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Comments

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Nonlinear Dynamical Systems and Humanistic Psychology

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Abstract

The recent debunking by Brown, Sokal, & Friedman (2013) of some high profile results applying chaos theory to positive psychology (i.e., Fredrickson & Losada, 2005) creates the opportunity to shed light on the quality work that has been done by others in this area. Too many humanists may be unaware of the large volume of legitimate work that exists in the literature apart from Fredrickson & Losada's (2005) paper. Often,, such legitimate lines of research are ignored, not for lack of scientific merit, but because of artificial guild boundaries and similar silos that separate groups of scientists—even when working in similar areas. It would be unfortunate to have one "bad apple" of an article spoil the reputation of the good scientific progress that has been made over the past couple of decades applying nonlinear dynamical systems theory to humanistic concepts. The present article is intended to help prevent and correct some of these problems, by providing an accesible review of some of this higher quality work.

Nonlinear Dynamical Systems and Humanism

In 2005, Fredrickson and Losada published an article in the journal *American Psychologist*, claiming to have found a critical 2.9 to 1 positivity to negativity ratio that could potentially serve as a threshold to explain human flourishing in general, across domains ranging from small group dynamics to mental health and resilience. In the years that followed, this compelling and highly marketable result became a key selling point among the leaders of the "new" science of positivity, helping to distinguish "positive psychology" from humanistic psychology, which predates the former by about fifty years (Rogers, 1951, 1957). This mathematically precise positivity threshold served as a shiny marketing tool, as its origins were clouded over by the exotic and technical realm of nonlinear differential equations. In nearly every respect, this result was ideal: mathematically grounded, empirical, extremely precise, and useful in nearly any human context.

However, the mathematical modeling (i.e., nonlinear differential equation simulation) at the heart of this work has since been soundly debunked (see Brown, Sokal, & Friedman, 2013). A number of other concerns have arisen since that time, including: the continuing criticism of positive psychology for essentially colonizing humanistic research and rebranding it for marketing purposes; the failure of the peer review process to catch the errors in this high profile paper; and the failure of the lead author of this manuscript to fully understand the methods she was utilizing.

One particular problem important to the field of nonlinear science was highlighted in Fredrickson's (2013) response following the initial criticisms of her article:

> Losada's mathematical work, which to date he has elected not to defend, may well be the smudge that needs removing. Whereas Brown and colleagues' article revealed this

> smudge, my hope is that the present article effectively washes it away. Perhaps we can now toss out the muddied bath water and move on to conducting the relevant empirical and mathematical work necessary for the continued healthy development of this growing research area…. system dynamics, network analysis, agent-based modeling, and other systems science approaches are likely to become ever more relevant to affective science and positive psychology, as they have for biology, economics, and public health. (Fredrickson, 2013, p. 820)

Nearly any systems scientist in psychology would agree with the sentiments in this response, especially the hope that the psychological community won't throw the nonlinear *baby* out with this *muddied bathwater*. Unfortunately, Fredrickson's response fails to fully acknowledge the current state of nonlinear science in psychology, particularly relevant in the areas of emotional dynamics and resilience. Similar to the plight of humanistic scientists, systems scientists may suffer from the mistaken impression that their work is aspirational at best or unscientific at worst. Effective incremental science should not concern itself with branding (e.g., "humanistic" "positive" "systems") and high impact results, but instead always begin with a thorough and objective literature review.

In the interest of serving a more *positive* function, the present article will now turn to providing a review of the scientific literature applying nonlinear dynamical systems (NDS) theory and methodology to humanistic concepts. The review will begin with a non-technical primer on some of some of the most common theoretical and methodological concepts and procedures from nonlinear dynamics applied to psychology (see Guastello, Koopmans, & Pincus, 2009, for a full text on the topic; Guastello & Gregson, 2011, for a complete methods text; or Butner, Gagnon, Geuss, Lessard, & Story, 2014, for a recent methodological article aimed at measuring topological processes). Next, it will highlight some ongoing work applying nonlinear science to humanistic psychology. In preparing for this review, we found numerous areas of overlap that we could potentially cover, including: creativity and meaning (cf. Allen & Varga, 2007; Guastello & Fleener, 2011), motivational flow (Navarro, Arrieta, & Ballen, 2007; Ceja & Navarro, 2009; Guastello, Johnson, & Rieke, 1999), the self-system (Delignières, Fortes, & Ninot, 2004; Marks-Tarlow, 1999; Wong, et al., 2014), intention (Dumas, de Guzman, Tognoli, & Kelso, 2014; Freeman, 2007; Haken & Tschacher, 2011; Hollis, Kloos, & Van Orden, 2009; Kay & Freeman, 1998; Kelso, 2012; Walther, Ramseyer, Horn, Strik, & Tschacher, 2013), and psychotherapy processes (Anders, Heinzle, Weiskopf, Ethofer, & Haynes, 2011; Hayes & Yasinski, 2015; Heinzel, Tominschek, & Schiepek, 2014; Peluso, Liebovitch, Gottman, Norman, & Su, 2011; Pincus, 2009, 2015, 2016; Ramseyer & Tschacher, 2011; Schiepek, Eckert, Aas, Wallot, & Wallot, 2015). Interested readers are encouraged to begin with these example citations as entry points into the various areas of humanism in which NDS have been applied. For the sake of expediency, the present review will focus on emotion and resilience, the two broad areas that are most closely related to Fredrickson's (2013) ongoing work in positivity ratios.

