluctuations in the duration of the gait cycle display $1/f$ behavior in healthy young adults. This fractal dynamics was systematically altered in elderly subjects and patients with Huntington's disease. In these cases, the fluctuations appeared more random and closer to a white noise process. In the same vein, Peng, Havlin, Stanley and Goldberger (1995) analyzed beat-to-beat fluctuations in heart rate and showed that congestive heart failure led to an alteration in the $1/f$ fractality observed for healthy subjects. In these two experiments the amplitude of the alteration was proportional to the severity of the disease.

The participants of the present study can be considered as healthy, physically and professionally active adults, and the $1/f$ behavior we evidenced can be conceived as the typical intrinsic dynamics of global self-esteem and physical self for such individuals. According to Marks-Tarlow (1999), psychological health resides at the edge of chaos, a transition zone between predictable order and unpredictable chaos. Within this zone, systems possess enough stability to maintain consistent functioning but sufficient randomness to ensure adaptability and creativity. Disabled systems behave away from this edge, in the direction of unpredictable chaos, as in hysterical patients, or in the opposite direction of deterministic order, as in obsessive-compulsive patients. Marks-Tarlow (1999) predicts that for such patients, specific alterations in fractality should be observed, in the direction of white noise in the first case, and in the direction of Brownian motion in the second. Gottschalk, Bauer and Whybrow (1995)

evidenced such results in the related domain of mood variation. They analyzed long-term daily mood records in patients with bipolar disorder and normal subjects and observed in both groups a 1/$f$-type noise in the collected series. ß exponents were significantly higher in the bipolar patients, suggesting that self-rated mood in such patients was more organized and characterized by a loss of complexity. In the same vein, Ninot, Delignières and Varray (2003) recently showed that the variability of self-esteem and physical self time series was higher and more random in patients suffering from chronic obstructive pulmonary disease than in healthy participants.

The application of fractal analysis to self-esteem series constitutes in our opinion only a first step in the characterization of their nonlinear properties. One of the most important results of the present study is the demonstration of the non-stationary nature of self-esteem over time. Such non-stationary processes can be characterized by a number of features, including changes in the dynamics or bifurcations. Such phenomena would be particularly expected in depressed or highly anxious subjects, but we saw even in the present data that specific episodes such as vacations caused local changes in self-esteem dynamics in healthy individuals.

Some methods have been specifically designed for the analysis of non-stationary series, and these would be useful to complement the present approach. Time-frequency methods, for example, were delineated to yield evolving spectral representation of non-stationary signals whose dynamics are suspected to change over time (see, for example, Scumann, Redfern, Furnam, El-Jaroudi & Chaparro, 1995). Recurrence plot analysis is a very appealing recent method that would allow the identification of transition points in non-stationary data sets or the detection of bifurcations (see, for example, Riley, Balasubramanian and Turey, 1999). In addition, this method permits a quantification of the determinist structure in the series. Finally, one can consider the application of various nonlinear regression models on the series and comparisons with their linear counterparts (Guastello, Johnson & Rieke, 1999; Warren, Hawkins & Sprott, 2003). The application of these methods is beyond the scope of the present paper but should be the object of future research.

Finally, our approach considered the collected series separately and neglected to examine their interactions. The assessed dimensions are conceived of as the interconnected components of a hierarchically organized system, but the way one dimension influences its neighbors in the model remains an open question. Diverse hypotheses have been proposed, suggesting that these processes of influence could act following a top-down (Brown, 1993) or conversely a bottom-up direction (Shavelson & Bolus, 1982). The dynamical systems approach to self-concept suggests a more complex functioning, based on nonlinear couplings between dimensions (Marks-Tarlow, 1999), and assumes that the processes of influence between neighbors in the model may be variable over time in terms of both direction and strength. The set of time series collected for the present study could provide the empirical material necessary for testing this hypothesis, and our current research aims at evidencing such nonlinear coupling phenomena by means of windowed cross-correlational analyses, a method for characterizing the association between variables when the assumption of stationarity over time may not be warranted (Boker, Xu, Rotondo & King, 2002).

