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How the Complexity of Psychological Processes Reframes the Issue of Reproducibility in Psychological Science

Christophe Gernigon¹

Ruud J. R. Den Hartigh²

Robin R. Vallacher³

Paul L. C. van Geert²

¹ Corresponding author

University of Montpellier & IMT Mines Alès

EuroMov Digital Health in Motion

700 avenue du Pic Saint-Loup, 34090 Montpellier, France

E-mail: christophe.gernigon@umontpellier.fr

ORCID ID: <https://orcid.org/0000-0002-3233-7551>

² University of Groningen

Department of Psychology

Grote Kruisstraat 2/1, 9712 TS, Groningen, The Netherlands

E-mails: j.r.den.hartigh@rug.nl & p.l.c.van.geert@rug.nl

³ Florida Atlantic University

Department of Psychology

Boca Raton, FL 33431

E-mail: vallacher@fau.edu

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Abstract

In the past decade, various recommendations have been published to enhance the methodological rigor and publication standards in psychological science. However, adhering to these recommendations may have limited impact on the reproducibility of causal effects, as long as psychological phenomena continue to be viewed as decomposable into separate and additive statistical structures of causal relationships. In this paper, we show that (a) psychological phenomena are patterns emerging from non-decomposable and non-isolable complex processes that obey idiosyncratic nonlinear dynamics; (b) these processual features jeopardize the chances of standard reproducibility of statistical results; and (c) these features call on researchers to reconsider what can and should be reproduced, namely the psychological processes per se, and the signatures of their complexity and dynamics. Accordingly, we argue for a greater consideration of *process causality* of psychological phenomena reflected by key properties of complex dynamical systems (CDSs). This implies developing and testing formal models of psychological dynamics, which can be implemented by computer simulation. The scope of the CDS paradigm and its convergences with other paradigms are finally discussed regarding the reproducibility issue. Ironically, the CDS approach could account for *both* reproducibility and non-reproducibility of the statistical effects usually sought in mainstream psychological science.

Keywords

Causality, complexity, reproducibility, complex systems, dynamical systems, intrinsic dynamics, ergodicity, non-linearity, formal models, computer simulation

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The repeated failures to reproduce causal effects in many domains of psychology has generated considerable concern and a call for greater methodological rigor and enhanced publication practices (e.g., Asendorpf et al., 2013; Nosek et al., 2022; Nosek et al., 2012; Simmons et al., 2011; Wagenmakers et al., 2021; Wagenmakers, Wetzels et al., 2012; Zwaan et al., 2018). Adhering to stricter research protocols and higher peer review standards is certainly warranted. However, these recommended solutions sidestep the real problem responsible for the non-reproducibility issue in psychological science, namely the gap between how causality is usually considered and tested and the processes actually at work in the emergence of psychological phenomena. On the one hand, mainstream theory and research rest on the implicit Laplacian assumption that a psychological phenomenon can be decomposed into separate and additive statistical structures of causal relationships (Hausman & Woodward, 2004; Pearl, 2009) that can be best revealed by specific interventions on samples of individuals (Freese & Kevern, 2013; Reutlinger, 2013; Woodward, 2016). On the other hand, the complex dynamical system (CDS) approach (Holland, 1998; Strogatz, 2003)—for which interest is gaining momentum in psychology—shows that psychological phenomena are patterns emerging from non-decomposable and non-isolable complex processes that obey idiosyncratic nonlinear dynamics (e.g., Guastello et al., 2009; Kelso, 1995; Nowak & Vallacher, 1998; Richardson et al., 2014; Thelen & Smith, 1994; van Geert, 1994; van Geert & de Ruiter, 2022; Ward, 2002).

Our aim in this paper is to show how the processual features of psychological phenomena affect the likelihood of obtaining standard reproducibility of statistical results and to call for a different view of what needs to be reproduced, namely the psychological processes per se as well as the signatures of their complexity and dynamics. Accordingly, we argue for a greater consideration of a *process causality* in the field of psychology. According to this type of causality, a process is both dynamic, because it obeys a temporal interdependence of the states of the psychological phenomenon under study, and complex because of the richness of the interactions involved in the emergence of this phenomenon (Dowe, 1992; van Geert & de Ruiter, 2022). Given these characteristics, the CDS approach is well suited to shed light on process causality. This requires the development and testing of formal models of psychological dynamics, which can be greatly facilitated by computer simulation. Ironically, this processual orientation could also account for *both* reproducibility and non-reproducibility of the statistical effects so eagerly sought after by mainstream psychological science.

Reframing the Reproducibility Issue

In canonical behavioral science research, the primary aim is to discover general or lawlike causal principles which hold on the population level (Freese & Kevern, 2013). These general causal relationships are customarily represented in the form of probabilistic statements such as “If some intervention with respect to X_i changes the probability distribution of some other variable X_j , then X_i causes X_j ” (Hausman & Woodward, 2004, p. 848). Causality, moreover, can be represented in the form of sparse structures of directional causal factors and effects (Pearl,

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2009) that can be isolated and exported to other contexts (Hausman & Woodward, 1999, 2004). Causality is also conceived as interventionist or manipulationist in the sense that nature or humans can intervene in processes and/or manipulate causes to intervene in processes (Reutlinger, 2013; Woodward, 2016). Finally, the complexity of causality is assumed to be cumulative since the addition of causal effects—including few-variable multiplicative interaction effects—would increase the amount of explained variance of a phenomenon (Ahadi & Diener, 1989).

Today, paradigms based on this approach have freed themselves from the original Laplacian determinism according to which certainty regarding scientific prediction would require a super intellect—a demon—to have absolute knowledge of the precise state of every element of the universe (Laplace, 1814). However, paradigms in psychology still seem to be guided by a sort of Laplacian demon—probabilistic this time—for whom psychological phenomena mainly result from the additive contributions of separate structures of causal relationships.

The Intractable Complexity of Causality

The combination of isolability of cause-effect relationships, their generalizability, and their additivity has met with a fair degree of success in psychological research. Achieving successful interventions, however, does not mean that such causality reflects the objective causal structure of the world (Botterill, 2010; Fried, 2020). Thus, most discoveries in psychology—even robust—can be considered discoveries of *non-causal* patterns (Eronen, 2020; Rozin, 2001). Relevant illustrations of this can be found in the theoretical controversies surrounding the nature of the mental processes that are assumed to produce people's post-manipulation attitude with respect to well-known and highly reproducible psychological phenomena such as cognitive dissonance reduction (Harmon-Jones & Harmon-Jones, 2007) or obedience to authority (Haslam & Reicher, 2017).

Despite the general acknowledgement of a complex interplay of myriads of factors, the statistical techniques classically used to account for the causal structure of psychological phenomena only allow us to intelligibly test moderation or mediation effects between two or at most three factors (Baron & Kenny, 1986). Moreover, if complexity were cumulative in nature, it would suffice to add variables and interactive combinations of variables in our prediction models to explain with certainty an increasing amount of variance in the psychological phenomenon under study. However, despite decades of research in psychology, this mainstream focus on the accumulation of a multitude of causes yields models that barely explain more than 30% of the variance of phenomena, with a reproducibility rate reaching less than 40% (Open Science Collaboration, 2015). As a result, it is obvious that the quest for probabilistic, interventionist, and additive causality has not led to a reliable account of the complexity of psychological processes.

The CDS perspective (Holland, 1998; Strogatz, 2003) and its applications to psychology (e.g., Guastello et al., 2009; Kelso, 1995; Nowak & Vallacher, 1998; Richardson et al., 2014; Thelen & Smith, 1994; van Geert, 1994; Ward, 2002) shed light on the richness of the dynamic interactions between components and offer universal explanations for the variability of psychological phenomena. In brief, a CDS can be defined as a set of components, the dynamic interactions among which give rise to the emergence of specific states with causal properties that cannot be reduced to the specific contributions of the underlying components (Wallot & Kelty-Stephen, 2018). Within this framework, causality is multiple and distributed (Haken, 1992;

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Kelso, 1995). Even the most basic phenomena, such as movement regulation (Sparrow & Newell, 1998), motivation (Gernigon et al., 2015), or self-concept (Nowak et al., 2000), emerge out of numerous components that are interacting consistently or conflictingly, both within and across individual, contextual, and situational levels. Self-organizing processes resulting from these interactions are distributed at all levels of organization, from the neural level to the level of social interaction (Nowak et al., 2017; Tognoli et al., 2020). This kind of distributed causation is circular in that lower-order self-organizing processes result in higher-order coordinated patterns which in turn constrain lower-order processes, and so forth (Kelso, 1995; Witherington, 2011).

In light of these properties of CDSs, causation is intractable in a traditional sense. Unlike the causal structures considered in mainstream paradigms, complex causal networks are not decomposable (Bechtel & Richardson, 2010). They cannot be understood in terms of cumulative contributions of many components (Den Hartigh et al., 2017), just as the wetness of water cannot be understood as the addition of the combustion-related properties of each of its two atomic constituents (Lickliter & Witherington, 2017). Therefore, Laplace's demon, in its probabilistic working clothes, would be surprised each time it passes a boundary of complex system organization, where emergent properties originate, fundamentally altering its current understanding of the world. Given this intractable causation, the current rates of reproducibility of effects may be consistent with what can be expected from a complex world, and therefore as only moderately improvable by the recommended research and publication practices.