Introduction to Nonlinear Dynamical Systems Theory

NDS can be challenging to understand. From the broadest and most philosophical perspective, it encompasses an approach to science that is holistic rather than reductionist, but without sacrificing scientific and mathematical rigor. NDS may be understood most simply by examining each term individually.

- *Nonlinear* refers to disproportional cause and effect. A simple example is a light switch, where movement has no effect until a critical threshold is reached that turns the light on or off. Common examples of nonlinear effects within psychology include emotional change (e.g., losing one's temper), interpersonal dynamics (e.g., involving reciprocal cause, feedback, and self-regulation), and discontinuous (stage-like) shifts in psychosocial development.

- *Dynamical* refers to processes in which time and timing are essential for understanding cause and effect—non-Newtonian, circular causality, precisely speaking. When combined with nonlinearity, a dynamical process may display various types of sensitive dependence, whereby small changes to inputs can lead to large changes to outputs, depending upon timing and the location of the change within the system. Common examples of dynamical processes would include the flow of information within the self and during interpersonal processes, each of which may show sudden and disproportionate shifts depending upon the state of the system at a given point in time.
- *Systems*, within this context, refer to a complex interaction of multiple factors, rather than simple linear cause and effect that are easily identifiable through controlled experimental methods. Complex systems contain multiple highly interactive elements. Combining all three terms, NDS theory is concerned with the non-reductionistic modeling and measurement of disproportional processes of cause and effect over time among multiple interacting elements.

Most noteworthy in psychology are models suggesting self-organization, where the elements of a system interact to produce an emergent process which may then serve as boundary-making factors, constraining the elements from which these boundaries emerge through reciprocal feedback. Over time, self-organizing systems are able to self-regulate, adjusting their levels of complexity up or down depending upon adaptive demands. A common example of such a process within psychology can be seen within interpersonal roles and relationships, which emerge from the interactions of individuals, but also serve to constrain the interactions of those same individuals over time (cf. Pincus, 2014). A variety of other common examples are well studied across the sciences, such as flocking behaviors (cf. Olfati-Saber, 2006), neural networks (cf. Freeman, 2005), or organizational dynamics (cf. Guastello, 2015a). When self-organization theory first became more widely known within psychological research, some responded with appropriate caution that the approach should not be used as a pseudoscientific façade to cover up weak science (Bunge, 2006). Fortunately, clear guidelines and methods have been developed to allow for the investigation of self-organization within psychological science (e.g., Carello & Moreno, 2005).

The primary concern in applying nonlinear models and methods to psychological data is no different than the primary concern within research grounded in the General Linear Model—psychological data is messy. Specifically, psychological data is usually found somewhere between ordinal and interval scales (e.g., Likert ratings), is prone to all sorts of bias, and is inherently noisy. Nonlinear dynamics approaches are not a panacea in this regard. Psychological scientists, whether using linear or nonlinear methods, bear the responsibility of demonstrating good enough reliability and validity in their data to support their conclusions. The limits of psychologists' data arguably require that we be better scientists in many respects than the "hard scientists"—showing greater skepticism with our results, focusing more on replication, understanding and utilizing statistics when necessary, and subjecting our measures to a wider array of validity checks.

Psychological scientists who use nonlinear dynamical approaches have the added burden of various types of non-reliability that are time-based. Psychological time series typically violate

the assumptions of many analytic techniques (e.g., classical Markovian models), which may require serial dependence (that each subsequent value depends on prior values), stationarity (that the underlying models generating data are not changing themselves), continuous measurement, and very long data streams. Psychological time series are most often noisy, non-stationary, and short. As is the case with linear approaches, then, nonlinear scientists in psychology have worked hard to identify and, when not available, to develop for themselves, approaches that are statistically-based, that allow for discrete processes of change, and that are robust against non-stationarity, noise, and limited numbers (Butner et al., 2014; Guastello & Gregson, 2011).
One of the great benefits, however, of using NDS on phenomena that are best conceived as changing over time is that nonlinear models are typically able to account for dependent error (i.e., error that fluctuates reliably with one or more control parameters in the model) and for momentum effects. Linear and static models from traditional psychological statistics training tend to oversimplify psychological phenomena into neat categories of “signal” and “noise,” throwing out otherwise useful sources of fluctuation. As a result, early comparisons of comparable linear and non-linear statistical models spanning from around 1990 to 2000 showed a 2 to 1 ratio in variance accounted for by nonlinear models (Guastello, 2001).