## Conclusion

This study showed that self-esteem and physical self time series were underlain by a fractal process close to $1/f$ noise. This result provides strong support for the conception of the self as a complex dynamical system (Nowak et al., 2000). This fractal behavior seems to reflect the intrinsic dynamics of global self-esteem and physical self of healthy adults, and its inherent properties may explain some macroscopic, commonly recognized features, such as stability, preservation, and adaptation.

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**Appendix**

Consider an fBm as $y(t)$, and the corresponding fGn as $x(t)$. $x(t)$ represents the series of successive increments in $y(t)$, and $y(t)$ the cumulative sum of $x(t)$.

*Rescaled Range analysis*

The $x(t)$ series is divided into non-overlapping intervals of length $n$. Within each interval, an integrated series $X(t, n)$ is computed:

$$X(t,n) = \sum_{k=1}^{t} \left\{ x(k) - \langle x \rangle_n \right\},\tag{6}$$

where $\langle x \rangle_n$ is the local average of the $n$ data. In the classical version of R/S analysis, the range $R$ is computed for each interval as the difference between the maximum and the minimum integrated data $X(t, n)$.

$$R = \max_{1 \le t \le n} X(t,\ n) - \min_{1 \le t \le n} X(t,\ n)\tag{7}$$

In the present paper, we used an improved version, *R/S-detrended*, where a straight line connecting the end points of each interval is subtracted from each point of the cumulative sums $X(t,\ n)$ before the calculation of the local range. In both methods, the range is then divided for normalization by the local standard deviation ($S$) of the original series $x(t)$. This computation is repeated over all possible interval lengths (in practice, the shortest length is around 10, and the largest ($N$-1$)/2$, giving two adjacent intervals). Finally the rescaled ranges $R/S$ are averaged for each interval length $n$. $\overline{R/S}$ is related to $n$ by a power law:

$$\overline{R/S} \propto n^H\tag{8}$$

$H$ is expressed as the slope of the double logarithmic plot of $\overline{R/S}$ as a function of $n$. R/S analysis is known to overestimate $H$ for series with $H < 0.7$ and conversely to underestimate $H$ for $H > 0.7$. Nevertheless, these biases are reduced for the detrended version of the R/S analysis (Caccia et al., 1997).

*Dispersional analysis*

The $x(t)$ series is divided into non-overlapping intervals of length $n$. The mean of each interval is computed, and then the standard deviation ($SD$) of these local means, for a given

length *n*. These computations are repeated over all possible interval lengths. *SD* is related to *n* by a power law:

$$SD \propto n^{H\text{-}1} \tag{9}$$

The quantity (*H*-1) is expressed as the slope of the double logarithmic plot of *SD* as a function of *n*. Obviously, the *SDs* calculated from the highest values of *n* tend to fall below the regression line and bias the estimate. Caccia et al. (1997) suggested ignoring the measures obtained from the longest intervals. In the present paper, we only considered the standard deviations obtained on the means of at least six non-overlapping intervals. Caccia et al. (1997) showed that Dispersional analysis gives reliable estimates of the *H* exponent for fGn signals. Estimates of *H* obtained from Dispersional analysis have lower bias and variance than those from classical R/S analysis.

*Scaled Windowed Variance method*

The *y(t)* series is divided into non-overlapping intervals of length *n*. The standard deviation of the points is then calculated within each interval using the formula:

$$SD = \sqrt{\frac{\sum_{t=1}^{n} y(t) - \bar{y}}{n-1}} \tag{10}$$

where $\bar{y}$ is the average within each interval. Finally the average standard deviation ($\overline{SD}$) of all intervals of length *n* is computed. This computation is repeated over all possible interval lengths. $\overline{SD}$ is related to *n* by a power law:

$$\overline{SD} \propto n^{H} \tag{11}$$

*H* is expressed as the slope of the double logarithmic plot of $\overline{SD}$ as a function of *n*. Cannon et al. (1997) showed that a detrending of the series within each interval before the calculation of the standard deviation provided better estimates of *H*, especially with short series. In this paper we used the *linear detrended Scaled Windowed Variance method*: a linear regression was computed for the points of each considered interval, and the standard deviation (*SD*) was calculated on the residuals of this regression.