The Role of Time in Psychological Processes

Beyond its problematic assumptions regarding causality, the canonical perspective is not well suited to capture the insight that psychological processes evolve over time. Any process is by definition a series of actions or changes leading to a particular outcome and is therefore dynamic. Although this obviously applies to psychological processes, most of the research in psychology is cross-sectional. By testing immediate effects of putative causes, then, the canonical paradigm provides incomplete and potentially misleading accounts of psychological processes. Besides, when the temporal process is accounted for, time is often treated as an independent variable that is uniformly sampled (Bijleveld et al., 1998). This approach ignores the *intrinsic dynamics* of psychological processes (Vallacher et al., 2015) and the different interconnected timescales on which such dynamics occur (Granic & Patterson, 2006; Lichtwarck-Aschoff et al., 2008; Thelen & Smith, 1994; van Gelder & Port, 1995).

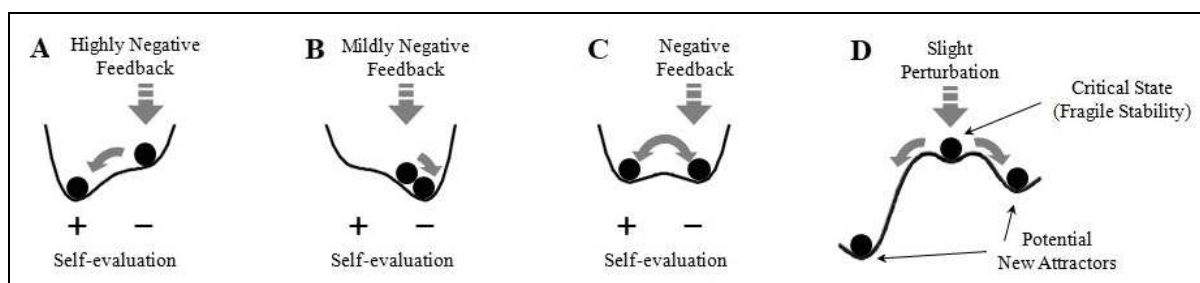
The intrinsic dynamics of a complex system result from self-organization processes that develop over time in the form of iterative interactions between system components. Hence, the state of a system at a given moment depends not only on the configuration of its components and their interactions at that moment, but also on its previous state, which itself depended on a previous state, and so on. Any complex system is thus necessarily a *dynamical system* which displays properties of *history dependence*. Its intrinsic dynamics both generate and are constrained by attractor dynamics (Guastello & Liebovitch, 2009), the regimes of which are often more meaningful than are the immediate effects and outcomes of a putative cause. As a process unfolds, the phenomenon at issue can display patterns of change in its global properties, even in the absence of external influences and sometimes in opposition to such influences. An initially small effect may polarize by growing over time, for example, whereas an initially large effect may diminish and become trivial over time.

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These two scenarios—as well as others, such as oscillation between two different states—are likely to be observed depending on the attractor landscape for the process in question. Thus, for instance, the effect of a negative social feedback on self-esteem can follow very different scenarios (Vallacher et al., 2002). For a person with a single attractor for positive self-evaluation, even highly negative feedback might be fleeting as the person's self-relevant thoughts converge fairly quickly on the positive attractor (Figure 1A). But for a person with a single attractor for negative self-evaluation, even mildly negative feedback might trigger a sustained pattern of negative self-evaluative thoughts (Figure 1B). And for yet another person, negative feedback might set in motion a sequence of self-evaluative thoughts that oscillate between positive and negative states if the person's attractor landscape is multistable, with attractors for both positive and negative self-evaluation (Figure 1C).

Figure 1

Effects of Different Perturbations on a System's Behavior Depending on its Attractor Landscape



Note. The ball represents possible states of the system's behavior.

Short-term experiences may represent mere perturbations of the state of a psychological system that is at its attractor, with—as mentioned above—the system returning to the equilibrium provided by the attractor. However, the accumulation of perturbations over time can weaken the force of attraction and modify the attractor landscape, resulting in a progressively slower return to the attractor (e.g., van de Leemput et al., 2014; Wichers et al., 2016). Then, a mildly perturbing experience may be sufficient to dislodge the system from its attractor, resulting in an abrupt transition towards a new attractor state.

Quite often however, CDSs remain poised in critical states that can be left as a result of tiny perturbations. This kind of permanent fragile stability—namely *self-organized criticality* (Bak, 1996)—is known to account for temporal fluctuations of systems' states, the frequencies of which remain invariant across timescales and obey typical $1/f$ power-law distributions also called $1/f$ noise or pink noise (e.g., Gilden et al., 1995). Self-sustained critical states also provide CDSs with the property of *metastability* (Usher et al., 1995), which is the capability to rapidly shift towards a variety of coexisting latent attractors (Figure 1D). Self-organized criticality and metastability give systems a certain flexibility that enables their rapid adaptation to novelty and environmental changes. Although prevalent in natural phenomena (Bak, 1996), these properties remain understudied in psychology (Kello et al., 2010; Tognoli & Kelso, 2014) and their systematic detection is only beginning to develop (see examples of studies on this subject below, at the end of the part devoted to the formal modeling of the intrinsic dynamics of psychological process).

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Reshaping an attractor landscape amounts to creating a connection between different timescales, which itself provides an additional account to the non-linearity of psychological phenomena (Granic & Patterson, 2006; Lichtwarck-Aschoff et al., 2008; Thelen & Smith, 1994; van Gelder & Port, 1995). With respect to cognitive development, for example, the Piagetian dialectics between assimilation and accommodation processes has been formally modeled and empirically evidenced as an instance of attractor dynamics in which short and long time scales influence each other (van Geert, 1998). In the short term, a child's first experiences with a new conceptual object are constrained by the developmental stage—the initial attractor—already reached by this child, so that this object is assimilated according to his or her current cognitive structures. But in the longer term, the repetition of similar experiences will trigger an accommodation process which consists in modifying these cognitive structures—the attractor landscape—until the object can rather suddenly be properly conceptualized. The new developmental stage thus reached will then serve as a new attractor for future assimilations, and so forth.

Reciprocal and nonlinear influences between short and long timescales have also received empirical support for many psychological phenomena, including personality development (Nowak et al., 2005; Shoda et al., 2002), motor learning (Zanone & Kelso, 1992), motor development (Newell et al., 2001; Thelen et al., 1993; Thelen & Ulrich, 1991), cognitive development (Steenbeek & van Geert, 2008), social development (Granic et al., 2003), psychological momentum (Den Hartigh, van Geert et al., 2016), and identity (Lichtwarck-Aschoff et al., 2008).

In sum, when self-maintaining stable states emerge, systems are highly predictable, as they actively counteract a wide range of perturbations (e.g., social influence, experimental interventions). But during transitory episodes between attractors, systems are virtually unpredictable, as any minor or insignificant influence can have very different effects (Haken et al., 1985; Kelso, 1995). Such dynamics promote relative unpredictability due to the lack of proportionality between the quantity or the magnitude of putative causes and the variations of the psychological phenomenon under study. Hence, the non-linearity that results from the attractor-governed intrinsic dynamics of psychological phenomena constitutes a headache for researchers in search of reproducibility of linear statistical effects.

The Ergodicity Issue in Nomothetic Science

Among the recommendations formulated to overcome the crisis of reproducibility in psychological science is the search for statistical power (Simmons et al., 2011; Szucs & Ioannidis, 2017), which would be better guaranteed by large-scale studies. This reassurance, however, assumes *ergodicity*, the property that a statistical model resulting from the analysis of variables carried out at the group level is confirmed by the analyses of individuals' time series (Fisher et al., 2018; Hamaker, 2023; Molenaar & Campbell, 2009). Satisfying ergodicity is extremely rare in psychology, where the idiosyncratic nature of processes is prevalent.

As an illustration in the field of personality, Molenaar and Campbell (2009) analyzed data from 90-day repeated measures with a 30-item Big Five personality inventory. The correlations between the item scores that were observed at the interindividual level could not be retrieved in separate analyses of intraindividual variations. The intraindividual and the interindividual models differed both in the number of factors and in how the factors related to the items. The authors

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concluded that the correlations among a person's repeatedly measured items scores cannot be explained by the Big Five personality factors. Empirical evidence for the non-ergodicity of psychological processes has also been observed for other models of personality (Kim & Rosenberg, 1980), affective processes (Fisher et al., 2018; Molenaar et al., 2009), cognitive development (van Geert, 2014b), teaching-learning processes (Geveke et al., 2017), talent development (Den Hartigh et al., 2018; Den Hartigh, van Dijk et al., 2016), motor learning (Liu et al., 2006), social interaction (Steenbeek & van Geert, 2008; van Geert & Steenbeek, 2005), and resilience (Hill et al., 2021).

The ergodicity problem posed by the large-scale studies does not invalidate the value of such studies. Finding robust non-causal patterns is indeed helpful in identifying successful interventions (Eronen, 2020). Moreover, averaging population data can provide valuable information when populations are the topic of interest (Weston et al., 2019). However, this tells us very little about the individual processes, which are typically the primary aim of psychological science. In the CDS framework, effects depend on the structure of the attractor landscapes to which perturbations are applied. In other words, the statistical features of phenomena hold as long as they occur in the same attractor landscape. However, as shown above, psychological attractor landscapes are likely to show quite considerable inter- and intraindividual differences that jeopardize homogeneity of psychological processes. By averaging over many attractor landscapes, the typical statistical features of psychological processes are all reduced to one, which limits reproducibility to samples of individuals with similar intra- and interindividual distributions of attractor landscapes. These conditions are rare and basically never controlled, which even raises doubts on the theoretical meaning of the reproducibility of an averaged phenomenon that, at worst, might not apply to any of the individuals involved in a study.

Reproducing the Dynamics of Psychological Processes

The CDS perspective exposes the limitations of the canonical approach for capturing the iterative dynamics defining psychological experience. Therefore, rather than trying to reproduce sparse structures of causal relationships, the CDS approach aims to reproduce the complex and dynamic interactions at the core of psychological processes, as well as the typical statistical signatures of these processes. With the advent of modern technology and the development of sophisticated methods and tools in recent years, it is now possible to go beyond inferring the processes of thought and behavior to investigating directly such processes as they unfold. There are many specific methods for doing so, but to a large extent they can be understood in terms of two general strategies: the formal modeling and empirical assessment of intrinsic dynamics, and the reproduction of the idiosyncratic and self-organized nature of psychological processes through computer simulations.