Before delving into specific areas, one may recognize already some of the more obvious theoretical connections that have been made in the literature linking NDS to humanistic processes. These themes include: nonlinear growth and complex adaptation processes, holism, a focus on the uniqueness of the individual, and the health associated with structural processes such as congruence and flexibility within and among personalities (Krippner, 1994, Pincus, 2009; Pincus & Guastello, 2005; Richards, 1996, 2001, Zausner, 2003, 2007). Each of these broader themes may be recognizable within the more specific topics of emotion and resilience to follow.

Emotion

Schuldberg & Gottlieb (2002) performed one of the earliest studies examining the dynamical characteristics of very short time scale changes in affect. Using a computerized "mouse paradigm," participants rated continuous fluctuations in affect, from "happier" to "sadder" over a 2.5 minute period—producing 1400 measurement points. They found evidence that the fluctuations were characteristic of "low dimensional chaos," meaning: (a) they were both deterministic yet also unpredictable; (b) they were fractal (i.e., with a smooth exponential relationship between small and large fluctuations); and (c) that happiness is a self-organizing process. Some initial evidence validated the usefulness of this chaotic measurement, as higher entropy (i.e., more chaotic fluctuations) was associated with global measures of positive emotional states and negatively associated with anhedonia.

A core distinction between humanism and positive psychology concerns whether one views happiness as a unique and variable process versus a goal that is to be attained. Several scientists have applied nonlinear dynamical systems theory to support the humanistic view that happiness is a unique process rather than a normative state to be achieved. For example, Sprott (2005) developed a simulation model of happiness using a differential equation. Given the context of Fredrickson and Losada (2005), it is important to point out that Sprott followed the expected scientific standard of being very clear that the model is a simulation only: "These models are gross simplifications since they assume that happiness is a simple scalar variable and that individuals respond in a consistent and mechanical way only to that variable" (p. 33). His approach is also praiseworthy because of its theoretical grounding, staying true to both the humanistic approach and nonlinear dynamical systems theory. For example, Sprott identified fluctuations and individual differences as key to understanding happiness within his model. As such, he set up a differential equation model of happiness based essentially on temporary fluctuations that are driven by external events and that dampen over time. The article plays out different simulated situations, from large negative shifts (e.g., the sudden death of a spouse) to large positive shifts (e.g., winning the lottery).

Of relevance to the themes of this special section focused on positive psychology, Sprott's (2005) article references Seligman (2002) throughout, comparing the dynamical model to the static (non-time based) model of happiness first introduced by Seligman—which instead focuses on finding a happiness set point based on one's inherited disposition, a set range for fluctuation, and life factors that people can voluntarily control. In arguing instead for the fluctuation-centric model, Sprott then ran a number of simulations of variables with known phenomenological features of happiness fluctuation, including for example: anticipation, psychiatric medication, and addiction processes. Schuldberg (2002) similarly criticized the tendency of positive psychology to rely too much on universal algorithms, rather than person-specific heuristics, in seeking ways to achieve greater happiness.

Within these early critiques, one can see some foreshadowing of the problems to come, as the leaders within positive psychology were perhaps attempting to over-interpret their mathematical approaches. Furthermore, Schuldberg (2002) responded to the attempts of positive psychology to define health in positive terms. He described the risk of oversimplifying health by viewing it as a dichotomy; making the case that health is not merely the absence or presence of symptomology but rather a series of characteristics, like self-improvement and adjustment.

In these critiques, grounded in an applied understanding of NDS, Schuldberg (2002) predated more recent empirically based critiques of the oversimplified and potentially dysfunctional notion that “negative” emotions should be evaluated negatively, or that avoiding such emotions will improve health (Gruber, Mauss, & Tamir, 2011). Instead, Schuldberg made a case for the necessity of negative emotions. He argued, for example, about the far reaching benefits of emotional conflict in adaptation and development.

Schuldberg (2002) also aimed to clarify and properly ground the ideas emerging from within positive psychology at that time, with chaos as a monolithic sign of health. While chaos is often an indication of health in specific systems, the presence of a chaotic pattern does not always equate to flexibility and creativity. Schuldberg acknowledged the compelling potential for chaos to be a sign of health in some circumstances, yet he argued against the type of promotion of chaos within positive psychology at the time, which he referred to as *chaos boosterism*. More than simply a critique, Schuldberg (2002) pushed the field forward as he described an approach to modeling health via systems that relies upon moderation between linearity and nonlinearity. More specifically, he argued that the degree of coupling among system components, or—when viewed from the other direction—the degree of modularity among system components (e.g., emotions, beliefs, behaviors) is key to understanding self-regulation and robustness, which are the most likely systemic factors contributing to health.