Formally Modeling Intrinsic Dynamics and their Signatures

The intrinsic dynamics (Vallacher et al., 2015) of complex systems follow evolutionary rules that can be expressed mathematically, generally in the form of iterative functions and differential or difference equations. These are equations of change, including equations of zero change describing stability. Iterative functions, such as those formalized by logistic equations, have proven particularly useful for modeling the dynamics of such phenomena as personality

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development (Nowak et al., 2005), language development (van Geert, 1991), cognitive development (van Geert, 1998), talent development (Den Hartigh et al., 2018; Den Hartigh, van Dijk et al., 2016), and social development (Steenbeek & van Geert, 2008). Relatedly, differential equations and difference equations have made it possible to model many psychological phenomena in areas such as motor coordination (Haken et al., 1985), visual perception (Fajen & Warren, 2003; Warren, 2006), emotions (Hoeksma et al., 2007), interpersonal relationships (Gottman et al., 2002; Steele et al., 2013), and learning-teaching interaction (Merlone et al., 2019).

Empirically examining attractor-governed nonlinear dynamics requires the collection of time series of behavioral or psychological data that may span different timescales. For example, short-term dynamics can be captured from encodings of recorded speech or behavior (de Ruiter et al., 2018; Steenbeek & van Geert, 2008; van Geert & Steenbeek, 2005) or from moment-to-moment measurements of psychological states using a computer mouse (Freeman & Ambady, 2010; Gernigon et al., 2004; Spivey & Dale, 2006; Vallacher et al., 2002; Wong et al., 2016). Long-term dynamics can be collected by means as simple as daily log recordings (Delignières et al., 2004; Olthof, Hasselman, & Lichtwarck-Aschoff, 2020; Olthof, Hasselman et al., 2020; van de Leemput et al., 2014; Wichers et al., 2016).

The resultant data sets lend themselves to specific time series analyzes capable of detecting idiosyncratic signatures of CDSs, which can be confirmed at the nomothetic level. For example, Recurrence Quantification Analysis (RQA; Zbilut & Webber Jr., 1992) enables the detection of attractors and Detrended Fluctuation Analysis (DFA; Peng et al., 1993) can estimate the complexity of a phenomenon based on its power-law temporal distribution. RQA has proven useful for identifying attractors in psychological phenomena such as shared regulatory strategies during collaborative learning (Dindar et al., 2019), affects and verbal interactions at work (Meinecke et al., 2020), the relationship between affective experiences and health (Jenkins et al., 2020), and individual (Shockley & Turvey, 2005) and interpersonal motor coordination (Richardson et al., 2005). DFA, meanwhile, has made it possible to reveal typical $1/f$ signatures of complexity with respect to cognitive performance (Holden et al., 2009; Kello et al., 2008; Kello et al., 2007; Van Orden et al., 2003), memory retrieval (Maylor et al., 2001), language learning (Lowie et al., 2014), mood variation (Gottschalk et al., 1995), self-esteem and physical self dynamics (Delignières et al., 2004; de Ruiter et al., 2015), motor learning (Nourrit-Lucas et al., 2015), motor performance (Den Hartigh et al., 2015; Den Hartigh et al., 2021; Delignières et al., 2009), and human gait (Delignières & Torre, 2009; Hausdorff et al., 1996). Interestingly, unlike Gaussian distributions, $1/f$ distributions have been found to satisfy the ergodicity assumption (Kelty-Stephen & Mangalam, 2022).

In sum, dynamic equations account for a process causality, the validity of which can be attested, among others, by the distributions of the products of computer simulations implementing these equations. More specifically, these distributions must exhibit the statistical signatures typical of the complex and dynamic features of the modeled processes. As will be illustrated in the next two sections, these features and their statistical signatures are often reproducible, whereas classical interventionist causations are hardly so (see Open Science Collaboration, 2015).

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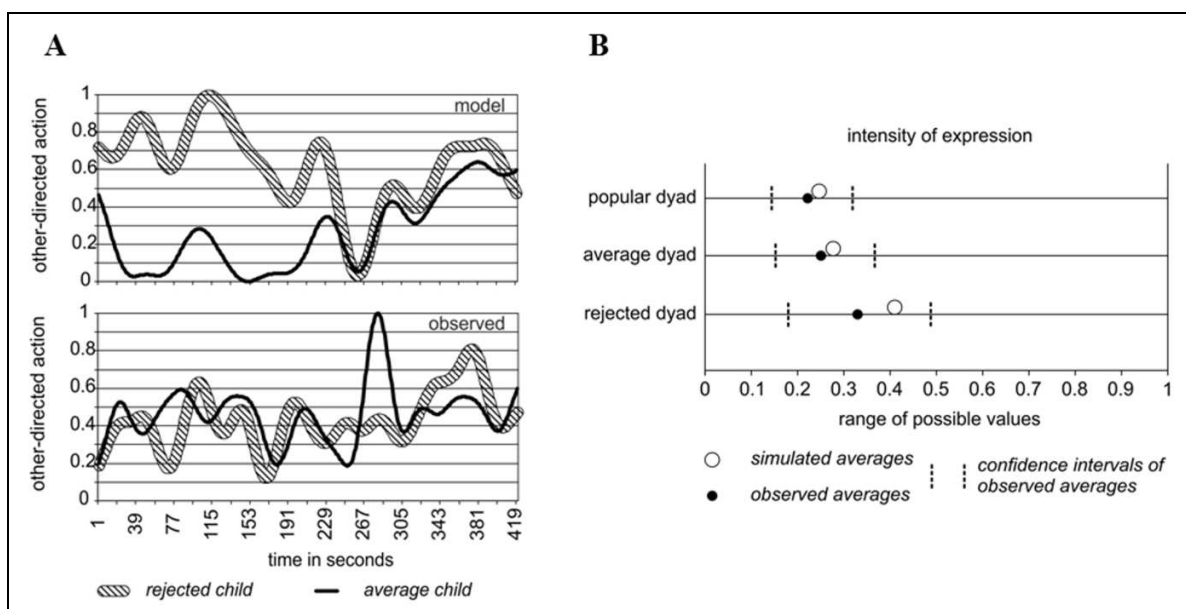
Reproducing the Idiosyncratic Nature of Psychological Process

Unlike nomothetic science, CDS research focuses on processes as they occur in individual cases which can nonetheless be generalized to population properties. However, the obtained generality is different from the general laws derived from large-scale studies. Therefore, the reproducibility that is aimed for will also be different. Consider, for example, dyadic play in children of different sociometric status (Steenbeek & van Geert, 2008; van Geert & Steenbeek, 2005). According to the classic relationship found between sociometric status and peer-relations among children, “rejected” children display more negative behaviors towards others than do “popular children” (Newcomb et al., 1993). However, behavior between children is shaped in an ongoing fashion by interacting concerns, emotions, and social skills, within and between children. The social behavior of a rejected child in a particular dyadic play situation, for instance, is an emergent, continuously co-constructed property of this concrete play context.

Temporal patterns of play behavior can be revealed by computer simulation, which generates an arbitrarily large number of realizations of possible dyadic play interactions. Qualitative similarities between simulated and observed temporal patterns can be determined and statistically tested (Figure 2A). In addition, one can compare the empirical results at the sample level (i.e., average sample properties statistically dependent on sociometric status) with sample outcomes of the simulation model (Figure 2B). That is, an “individualizing” dynamic model of specific individual cases of dyadic play also generalizes to the population level by, for instance, predicting group averages and dispersion measures such as standard deviations. Finally, while such a model may replicate tendencies observed in mainstream nomothetic research, it can also provide results that are contrary to these tendencies (e.g., rejected dyads experiencing relatively positive rather than negative outcomes in slightly different parameter contexts).

Figure 2

Simulations and Empirical Observations of Single Dyads (A) and Sample Averages (B)



Note. Reprinted from van Geert and Steenbeek (2005) and Steenbeek and van Geert (2008) with permissions from Elsevier Inc. and Wiley & Sons Ltd, respectively.

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As a result, the CDS approach—as implemented by formal modeling and computer simulations—allows the characterization at an idiosyncratic level of psychological processes hypothesized from traditional empirical research, while offering the opportunity to test their generalizability. Hence, unlike reproducibility of statistical models derived from large-scale studies, reproducibility here applies from the statistical properties of data resulting from the simulations to those of samples of individuals.

Simulating Self-organization in Psychological Process

Self-organization processes that give rise to the properties of history dependence, non-linearity, timescales interconnection, and idiosyncrasy of psychological phenomena can be modeled and tested using computer simulations. A computer simulation is a computational model of the behavior of a system associated with an experimental research design—in other words, a virtual experiment (Harrison et al., 2007). It can offer conceptual explanations of the dynamics of psychological phenomena, thereby providing insights into the necessary and sufficient *theoretical principles* underlying the phenomena. Thus, it makes it possible to implement self-organization processes and hence to observe and test how psychological phenomena identifiable at a macroscopic level emerge from the rules modeled at the microscopic level, and conversely how to arrange these rules to bring out a targeted global pattern (Nowak, 2004). The explosion of digital sciences has led to a profusion of computer simulation methods, some of which have found fruitful application in psychological science (see Vallacher et al., 2017). We present here five relevant methods—dynamic networks, dynamic field models, agent-based models, cellular automata, and genetic algorithms—and highlight how each can shed light on (non)reproducible psychological effects.