Hoeksma, Oosterlaan, Schipper, and Koot (2007) built upon this early experience sampling research on happiness, and extended it to the study of anger. They sampled anger on an hourly basis and used an empirical differential equation (EDE) method to identify fixed-point attractors (areas toward which emotion is likely to move) for anger among different individuals. Essentially EDE involves building a regression model, which sets up acceleration of anger as the criterion (response) variable and level of anger and velocity as predictors. Because the model is statistical, it is more robust to the shortcomings of psychological data than a formal differential equation model like the one used as a simulation by Fredrickson and Losada (2005). This methodology allowed Hoeksma and colleagues to empirically derive each individual's set point for anger, and also to examine each person's rate of anger acceleration or damping in relation to that set point. The general conclusion across individuals was that anger tends to settle back into a set point in a slow, meandering fashion after a stressor has perturbed it, especially for more impulsive individuals.

These pioneering works of experience sampling have recently led to a more theoretically integrated concept known as emotional momentum (Kuppens, Oravecz, & Tuerlinckx, 2010), defined most simply as stuckness or stability in emotional flow over time, or operationally as emotional autocorrelation. Early studies found that higher emotional inertia is generally unhealthy. For example, Kuppens, Allen, and Sheeber (2010) found that higher inertia was associated with lower self-esteem. Interestingly, this effect held not only for negative emotion (e.g., sad, $b = -5.20$; $p = .005$; depressed, $b = -7.11$; $p < .001$; anxious, $b = -8.84$, $p = .003$) but also for positive emotions (happy, $b = 7.45$, $p = .005$; excited, $b = 8.54$, $p = .001$; satisfied, $b = 9.29$, $p < .001$), and when comparing depressed with non-depressed individuals (dysphoric, $b = .24$, $p = .010$; angry, $b = .26$, $p = .024$; happy, $b = .21$, $p = .005$). If these results hold in the face of ongoing replications, then it would appear that positivity is only healthy if it is also flexible over time—*structure and process are key components*. Indeed, emotional momentum and related dynamical change measures have been applied to a wide range of applied areas, including personality (Brose, de Roover, Ceulemans, & Kuppens, 2015; Kuppens et al., 2010; Suls, Martin, & David, 1998), psychopathology (Bonsall, Wallace-Hadrill, Geddes, Goodwin, &

Holmes, 2012; Ebner-Priemer et al., 2015), and psychotherapy (Bornas, Noguera, M., Pincus, D., & Buela-Casal, 2014). Thus far, the empirical work in this area has supported these initial conclusions, suggesting that a lack of flexibility in both positive and negative emotion is associated with lower emotional resilience and higher psychopathology.

Most recently, meta-analytic evidence suggests an even richer view of emotional dynamics and their relationship to mental health (Houben, Van Den Noortgate, & Kuppens, 2015). Houben and colleagues found evidence across studies supporting Kuppens et al.'s (2010) findings that emotional inertia (i.e., point-by-point autocorrelation) predicts lower psychological well-being ($r = -.151$, $p < .001$). Most interesting, however, emotional variability (i.e., variance; $r = -.178$, $p < .001$) and instability (i.e., mean point-by-point difference scores; $r = -.205$, $p < .001$) were also found to predict lower well-being. It appears that emotional "flexibility" can be either healthy or unhealthy depending upon the specific operational definition one is using. Smooth, fluid emotional shifts in response to life experiences in either positive or negative directions appear to be associated with higher well-being; while stuckness (i.e., inertia), abruptness, and extremeness in these shifts is associated with lower well-being. The devil (or angel) is in the details when it comes to different types of emotional change (as well as for different scales of time; see Hollenstein, Lichtwark-Aschoff, & Potworowski, 2013, for a complete discussion).

One general take-away from this long line of research into the dynamics of emotion is that humanistic scientists should continue to ground their work in phenomenology and idiographic perspectives on human emotion, rather than attempting to find a single pattern or threshold that is optimal across individuals. Moreover, beyond the technical details of these different indices of change over time, it makes good common sense that extreme emotional range (i.e., high variance), extreme shifts (i.e., mean differences), and stuckness (i.e., autocorrelation) would each be uniquely related to individual well-being.

Resilience

Resilience is a broad topic, spanning from small-scale physiological systems to psychosocial processes. Moreover, depending on the context in which it is studied, it has a variety of functional meanings. Humanistic approaches have placed resilience front and center, inasmuch as the humanistic traditions view individuals as self-correcting given a context where basic psychological and social needs are sufficiently met. For example, Rogers (1951, 1957) built his personality and psychotherapeutic frameworks around the idea that human psychological growth is an inevitable outcome as long as the interpersonal context is sufficiently empathetic. The interpersonal process of empathy was posited to contribute toward the dual processes of accurate self-awareness and self-acceptance, allowing for congruence between the objective and the perceived self.

Historically, scientists have categorized healthy biopsychosocial systems through linear methodologies, analyses, and descriptions to identify robustness via stability. The thinking goes: A system that is invariant to moderate perturbations, or stress, is one that can appropriately withstand major stressors as well. The problem with this approach is one of scalability. Consider that an individual may be robust to the common events of the day, and even less frequent stressors such as the break-up of a relationship or a traffic citation on the drive to work. However, the stress-health relationship is linear only to a point. Once faced with new or more extreme events (e.g., the sudden loss of a job or a death in the family), the previously “stable” system will quickly and unexpectedly exhibit an extreme response. The causal event, termed a

Black Swan Event by Taleb (2007), is a stressor that pushes the system outside of its functional range of health. While the range of a biopsychosocial system can slowly increase over time via minor stressors, if an otherwise healthy system (as defined through linear robustness) has not experienced an extreme event before, it will not survive it.

This is different from how resilient systems have been defined in recent literature (Kiefer & Myer, 2015, Pincus & Metten, 2010). Resiliency is more than robustness in that a resilient system can reconfigure itself to adapt to and survive these new, never-before experienced stressors (Pincus & Metten, 2010). Such systems have been described as those that exhibit positive adaptation in the face of adversity (Tugade, Fredrickson & Barrett, 2004), or positive outcomes despite serious stressors that would otherwise limit adaptation or development (Masten, 2001).

Pincus and Metten (2010) pushed the discussion a step further with their term *metaflexibility*, which they used to describe the way in which resilient systems increase or decrease their flexibility to cope with stress, while concomitantly preserving the healthy system as a whole. Physiological, psychological, and social processes are considered to be embedded within a complex and interconnected network structure—imagine, for example, a hammock as a visual network structure. Within this structure, resilience may be defined as the degree to which a biopsychosocial system is metaflexible, meaning that the system can move smoothly between states of coherence versus flexibility (depending upon the stress it is carrying) without certain aspects getting stuck or disintegrating from the larger network. A good hammock can carry the load of a heavy person (transforming to relative rigidity in response), and then bounce back to its original shape once the person leaves. Likewise, an individual with a high degree of metaflexbility can manage an unexpected and extreme stressor, eventually readapting and maintaining the original and healthy system.

Using four classes of methodologies from NDS (time-series analysis, state-space analysis, catastrophes, and network models), Pincus and Metten (2010) provided a framework and examples for how resilience may be measured. Generally speaking, each of these models is able to capture rigidity versus flexibility, structural integration versus discontinuity, and the degree of smoothness versus stuckness in response to perturbation. Pincus and Metten framed this in the context of system coherence, and related health (i.e., stability) to stronger connections among system components. For example, disconnection with one's emotional states tends to be unhealthy, as physiological systems driven by emotion run unchecked, without the opportunity for healthy psychological or social responses by the upset individual (e.g., assertiveness or self-care responses).

Although emotional awareness and acceptance are fundamentally humanistic concepts, they are also essentially non-linear conceptions of health when one considers awareness and acceptance as facilitating biopsychosocial connectivity within a complex network structure. Within this frame, interaction between biopsychosocial components gives rise to stable, emergent behavior. The resiliency of such emergent behavior can be measured using fractal indices to identify the intermittency, or impermanency, of behavior, with greater impermanency suggested to be emblematic of a healthy, system-wide metaflexible resilience (Kiefer & Myer, 2015).

Building on the concept of resiliency, Taleb (2012) coined the term *antifragility*. He defined an antifragile system as one that gains strength with each perturbation or stressor. In fact, it is not even necessary for an antifragile system to have experienced a stressor previously in order for the system to gain strength from it. This is an important distinction between antifragility and resiliency. Another is the notion that stability, in and of itself, does not matter. Volatility breeds antifragility as the biopsychosocial system communicates with the environment via stressors, and gains strength from the instability of that relationship. One example of this in biopsychosocial systems is post-traumatic growth (Barskova & Oesterreich, 2009; Calhoun & Tedeschi, 2006). It can be said that all healthy biological systems are antifragile from the molecular scale up to the personal and interpersonal scale. Within such a framework, variability of behavior matters less while the structure of behavioral variability matters more.

This model of antifragility is similar to metaflexibility, except that the measurements of the structure of variability span myriad time scales, so that the components are not only connected at one temporal scale, but across many other scales as well. One of the great advantages of NDS theory and measurement is the ability to measure flexibility *and* structural integrity as potentially complementary to one another. Given that instability reigns within this antifragile framework, it makes sense that a system that exhibits more intermittent behavior is freed up and better poised to take advantage of new behavioral contexts (Kiefer & Myer, 2015). Several empirical lines of inquiry have been developed to test these NDS models of resilience. For example, time-series methods have been used to assess for physiological resilience by examining the complexity of movement patterns and electromyography (EMG) to predict physiological and musculoskeletal (i.e., injury) resilience in competitive athletes (Kiefer & Myer, 2015). Specifically, following an injury prevention training program, a significant test time (pre- vs. post-training) x group (untrained vs. trained) interaction was observed, $F(1, 14) = 3.24$, $p = .047$, with follow-up tests indicating that athletes exhibited increased intermittency (i.e., impermanency of states) in their preparatory EMG dynamics—objectively measured via percent laminarity, an output measure from recurrence quantification—from pre- to post-training (pre-training mean = 0.80 ± 0.01 vs. post-training mean = 0.58 ± 0.03) and also differed from the post-training dynamics of those who did not participate in the training program (post-training mean = 0.81 ± 0.01). Such characteristic dynamics underlie metaflexibility, and provide a physiological foundation for the preparedness of the athlete's system for behavioral action.