Dynamic Networks

Dynamic networks represent networks of variables (nodes) connected by different types of links. There are various forms of dynamic networks (see Albert and Barabási, 2002, for a review). In developmental psychology, for example, the dynamic interactions between variables can be expressed by a system of coupled logistic growth (differential) equations (see van Geert, 2014a, for a tutorial). Such is the case for the CDS model of cognitive development that was presented above to illustrate the notion of attractor dynamics (van Geert, 1998). In this model, a dynamic network linked an individual's internal array, specifying a range of possible actions or experiences, and an external array of experiences that this individual may have to face and that constitute potential sources of learning and development. In the model, the probability of an actual activity or experience at a particular level (e.g., on a cognitive dimension ranging from sensorimotor to abstract thought) is defined by a dynamic (i.e., changing) weight function. For a young infant, for instance, the weight would be zero for anything that exceeds the sensorimotor level. At any moment in time, the weight function depends on a confluence between an internal content (e.g., a real-time activity at a particular cognitive level) and an external content (e.g., an event, problem or instruction that triggers a particular experience).

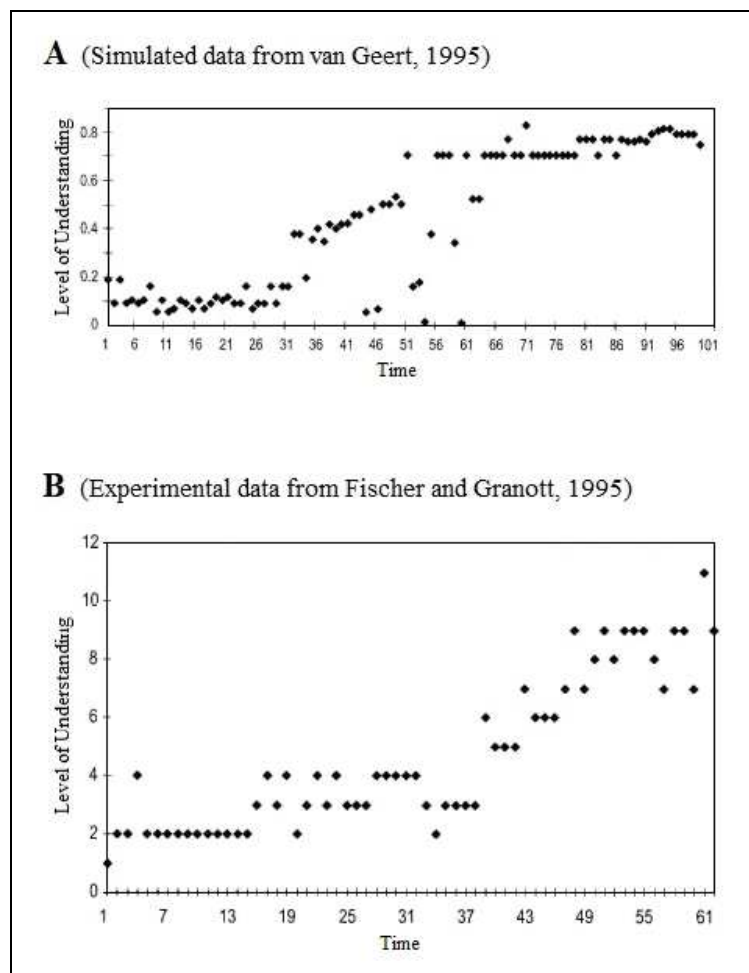
The dynamics of the model incorporates classic developmental mechanisms. The first includes the consolidation of the current familiar level of performance (actual level of development) and the adaptation to new challenges, close to but more advanced than this

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familiar level (potential level of development). Maximal adaptation occurs at levels that correspond to the crossing of two exponential functions, a familiarity and a novelty function. This mechanism implements the system's potential level of development and expands the system's range of possible activities and experiences, thus accounting for and generalizing the Piagetian assimilation-accommodation principle. The second mechanism involves the principle of adapting externally triggered experiences, challenges, etc. to the currently dominant level of performance. Help provided by more competent others and the benefit of facilitating contexts exemplify this principle. This mechanism implements and generalizes the Vygotskian principle of the zone of proximal development.

Figure 3

Outputs of Computer Simulations of van Geert's (1998) Dynamical Model of Cognitive Development (A) and Data from Fischer and Granott's (1995) Experimental Study of Cognitive Microdevelopment (B).



Note. Adapted from van Geert (1998) with the permission of the *American Psychological Association (APA)*.

Van Geert (1998) compared the outputs of computer simulations implementing his model with a wide variety of empirical data. A study by Fischer and Granott (1995) on cognitive micro

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development, for instance, provided a relevant comparison. In this study, graduate students had to interact to understand the behavior of a mini robot. The content of their interactions over time was coded and scored according to their level of conceptualization ranging from sensorimotor actions to abstractions. The properties of the data yielded by van Geert's computer simulations (Figure 3A) resembled Fischer and Granott's experimental data (Figure 3B) in that they revealed stagewise nonlinear development, relatively broad ranges of developmental levels, occasional multimodality in terms of simultaneous activation of distinct levels, and temporary regressions towards lower levels of development. These typical features of CDSs may explain why psychologists who view cognitive development in terms of discrete stages resulting from continuous growth have difficulty replicating Piaget's fixed stages of development.

Dynamic networks of various forms have proven to be relevant to many topics, including the development of general intelligence (van der Maas et al., 2006), language development (van Geert, 1991), parent-child interaction (van Dijk et al., 2013), adolescent development (Kunnen et al., 2019), affective states (Thagard & Nerb, 2002), psychopathology (Borsboom & Cramer, 2013; Borsboom et al., 2018), attitudes (Monroe & Read, 2008), goal-directed motivation (Westaby et al., 2014), social interaction (Westaby et al., 2016), and the development of talent and exceptional performance (Den Hartigh et al., 2018; Den Hartigh, van Dijk et al., 2016). Dynamic networks can be relatively easily implemented by researchers with the aid of free, open source, and user-friendly software such as *Insight Maker* developed by Bellinger (<https://www.insightmaker.com>). The software provides many examples of models, including the mathematical formats of the underlying dynamics.

Dynamic Field Models

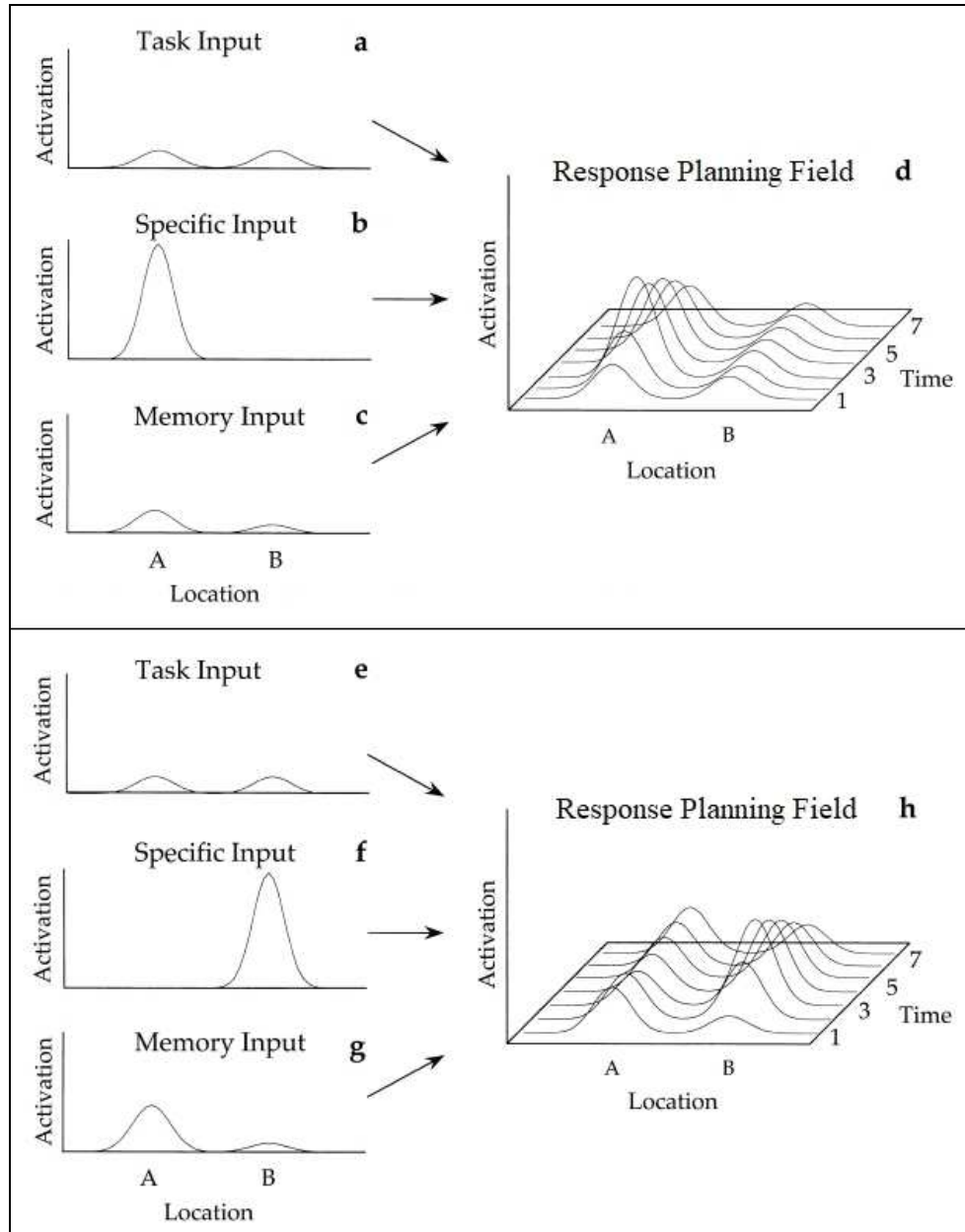
Dynamic field models are mathematical and simulation methods associated with dynamic field theory (Erlhagen & Schöner, 2002; Schöner et al., 2015; Thelen et al., 2001). According to this theory, continuous perceptual, motor, and cognitive dimensions, such as spatial location or degree of similarity between objects, are represented in the brain in the form of dynamic neural fields, generated by the changing and adaptive activity of populations of neurons.