Connecting physiology to psychosocial processes, Guastello, Pincus, and Gunderson (2006) have demonstrated that *physiological linkage*, the coordination of arousal patterns during social interaction, is most often asymmetrical, displaying driver-slave dynamics, while also highly nonlinear with complex exchange of entropy in arousal levels above and beyond the simple driving up and driving down of stress. Specifically, they examined the physiological arousal levels of 74 female undergraduate strangers involved in 37 dyadic conversations. Two analysis were compared: (1) linear lag-sequential correlations (i.e., simple up and down prediction of one person's physiological arousal change 20 seconds after the other person's change above and beyond autocorrelation); and (2) a nonlinear lag-sequential correlation—equivalent to the linear regression except for placing the beta-weight of interest on an exponential value for the other person's physiological changes. The non-linear model as such represents exponential change, that is either deviation amplifying (a positive *b*-value), or deviation dampening (a negative *b*-value). Amplifying values (significantly above zero) were then interpreted as estimates of Lyapunov dimensionality (a measure of entropy; Guastello et al., 2006). The nonlinear analysis resulted in detection of linkage in all 37 dyads, and 70 of the 74 people within those dyads. The linear analysis by contrast, detected linkage in 26 of 37 dyads, and 35 of the 74 participants. Furthermore, the estimated fractal dimension for each person's physiological arousal fluctuation was found to lie between 1.0 and 2.0, with an average of 1.57—a range that is typical of behavior of self-organizing systems (with a mixture of flexibility and stability). Together, all of these results suggest that the physiological component of emotional experience is likely self-organizing, with low-level chaotic output, and that this output may drive the physiology of others with whom we are interacting at levels higher than simpler linear ups-and-downs.

On the psychological level, Marks-Tarlow (1999) has done theoretical work positing that the self-system is organized as a fractal. Guastello (2015b) has further connected these theoretical ideas to the area of self-complexity research (Linnville, 1987), suggesting that an NDS framework focuses on optimal (rather than maximal) complexity, and more appropriate measures of entropy may be ideal for clarifying nagging shortcomings in this line of study. In the empirical domain, Delignières et al. (2004) showed that fluctuations in self-esteem are organized as self-similar fractal structures. They gathered self-esteem and physical-self ratings from four individuals, twice per day, over the course of 512 consecutive days. Using spectral analysis, they found that these time series satisfied criterion for fractional Brownian motion, which means that there were long range correlations within the data, decaying over time, and that the distribution of change scores over time were fractal (with exponentially more small fluctuations compared to large). They used three additional fractal analysis measures to provide convergent validity (i.e., Rescaled Range analysis, Dispersional analysis, and Scaled Windowed Variance analysis), each of which produced consistent results.

Wong, Vallacher, and Nowak (2014) followed up and extended this work, finding that complexity within fractal fluctuations in self-image correspond experimentally to inductions that increase self-concept clarity. They used a computer mouse paradigm, during which participants were instructed to move a mouse to rate self-evaluation (positive to the right and negative to the left) across a computer screen as they listened to four-minute recordings of themselves during a prior self-narrative task. Much simpler to carry out than 500+ days of self-evaluation, this mouse paradigm is able to capture up to 500 continuous shifts in self-evaluation during a typical 4 minute task. Wong et al. (2014) used three distinct, yet converging methods to analyze potential fractal (i.e., self-similarity) dynamics in the data (i.e., detrended fluctuation analysis, signal summation conversion, and spectral regression) as well as modeling to examine long-range correlations in the time series consistent with fractal noise signatures (i.e., ARFIMA). The results were consistent with predictions, with each of the three frequency-based methods suggesting that self-evaluation fluctuations were fractal (i.e., exponentially more small fluctuations compared to large ones), and that these fluctuations showed long range temporal correlations with a mixture of persistence (deviation amplifying correlations) and anti-persistence (deviation dampening correlations). Using a composite parameter for dimensionality (i.e., complexity) comprised of the three frequency-based analyses (β), Wong et al. then tested the correlation between structure in the time series (i.e., lower β–values indicating higher anti-persistence) and participants' ratings on a scale measuring self-concept clarity. In a multiple-regression analysis controlling for relatively static features of the time series that had shown significant bivariate associations with self-concept clarity (i.e., length of static periods and number of switches from positive to negative), they demonstrated that the composite β parameter was a unique predictor of self-concept clarity ($b = -2.39$, $p < .01$).

Each of these studies on the dynamics of self-esteem provide some initial support for a more technically specific, but also classically humanistic, theory that defines the self-system as a well-integrated yet dynamically meta-flexible fractal structure, with resilience defined by the combination of structural integrity and flexibility. This fractal “meta-flexibility” definition of resilience was tested in the context of shifts to behavioral flexibility associated with severe and persistent self-injurious behaviors (SIB; Pincus, Eberle, Walder, Kemp, Lenjav, & Sandman, 2014). Using a sample of 32 intellectually disabled individuals in long-term hospital placements for SIB, Pincus et al. showed: (a) that the flow of discrete behaviors over time is fractal; (b) that behavioral flows containing SIB are *more* flexible while also being more coherent than those without SIB on average; (c) by contrast that higher levels of SIB (i.e., perseverative SIB) are associated with lower flexibility and structural integrity; and (d) that short bouts of SIB appear to serve a resilience-making function for this population, providing a means to either increase or decrease their levels of behavioral flexibility depending on pre-SIB baselines. More specifically, orbital decomposition (Guastello, 2011; Pincus, Ortega, & Metten, 2011) was used to identify statistically significant (using X^2 tests) behavioral patterns in the categorical time series comprised of two and one-half hour blocks of continuously coded behaviors (range of inter-rater *r*s from .83 to .97) from each of the 32 individuals (N = 230). The resulting pattern frequency distributions were examined first for fits to inverse-power law distributions (IPL’s; i.e., fractal, characterized by exponentially more small recurrences of patterns compared to large recurrence values across the two and one-half hours). Out of the group of 230 series, 222 (97%) had R^2 values > .60, and the mean IPL R^2 for these remaining series was .93. Further evidence for behavioral self-organization was provided by mean Lyapunov dimension (D_l) falling between one and two (mean D_l = 1.2) and mean fractal dimension values between two and three (mean D_f = 2.542).

Comparing the series with and without SIB (N = 96 and 136 respectively), the SIB series contained significantly longer patterns (mean SIB = 12.48, mean non-SIB = 8.47, t = 2.658,

p = .008), greater variety of occurrence of the 24 possible behavioral codes (mean SIB = 10.70, mean non-SIB = 9.4, t = 3.404, p = .001), more behaviors observed over the same period of time indicating more switching (mean N SIB = 173; mean N non-SIB = 234), and higher levels of Shannon entropy (H_s; mean SIB = 4.61; mean non-SIB = 4.36; t = 3.642, p < .001). Longer patterned sequences of behavior within the SIB series suggest that they were more coherent, while at the same time the greater variety of behaviors, switching among behaviors, and Shannon entropy values suggest that the SIB series were also more flexible. On the other hand, a multiple-regression analysis controlling for other predictors of H_s (i.e., number of behaviors in the series, D_f, and IPL-R^2) showed a significant negative relationship between number of SIB behaviors in a series and Shannon entropy (partial-r = −.391, p < .001). If Pincus and Metten (2010) are correct, and psychosocial resilience does indeed involve the combination of flexibility combined with coherence, then it would appear that small amounts of SIB provide behavioral resilience to these individuals, while large amounts of SIB decrease behavioral resilience.

Finally, Pincus et al. (2014) tested the notion that SIB serves a transient function for meta-flexibility, serving as a transition behavior that rapidly shifts levels of behavioral flexibility. To test this hypothesis, they identified a subsample of 26 time series (from 130 total SIB series) containing a discrete bout of SIB around the middle of the series (i.e., with at least 10 behaviors pre- and post-SIB and fewer than 50 total SIB events). Next, they regressed pattern frequency (i.e., a moving window of the total frequency values for all patterns) over time (linear or quadratic). This method allows for the identification of changing structure (higher or lower patterned recurrences) from the beginning to the end of the series. Statistically significant shifts in patterned recurrence were found in 22 of the 26 series analyzed (12 linear and 10 quadratic; linear negative, β = −.287, p < .01, N = 6; linear positive, mean β = .376, p < .001, N = 6;

quadratic negative, $\beta = 1.149, -1.197$ $p < .05$, $N = 5$; and quadratic positive, $\beta = -1.457, 1.443$, $p < .01$, $N = 5$). It is important to add that the mode behavioral lag between the SIB bout and the observed shift in structure in these 22 shifting series was one behavior (although the skew was large, mean = 7, standard deviation = 9). Altogether, this result was interpreted as evidence that SIB appears to serve a function in providing meta-flexibility for individuals who use it, rapidly shifting behavioral flexibility either up, or down, depending upon initial trajectories.