In dynamic field models, all the neural fields that can potentially be activated for a particular dimension are graphically represented along an axis. Thus, each point on the axis corresponds to a particular neural configuration, and each configuration is characterized by a fluctuating level of activation propensity which takes the form of a peak that locally alters the axis. Levels of activation depend on three types of inputs: task input, specific input, and memory input. Task input is the stationary configuration of a task that includes its goal, its spatial and material environment, and the different response alternatives. For example, graphs a and e in Figure 4, adapted from Spencer et al. (2001), show how the input of a task offering two response alternatives, A and B, activates two corresponding neural fields. Specific input refers to any transitory information (e.g., clues) that can guide the response to one of the alternatives. Graphs b and f in Figure 4 show the field activations resulting from specific inputs in favor of response A or response B, respectively. Memory input represents memory traces of past activation distributions resulting from prior experience. These traces provide the system with its property of history dependence. Graphs c and g in Figure 4 show two examples of field activation resulting from different memory inputs.

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Figure 4

Dynamic Field Model of the Propensity to Provide a Response (A or B) in a Dichotomous Choice Task



Note. Over the course of experiences with the task, neural fields activation evolves (Graphs d and h) by integrating a stationary task input (Graphs a and e), varying specific inputs (Graphs b and f), and varying memory inputs (graphs c and g). Adapted from Spencer et al. (2001) with the permission of Wiley & Sons Ltd.

Over time, localized patterns of activation can self-stabilize through an integrative mechanism accounted for by a set of equations originally created to describe the temporal evolution of neural activation in the cortex (e.g., Amari, 1977; Grossberg, 1988). This integration

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mechanism—the strength of which can be tuned with some equation parameters—is based on cooperative and competitive interactions between activated fields: Fields that are close together are mutually excitatory and merge while gaining magnitude, whereas more distant fields are inhibitory at the expense of the most fragile which fade. The resulting self-sustained peaks depict an attractor landscape that accounts for the probability of occurrence of certain decisions or actions with regard to the task to be performed (e.g., graphs d and h of Figure 4).

Using dynamic field modeling, Thelen et al. (2001) attempted to account for the diversity of findings from research on the famous Piagetian "A-not-B error". The A-not-B error, which is typical of 7–12 month-old-infants, consists of continuing to search for a toy in location A based on previous successes in this location, although the toy has been hidden, in view of the infant, in location B. While research based on this canonical form of investigation has robustly supported the A-not-B error, the many contextual variations (e.g., environment and hiding place configuration, delay between hiding and search, nature of what is to be sought) that have been applied to the paradigm have resulted in inconsistent findings as well as disparate theoretical explanations. The aim of the dynamic field model developed by Thelen et al. was to examine how the probabilities of the A and B responses evolve over trials in the task, depending on varying conditions set by the manipulation of the model parameters. The computer simulations implementing the model faithfully reproduced the A-not-B error when the parameters were set according to the canonical Piagetian paradigm. With different parametric settings, the model also accounted for known effects of age, delay, and various contextual characteristics. Radical shifts in simulation outputs appeared over time, resulting from small changes in model parameters and from system history. This non-linearity, typical of CDSs, helps explain the sensitivity of the A-not-B error paradigm to contextual variations and why the results obtained with this paradigm cannot be easily reproduced using the classic nomothetic approach.

The mathematical implementation of dynamic fields has been shown to successfully simulate a wide variety of cognitive, performance, and developmental phenomena based on experimental data. Examples are various features of working memory (Schutte et al., 2003), executive functions and their development (Buss & Spencer, 2014), higher cognitive functions including visual and embodied cognition (e.g., Johnson et al., 2008), and word learning (Samuelson et al., 2017; Samuelson et al., 2009). As with dynamic networks, researchers wishing to familiarize themselves with dynamic field modeling will find valuable help at <https://dynamicfieldtheory.org>, in the form of tutorials, online simulators, and free modeling software.

Agent-based Models

Agent-based models are computer interfaces that simulate the actions of a large number of virtual agents (i.e., components of living or non-living systems) that interact with each other and with a virtual environment within which they evolve, on the basis of properties attributed to both agents and their environment. To be considered an agent, a component of a system must be discrete, endowed with its own goals, equipped with goal-related perceptual and action tools, autonomous—though limited by the local nature of the usable information—in goal pursuit, and adaptable as a result of interactions with other agents and with the environment (Conte & Paolucci, 2014; Jackson et al., 2017; Smaldino et al., 2015; Smith & Conrey, 2007). Agent-based models make it possible to observe the emergence of global psychological and behavioral

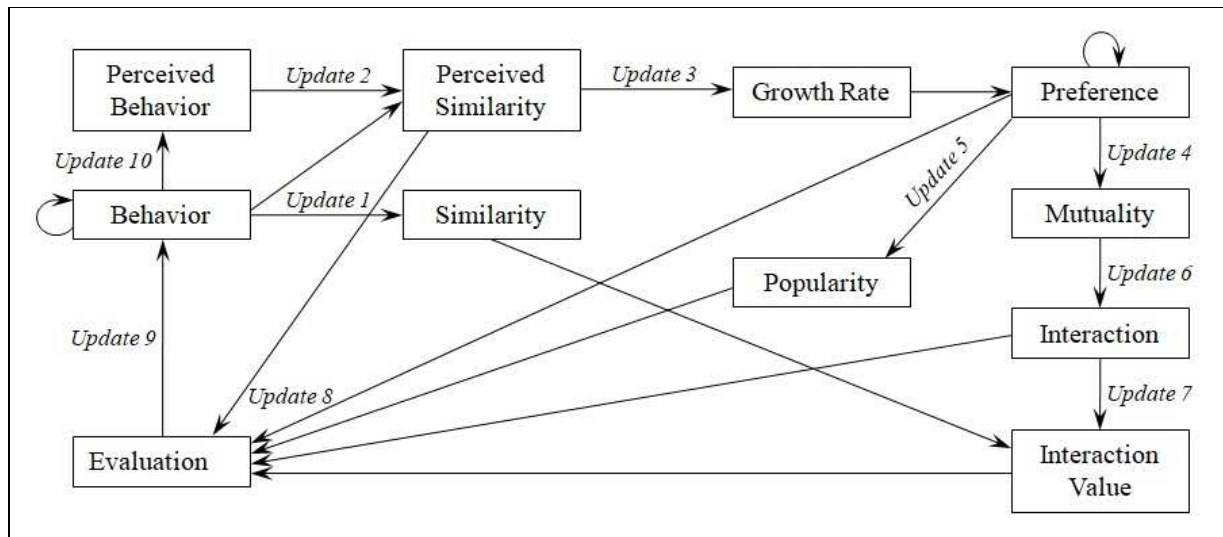
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patterns. Such patterns result from both the initial conditions of the system and its self-organization process, as driven by the iterative application of defined local interaction rules.

An example illustrating the interest of agent-based models is Schuhmacher et al.'s (2014) modeling of the development of risk behaviors during adolescence. This study aimed to shed light on the self-organization processes at work in the formation and evolution of friendship groups and in the emergence of homogeneity between peers with respect to conventional (i.e., school attendance, sports, work) or risky (i.e., aggressiveness, alcohol use, soft drugs) behaviors. Each agent in the model is endowed with numerically translated properties (some randomly initialized) concerning its behavior (conventional, mixed, or at risk), perceptions of other agents' behaviors, real and perceived similarity with other agents, preference for other agents, mutuality of preference between two agents, interactions with other agents (present or absent), value (positive or negative) of these interactions, popularity, and evaluation of the quality of interactions. These properties are dynamically linked by a set of coupled equations and decision rules that update their values at each simulation step. These equations and rules account for the cycle of mutual influences and updates summarized in Figure 5. In such a model, every agent is both influenced and influential. Its behavior update—ultimately depending on the evaluation of its interactions with other agents—is both the output of a simulation step and the input of the next one.

Figure 5

Summary of the Cycle of Influences and Updates for Each Agent and for Each Simulation Step of Schuhmacher et al.'s (2014) Model of Development of Risk Behaviors



Note. Behavior and perception of others' behaviors first influence real and perceived similarity with others (updates 1 and 2), which then influences the growth rate for preference and consequently preference (update 3), which influences mutuality of preferences (update 4), popularity (update 5), and contributes to influence the evaluation of the interaction (update 8). Mutuality influences the decision of interacting or not with another agent (update 6), which influences the value of this interaction (update 7) and also contributes to influence the evaluation of the interaction (update 8). The value of this interaction and popularity also contribute to influence the evaluation of the interaction (update 8), which influences the behavior (update 9), which ultimately influences the perception of the other agents' behaviors (update 10) to enter a new cycle, and so forth.

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The model simulations resulted in (a) the formation of distinct friendship groups with varying degrees of clustering; (b) positive correlations between agents' behavioral similarity and between-agent proximity in the friendship network; (c) a decrease, from beginning to end simulations, in behavioral variance within the groups; and (d) a moderate amount ($\approx 30\%$) of cases of influence (i.e., behavioral changes) and a large amount ($\approx 80\%$) of cases of reinforcement (i.e., stabilization of behavioral profiles). Thus, this dynamical model alone is able to account for a variety of results from a disparate research on peer interaction and adolescent behavior showing that (a) dyadic relationships lead to the formation of friendship groups or cliques (e.g., Brown & Klute, 2003); (b) friendship relationships among adolescents promote homogeneity in their conventional behaviors (e.g., Henrich et al., 2000) as well as in their risky behaviors (e.g., Espelage et al., 2003); (c) there is discrepancy-proportional peer influence whereby peers who are different, as in a beginning friendship, influence each other more than peers who have an established friendship (Boxer et al., 2005), and (d) the search for similarity promotes peer influence and peer selection, two processes that may explain, to varying degrees, the emergence of risky behaviors in adolescents (e.g., Burk et al., 2007; Hoffman et al., 2007). In addition to simulating mechanisms capable of accounting for varying and therefore poorly replicable research findings on peer influence on adolescent behavior, this model can simulate and test the effects of scenarios that are difficult to explore in a natural context, such as those involving individuals with extreme power of influence, as well as the effects of interventions aimed at preventing or punishing inappropriate behavior.

Agent-based models have been employed to model a diverse array of psychological processes, including the dynamics of motivational processes such as intrinsic motivation (Merrick & Shafi, 2013) and approach-avoidance conflict (Jager et al., 2001), the development and expression of self-concept coherence (Nowak et al., 2023), the development of language (Steels & Belpaeme, 2005), parent-child interaction (Hesp et al., 2019), between-children dyadic play and interaction (Steenbeek & van Geert, 2008), the emergence of collective memory (Luhmann & Rajaram, 2015), interpersonal cooperation (Axelrod & Hamilton, 1981; Bear & Rand, 2016), collective decision making (McHugh et al., 2016), leadership emergence (Serban et al., 2015), and the management of collective effectiveness (Schein et al., 2020). Like other computer simulation methods, agent-based models can be very easily implemented through free, open source, and easy to master programming platforms (e.g., *NetLogo*; Wilensky, 1999).

Cellular Automata

Cellular automata, popularized by Conway's famous *Game of Life* (Gardner, 1970), are a particular case of agent-based models involving the cells (the agents) of two-dimension lattices (or sometimes even a line, Wolfram, 2002). At each moment, each cell can adopt a specific state among a finite set of possible states. The state of any cell at each moment is a function, according to a defined rule, of the state at the previous moment of a finite number of neighboring cells. The rule is applied simultaneously to all the cells of the lattice or the line, thus yielding a new generation of cells which depends entirely on the previous generation. Despite their simplicity—space with a reduced number of dimensions, limited possible states of cells (e.g., two), simple rules of influence between cells—cellular automata can produce the emergence of highly complex behavioral patterns (Wolfram, 2002).

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The cellular automata approach has been employed, for example, to model in a singular way the diversity of the modalities of emergence of structure in people's self-concept (Nowak et al., 2000). In the model, the self-concept consists of n elements, each representing a specific self-aspect, represented as cells arranged on a two-dimensional grid (see Fig. 6). These elements can be highly diverse with respect to content (e.g., specific actions, memories, desires) but all can be scaled in terms of evaluation—how well or poorly they reflect on one's sense of self. Each element is characterized by its current evaluation, which is either positive (denoted by light gray) or negative (dark grey), and which is subject to change in the course of simulation. The elements also differ in their relative importance, denoted by their relative height, a feature that remains constant throughout the simulation. The proximity of elements represents their degree of relatedness, with neighboring elements relevant to a shared higher-order characteristic (e.g., region of competence, personality dimension).

The basic rule of influence is a press for evaluative integration which accounts for a person's concern for a consistent self-evaluation. Thus, neighboring elements adjust their current evaluation, if necessary, to achieve the same evaluation. Specifically, an element chosen at random checks how much influence it receives from its neighbors. It does so by weighting the evaluation of each neighbor by the neighbor's importance and proximity, with nearby important neighbors having the greatest influence. The element's current evaluation changes if it is lower than the weighted sum of its neighbors' evaluation. So while it is easy for neighboring elements to change the evaluation of a relatively unimportant element, it is difficult to change the evaluation of a relatively important self-aspect. During one simulation step, this process is repeated for all elements in random order. Such simulation steps are iterated until the self-structure shows no further changes, indicating a static equilibrium, or a stable pattern of changes, indicating a dynamic equilibrium.

To simulate variation in press for integration, Nowak et al. multiplied the computed influence on each element by a value, P , with higher values of P representing stronger influence. With a high press for integration, the mutual adjustment process promotes a differentiated self-structure characterized by the emergence of clusters of elements with the same evaluation. So while each element's evaluation is independent of its neighbors' evaluation at the outset (Figure 6A), the mutual influence among neighboring elements promotes evaluatively coherent regions of self-structure (Figure 6B). Because specific self-aspects become integrated in this fashion, people can think about themselves in terms of global properties (e.g., personality traits, skills) rather than in terms of specific lower-level actions, concerns, and the like.

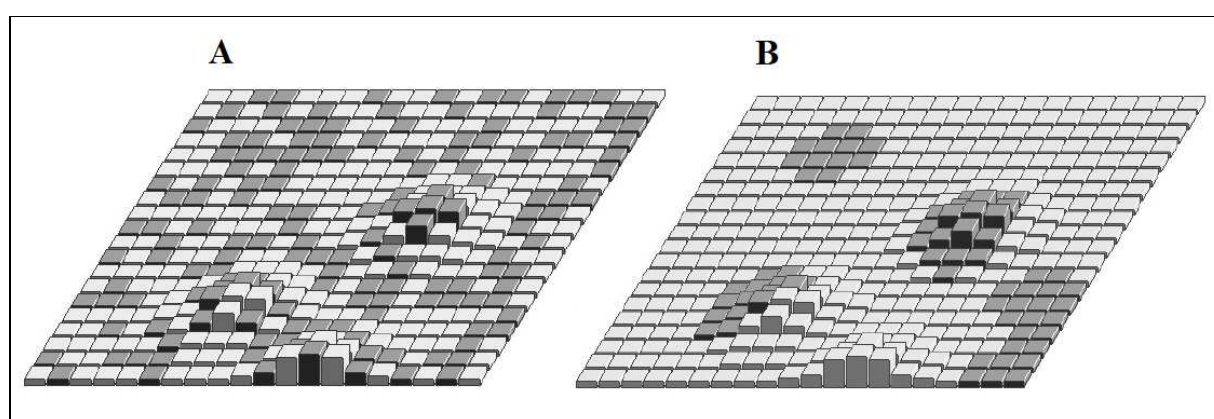
The results of the computer simulations showed that when the press for integration is strong, the self-structure is temporarily perturbed by inconsistent external information, but eventually recovers its previous state of equilibrium. Such a recovery does not happen when the press for integration is weak. Interestingly, under a high press for integration, external information of a random nature entering an initially disordered system as in Figure 6A was found to enhance the emergence of a differentiated and stable self-structure as in Figure 6B. However, external information, whether random or coherent, has little impact on an already well-structured self. These findings are consistent with seemingly inconsistent empirical findings from the literature on self-concept. Self-concept differentiation (e.g., Linville, 1987; Showers, 1992), for example, reflects the tendency for self-relevant information to form locally coherent clusters representing different domains of self-concept. The resistance to change in an organized self-structure, meanwhile, reflects the self-verification demonstrated by individuals with a highly certain self-

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concept (Swann, 2012)—a tendency that is typically manifest as maintenance of high self-esteem because of the positivity bias in self-concept (e.g., Tesser, 1988). A weak press for integration, on the other hand, is associated with a lack of locally coherent clusters and thus provides the structural basis for such constructs as low self-concept clarity, certainty, and stability (e.g., Baumgardner, 1990; Campbell et al., 1996; Kernis & Waschull, 1995; Vallacher et al., 2002) and for heightened reactivity to contradictory social feedback and social comparison (e.g., Baumeister et al., 1996; Vallacher & Wegner, 1989). This last configuration accounts for the conditions of extreme variability and therefore low reproducibility of self-concept measures.

Figure 6

Disordered (A) and Differentiated (B) Self-systems as Represented by Cellular Automata



Note. Reprinted from Nowak et al. (2000) with permission from *American Psychological Association (APA)*.

The cellular automata approach is scalable and represents a potential integrative platform for psychological dynamics at work at both intra- and interpersonal levels (Vallacher et al., 2017). At the interpersonal level, the relevance of cellular automata has been demonstrated with respect to a wide variety of psychological and social processes, including cooperation and competition (Messick & Liebrand, 1995), polarization of public opinion (Nowak et al., 1990), culture of honor (Nowak et al., 2015), social change (Nowak & Vallacher, 2019), and the emergence of populism (Vallacher & Fennell, 2021). Cellular automata can also be implemented through open-source platforms such as *Golly* (<http://golly.sourceforge.net>), which allows the exploration of Conway's Game of Life and many other types of cellular automata.

Genetic Algorithms

Genetic algorithms (Holland, 1975) mimic Darwinian natural selection processes. As in any agent-based model, virtual agents endowed with characteristics—here called genes—interact with each other and with their environment. The iterative application of a selection rule eliminates agents whose characteristics are incompatible with the environment while allowing agents with the most suitable characteristics to reproduce. Reproductive process endows the offspring with a recombination of the parental genes as well as random mutations, thus making them unique. From simple rules, genetic algorithms can therefore generate adaptation patterns whose complex and dynamic nature makes them virtually impossible to reproduce with classic nomothetic approaches. Genetic algorithms are also capable of seeking and finding solutions to

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very complex problems (Goldberg, 1989). Variations on this approach have provided insight into how cooperative behavior can develop in a system of self-interested agents (Axelrod, 1984; Axelrod & Dion, 1988) and how social norms emerge in societies (Kameda et al., 2003). Despite the promising qualities of genetic algorithms, however, their use is still marginal in psychological science. Downloadable packages to easily program and use a wide range of genetic algorithms are available for free (e.g., <https://sourceforge.net/projects/jgap>).