Finally, Pincus (2014) has demonstrated that intra- and interpersonal dynamics produce fractal patterns as well, and further that internal conflict and conflict resolution (i.e., incongruence and congruence processes) are sufficient to shift the complexity levels of the social dynamic in which an individual is nested. Using experimental groups of four individuals, it was found that conversational turn-taking dynamics showed patterned recurrences consistent with IPLs (R^2 range from 0.86 to 0.99), while experimentally induced internal conflict (i.e., bogus critical interpersonal feedback from group members to one or more other group members) was negatively correlated with flexibility (i.e., fractal dimension; $r = -.42$, $p = 0.037$, $N = 24$). Prior research has demonstrated the ubiquity of fractal interpersonal conversation dynamics, and their connection to emergent relationship properties (i.e., closeness, conflict and control) beyond experimentally created groups, from family systems (e.g., Pincus, 2001), to group therapy contexts (e.g., Pincus & Guastello, 2005). Altogether, these results are consistent with a model of psychosocial resilience built upon a fractal structure (combining coherence with flexibility) and meta-flexibility—the ability to shift levels of flexibility in response to challenges such as conflict and conflict resolution.

Concluding Thoughts and Recommendations

Progress in science, particularly psychological science, relies on the balance between numerous complementary philosophical perspectives (e.g., induction versus deduction; positivism versus constructivism; and idiographic versus nomothetic strategies). Most pertinent perhaps to the positivity ratio controversy is the distinction between the contexts of discovery and justification (Reichenbach, 1938). On one hand, scientists must push past the present understanding of nature in an attempt to promote further discovery. This requires creativity and open-mindedness in considering the limitless ways in which nature may ultimately work. At the same time, scientists must always do their best to try to disprove their own theories, subjecting them to the most rigorous attempts at falsification possible. When it is well-balanced, the scientific process then should usually be a rather cautious enterprise building upon one's own work and the work of others through replication and incremental discovery. This slow, tedious process of scientific exertion may then eventually set off a paradigm shift (Kuhn, 1962), developed through a broad collective effort of independent scientists and their appropriately vetted research activities.

However, the most recent evidence is rather clear at this point that faulty incentives have corrupted this process, leading to a crisis of confidence in the products of science as a whole, for which psychological science is no exception (Ioannidis, 2012; Open Science Collaboration, 2015). Rather than an egoless pursuit of truth, competitive pressures—particularly within the American Academy—have motivated scientists to take on a competitive marketing function, well beyond the traditional evidence-based battles to find a clearer and truer view of nature. There has been an explosion of rating activities within the American Academy over the last decade or two, including university rankings (e.g., *US News and World Report* scores), journal rankings, article rankings (e.g., impact factor scores), and even rankings for individual scientists (e.g., H-indexes). Ratings are not bad in and of themselves, but this pressure for superstar status can work against the pursuit of good science, and is likely a key driver of the replication crisis in science as a whole.

A variety of other subtle problems emerge as well, however, for which the positivity ratio controversy is a prime example. First, one finds the emergence of branding and marketing guilds which may to some extent drive the separation and sometimes conflicts between overlapping fields such as positive psychology and humanism. Wouldn't it make more sense for these groups to come together as scientists around a shared area of scientific inquiry without regard to brand name? One critical problem lies in the tendency of such guild-like groups to side-step existing lines of inquiry and to reinvent wheels that are different only in brand rather than in theoretical substance. A second problem lies in the tendency to use sophisticated methods, not because they are necessary to ask a novel question, but because they serve a marketing purpose, and worse—to blur the ability to have ones results fully scrutinized within the context of justification.

Solutions to these faulty incentives are not readily apparent. However, for psychological scientists attempting to investigate humanistic concepts using NDS, the correct path is rather clear. They are the same basic scientific processes we teach our students in Psychology 101. First, start your research process with a broad literature review. Of course there will be some self-citation, as people tend to be quite familiar with their own work (this article is certainly no exception in this regard). However, no distinctions should be drawn in a good literature review based primarily on branding or the drive toward self-promotion. Second, form a theoretically grounded hypothesis that is sufficient to falsify one's theory. Ideally, one tests central claims first, and acknowledges shortcomings and limitations. In this way, incremental replication and a collective scientific effort is supported. Third, use the simplest methods possible to answer the question at hand. A bivariate correlation is always better than a structural equation model if they provide equivalent information about the same hypothesis. On the other hand, a great many questions in psychology truly cannot be addressed using methods aimed at simple and static cause. As such, there is a proper, yet responsible role for NDS—essentially when a psychological phenomenon would be expected to be non-linear, dynamical, or systemic. Finally, if one's ideas are shown to be wrong, they should be abandoned in favor of solutions with a greater combination of explanatory power and parsimony.

All good scientific outcomes begin with a good enough literature review. In that light, we invite all researchers working to better understand nonlinear dynamics applied to humanistic (including positive) psychology to look up and to reference some of the work cited here, or to cite this review itself if relevant. The research cited here only scratches the surface of the good work that is being done applying NDS to topics such as emotion and resilience. If this existing work is ignored, or gets re-invented as a different brand of "truth" in 20 years, positive psychology, humanism, and NDS scientists will each miss out, and in the long-run only ignorance (and purveyors of snake oil) will succeed.

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