Computer Simulation in Perspective

The development of formal models implemented in computer simulations has several advantages when investigating the dynamics of psychological processes. Foremost, each of the methods described above facilitate theoretical understanding of the complexity of psychological processes by making it possible to observe and test how multiple factors contribute in an interactive way to the emergence of identifiable higher-order psychological patterns, which in turn constrain the behaviors of those factors. Moreover, by reducing to a few seconds of computer time the (sometimes long) timescales with which psychological processes unfold, computer simulation methods provide time-based representations of real processes and thus permit one to observe and test the emerging consequences of these processes at various timescales. Finally, this approach allows for visualization of self-organization as it occurs in response to the number and properties of agents, the interactions among agents, and the environment in which the interactions take place.

In sum, by foregoing causal explanations based on the accumulation of hardly reproducible statistical effects, the computer simulation approach is methodologically reproducible and thus contributes to a growing body of information about the populational or contextual variation of a particular kind of process, and hence contributes to the growth of general theory. Computer simulations, however, should be embraced as part of a larger strategy that includes empirical methods and theory development. It is through the iterative feedback among these components—dynamical theory, computer simulation, and processual empirical research—that progressive and reproducible insight into the complexity and dynamism of human experience is attainable.

The Complex Dynamical Systems Approach to Reproducibility in Perspective

The reframing of psychological phenomena as complex dynamical systems has emerged as a viable paradigm in recent years, providing heuristic and integrative value for a wide range of topics. Nonetheless, as a relatively new development, this approach has come under scrutiny for its added value in light of the decades of theory and research that preceded it. In the present context, the specific issue is whether it is better positioned than mainstream approaches to understand when and why the results of research have proven stubbornly difficult to replicate.

The Unique Relevance of the Complex Dynamical Systems Approach

The CDS approach has been criticized by some for being too general. In particular, critics claim that the approach describes the properties of time series without revealing latent psychological processes (e.g., Wagenmakers, van der Maas, & Farrell, 2012) or accounting for the specific features of individuals, environments, and tasks (e.g., Rosenhead et al., 2019;

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Wagenmakers, van der Maas, & Farrell, 2012). These criticisms, however, do not hold for process causality, where sequences or temporal flows of events or states are linked to each other in a causal or functional manner. With respect to time series, both RQA and DFA provide information regarding the complexity and dynamics of latent psychological processes—RQA by identifying attractor dynamics and DFA by assessing self-organized criticality. Dynamic equations and computer simulations, meanwhile, reveal the processual functioning associated with a system's complexity and dynamic properties, thereby enabling the specification of parameters that reveal possible individual and contextual features. Ironically, the criticism does hold when statistical models of relationships based on non-ergodic interindividual variability obtained from representative samples of participants are uncritically applied to individual processes. These types of models, which are currently proving difficult to reproduce, do not provide the specificity that is afforded by the CDS approach.

Some authors have raised doubts about the ability of the CDS paradigm to offer novel predictions, especially where other approaches fail (e.g., Rosenhead et al., 2019; Wagenmakers et al., 2005; Wagenmakers, van der Maas, & Farrell, 2012). Traditionally, prediction is assumed to be actuarial and thus best ensured by statistical models of relationships among variables, based on interindividual variability in representative samples. These models are then predicted to be exportable to broader statistical models, or to other samples of individuals or contexts (Hausman & Woodward, 1999, 2004). From a CDS perspective, prediction addresses typical qualitative features of a broad range of phenomena, based on principles of change (e.g., in the form of evolution rules). These principles have enabled the prediction of interesting properties, such as power law distributions (Den Hartigh et al., 2015; Den Hartigh et al., 2021; Delignières et al., 2009; Holden et al., 2009; Kello et al., 2008; Kello et al., 2007; Van Orden et al., 2003), low correlation between initial and later levels of performance (Den Hartigh, van Dijk et al., 2016), leap-like changes in learning (van Geert, 1991; van Geert, 1998), and increasing contribution of genetic factors over the life span in some performance domains (Den Hartigh, van Dijk et al., 2016). As a result, the CDS approach to psychology can predict the idiosyncratic and nonlinear dynamics of psychological phenomena, properties that may explain why the other approaches struggle to support actuarial predictions.

The CDS approach is sometimes criticized for lacking practical applications (e.g., Rosenhead et al., 2019). However, this approach permits the simulation and testing of effects of person-specific interventions that are situated in time and context. Dynamic models can thus shed light on why, when, and under what circumstances specific interventions or events may or may not have consequences. As such, these models represent working models capable of guiding interventions by professionals in various domains, including education (e.g., Menninga et al., 2022), social work (e.g., Schuhmacher et al., 2014), and psychotherapy (e.g., Borsboom & Cramer, 2013; Borsboom et al., 2018; Fried et al., 2022). Interestingly, dynamic models can also alert when the critical threshold of a system is about to be reached through generic warning signals (Scheffer et al., 2009). For instance, the critical slowing down of emotional fluctuations has been found to be an early warning signal of the onset and termination of depressive episodes (van de Leemput et al., 2014; Wichers et al., 2016).

In sum, while traditional nomothetic research looks for sparse structures of causal factors, the CDS approach emphasizes a process causality based on the complexity and history dependence of psychological systems. By testing the effects of evolutionary rules and person-specific interventions situated in time and context, this approach reveals nonlinear intraindividual

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variations of psychological phenomena that can explain the non-reproducible results obtained in mainstream psychological science.

Convergence and Complementarity with Mainstream Approaches

Although distinct in important respects, the CDS and mainstream paradigms have points of convergence. Importantly, CDS offers an explanatory framework for results that prove to be reproducible in mainstream research. Thus, a reproducible effect can be seen as one that reflects an intervention that promotes a radical change in the phenomenon's attractor landscape, such as that visualized in Figures 1A and 1B. In the domain of motor learning, for example, Zanone and Kelso (1992) have shown how an initial skill attractor can be replaced with a skill-to-be-learned attractor, due to instruction and training. The CDS and mainstream approaches, then, may observe the same reproducible psychological phenomenon, provided that its measurement is carried out outside the phase of high variability that accompanies the transition from the former attractor to the new one.

Beyond that, the CDS and mainstream approaches may sometimes be compatible in their respective consideration of how factors interact to produce certain phenomena. This may be the case, for example, with respect to the circular interactions among three types of negative mental states—relating to the self, the world, and the future—in Beck's (1979) model of psychopathology. According to Bringmann et al. (2015), this conception and its application are similar to the dynamic network model of psychopathology developed by Borsboom et al. (Borsboom & Cramer, 2013; Borsboom et al., 2018). In a related vein, a reconciliation between the CDS approach and traditional approaches with respect to psychopathology is currently in progress (Bringmann & Eronen, 2018), in which latent causal variables (e.g., a biological factor responsible for a disease) can be integrated into processual causality models (e.g., a network of symptoms whose interactions account for a mental disorder). The resulting mixed models remain dynamic networks capable of accounting for both the stability and the variability of psychological states. Given these shared conceptualizations of psychopathology, it is not surprising that the CDS approach and more traditional perspectives also converge on similar therapeutic proposals as well as on the conclusion that the idiosyncratic nature of the interactions to be treated makes it difficult to reproduce the effectiveness of a given intervention at a group level.

The CDS approach also has points of convergence with some prominent conceptualizations of personality, such as the Cognitive-Affective Personality System (CAPS, Mischel & Shoda, 1995, 1998). By combining the role of a person-specific relatively stable network of interconnected cognitive and affective units and the role of situational experiences in activating some of these units, this model reconciles the paradoxical findings of personality invariance and behavioral variability across situations. Computer simulations of the CAPS in the form of a dynamic network (Shoda et al., 2002) have inspired other dynamic network models of personality (e.g., Cramer et al., 2012). These models and the CAPS reliably account for the idiosyncratic and dynamic nature of personality and thus explain why the expressions of a system that is stable by definition may sometimes not reproduce.

The idea that psychological phenomena result from circular causations distributed at the individual, contextual, and situational levels is consistent with the contemporary emphasis on embodied cognition. In this perspective, cognitions and emotions emerge from the organism's

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momentary interactions with the external world (Varela et al., 1991). To a certain extent, this school of thought reflects a traditional framework, in that cognitive processes are assumed to be implemented within the brain in the form of representations of past sensory-motor and emotional experiences capable of governing the system's functioning (Barsalou, 1999). Some embodied cognition researchers, however, reject this centralist assumption, fully embracing instead the CDS perspective and actively advocating for bridging the two approaches (Chemero, 2009; Marsh et al., 2009). Meanwhile, both approaches agree that psychological phenomena are complex and situated in a here-and-now that can undermine their reproducibility.

In sum, although the CDS approach differs in important respects from mainstream approaches, there are nonetheless points of convergence that can facilitate dialogue and collaboration among scholars from both camps. Within the CDS approach, interventionist causation can be accounted for in a specific attractor landscape and can play a role in models that focus on complex interactions among interventions. Beyond that, some prominent models based on traditional assumptions are quite compatible with the CDS paradigm. Such convergence suggests that the CDS approach and mainstream psychology are somewhat complementary, each emphasizing different features of psychological experience. The points of convergence and complementarity, however, are ultimately grounded in a shared view of the complex, dynamic, and idiosyncratic nature of psychological phenomena—defining features that seriously limit the reproducibility of classical causal effects at the nomothetic level.

Conclusion

No one can dispute the importance and necessity of building a reproducible and cumulative psychological science. The issue is how best to accomplish this self-evident goal. Concerted efforts to enhance methodological rigor and publication standards are clearly important, but such efforts are destined to result in minimal success if conducted in research paradigms that ignore the complex interaction of causal forces, intrinsic dynamics, and idiosyncratic variability in psychological phenomena. These defining features of CDSs reframe the issue of reproducibility, from a misguided focus on (hardly) reproducible statistical structures of eventually *non-causal* relationships that operate at a nomothetic level to an emphasis on reproducible processes that emerge over time at the individual level in accordance with dynamic principles. This focus is facilitated by significant advancements in tools and statistical techniques that can capture dynamics at different timescales, and by computer simulations that enable the construction and testing of formal models that can accommodate, at the idiosyncratic level, the interactions of multiple system elements and external forces over time.

Although the CDS approach sheds light on why psychological phenomena can be volatile, unpredictable, and hence hardly reproducible, it nevertheless contributes to the construction of a reproducible science. What is reproducible in this approach are complex and iteratively evolving interaction processes, rather than sparse structures of causal relationships. Also reproducible are the typical statistical signatures of the complexity and the dynamics of the phenomena emerging from these processes, as well as from their simulation based on formal and computer modeling. Moreover, what can be reproduced by the mainstream approach can also be reproduced within the dynamical paradigm. As a result, the CDS approach is in service of a reproducible psychological science, one whose mission is to reproduce process causality.

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Focusing on the idiosyncratic nature of psychological processes does not mean turning away from the construction of a cumulative psychological science. Understanding the here-and-now functioning of individuals offers valuable insights into the general principles that govern human experience. Computer simulations of these principles yield outcomes whose distributions can be appraised according to a variety of parameters and then compared to empirical data distributions. Thus, the CDS approach consists of reciprocal and iterative feedback among dynamical theories, formal modeling, computer simulations, and empirical methods to identify temporal patterns. Studying psychological processes in the form of individual cases based on reproducible methodology is a way of building a cumulative psychology that can account for both consistent and inconsistent effects of interventions (e.g., van Geert & de Ruiter, 2022). Whether the dynamical principles uncovered through a given study consistently apply only to small samples of individuals, situations, and moments should not be a problem, provided that the scope of this study is explicitly defined (Simons et al., 2017). A cumulative science, which may or may not lead to ultimate generalizations, builds on the contribution of many such specific studies (Shoda et al., 2015).

Despite the broad agenda of the CDS approach, our advocacy of this paradigm has no imperialist ambition. Although it does not address the same type of causality as mainstream research, the dynamical paradigm has points of convergence with some traditional approaches. Moreover, by focusing on the complex, dynamic, and idiosyncratic nature of psychological processes, it usefully complements mainstream research, particularly by providing an explanatory framework for results that are non-reproducible. Finally, despite the increasing adoptions of the CDS approach in many fields of psychological science, it is still in its nascent stage and thus cannot claim imperialist status. Nonetheless, a seeming lack of tangible improvement after years of struggling to establish reproducible causal effects might well be the signal that it is time for the field of psychology to break the Kuhnian resistance to recognition of the CDS paradigm, and to embrace what this paradigm has to offer.

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References

- Ahadi, S., & Diener, E. (1989). Multiple determinants and effect size. *Journal of Personality and Social Psychology*, 56(3), 398-406. <https://doi.org/10.1037/0022-3514.56.3.398>
- Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of Modern Physics*, 74(1), 47-97. <https://doi.org/10.1103/RevModPhys.74.47>
- Amari, S. (1977). Dynamics of pattern formation in lateral-inhibition type neural fields. *Biological Cybernetics*, 27(2), 77-87. <https://doi.org/10.1007/BF00337259>
- Asendorpf, J. B., Conner, M., De Fruyt, F., De Houwer, J., Denissen, J. J. A., Fiedler, K., Fiedler, S., Funder, D. C., Kliegl, R., Nosek, B. A., Perugini, M., Roberts, B. W., Schmitt, M., Vanaken, M. A. G., Weber, H., & Wicherts, J. M. (2013). Recommendations for increasing replicability in psychology. *European Journal of Personality*, 27(2), 108-119. <https://doi.org/10.1002/per.1919>
- Axelrod, R. (1984). *The evolution of cooperation*. Basic Books.

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Axelrod, R., & Dion, D. (1988). The further evolution of cooperation. *Science*, 242(4884), 1385-1390. <https://doi.org/10.1126/science.242.4884.1385>
- Axelrod, R., & Hamilton, W. D. (1981). The evolution of cooperation. *Science*, 211(4489), 1390-1396. <https://doi.org/10.1126/science.7466396>
- Bak, P. (1996). *How nature works: The science of self-organized criticality*. Springer-Verlag.
- Baron, R. M., & Kenny, D. A. (1986). The moderator-mediator variable distinction in social psychological research: Conceptual, strategic, and statistical considerations. *Journal of Personality and Social Psychology*, 51(6), 1173-1182. <https://doi.org/10.1037//0022-3514.51.6.1173>
- Barsalou, L. W. (1999). Perceptual symbol systems. *Behavioral and Brain Sciences*, 22(4), 577-609. <https://doi.org/10.1017/S0140525X99532147>
- Baumeister, R. F., Smart, L., & Boden, J. M. (1996). Relation of threatened egotism to violence and aggression: The dark side of high self-esteem. *Psychological Review*, 103(1), 5-33. <https://doi.org/10.1037/0033-295x.103.1.5>
- Baumgardner, A. H. (1990). To know oneself is to like oneself: Self-certainty and self-affect. *Journal of Personality and Social Psychology*, 58(6), 1062-1072. <https://doi.org/10.1037/0022-3514.58.6.1062>
- Bear, A., & Rand, D. G. (2016). Intuition, deliberation, and the evolution of cooperation. *Proceedings of the National Academy of Sciences*, 113(4), 936-941. <https://doi.org/10.1073/pnas.1517780113>
- Bechtel, W., & Richardson, R. C. (2010). *Discovering complexity: Decomposition and localization as strategies in scientific research*. MIT Press.
- Beck, A. T. (1979). *Cognitive therapy of depression*. Guilford Press.
- Bijleveld, C. C. J. H., van der Kamp, L., Mooijaart, A., van der Kloot, W. A., van der Leeden, R., & van der Burg, E. (1998). *Longitudinal data analysis: Designs, models and methods*. Sage.
- Borsboom, D., & Cramer, A. O. J. (2013). Network analysis: An integrative approach to the structure of psychopathology. *Annual Review of Clinical Psychology*, 9(1), 91-121. <https://doi.org/10.1146/annurev-clinpsy-050212-185608>
- Borsboom, D., Cramer, A. O. J., & Kalis, A. (2018). Brain disorders? Not really... Why network structures block reductionism in psychopathology research. *Behavioral and Brain Sciences*, 42(e2), 1-11. <https://doi.org/10.1017/s0140525x17002266>
- Botterill, G. (2010). Two kinds of causal explanation. *Theoria*, 76(4), 287-313. <https://doi.org/10.1111/j.1755-2567.2010.01079.x>
- Boxer, P., Guerra, N. G., Huesmann, L. R., & Morales, J. (2005). Proximal peer-level effects of a small-group selected prevention on aggression in elementary school children: An investigation of the peer contagion hypothesis. *Journal of Abnormal Child Psychology*, 33(3), 325-338. <https://doi.org/10.1007/s10802-005-3568-2>
- Bringmann, L. F., & Eronen, M. I. (2018). Don't blame the model: Reconsidering the network approach to psychopathology. *Psychological Review*, 125(4), 606-615. <https://doi.org/10.1037/rev0000108>
- Bringmann, L. F., Lemmens, L. H. J. M., Huibers, M. J. H., Borsboom, D., & Tuerlinckx, F. (2015). Revealing the dynamic network structure of the Beck Depression Inventory-II. *Psychological Medicine*, 45(04), 747-757. <https://doi.org/10.1017/s0033291714001809>
- Brown, B. B., & Klute, C. (2003). Friendships, cliques, and crowds. In G. R. Adams & M. D. Berzonsky (Eds.), *Handbook of adolescence* (pp. 330-348). Blackwell.
- Burk, W. J., Steglich, C. E. G., & Snijders, T. A. B. (2007). Beyond dyadic interdependence: Actor-oriented models for co-evolving social networks and individual behaviors. *International Journal of Behavioral Development*, 31(4), 397-404. <https://doi.org/10.1177/0165025407077762>
- Buss, A. T., & Spencer, J. P. (2014). The emergent executive: A dynamic field theory of the development of executive function. *Monographs of the Society for Research in Child Development*, 79(2), vii. <https://doi.org/10.1002/mono.12096>
- Campbell, J. D., Trapnell, P. D., Heine, S. J., Katz, I. M., Lavallee, L. F., & Lehman, D. R. (1996). Self-concept clarity: Measurement, personality correlates, and cultural boundaries. *Journal of Personality and Social Psychology*, 70(1), 141-156. <https://doi.org/10.1037/0022-3514.70.1.141>
- Chemero, A. (2009). *Radical embodied cognitive science*. MIT Press
- Conte, R., & Paolucci, M. (2014). On agent-based modeling and computational social science. *Frontiers in Psychology*, 5(668). <https://doi.org/10.3389/fpsyg.2014.00668>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Cramer, A. O. J., van der Sluis, S., Noordhof, A., Wichers, M., Geschwind, N., Aggen, S. H., Kendler, K. S., & Borsboom, D. (2012). Dimensions of normal personality as networks in search of equilibrium: You can't like parties if you don't like people. *European Journal of Personality, 26*(4), 414-431. <https://doi.org/10.1002/per.1866>
- Delignières, D., Fortes, M., & Ninot, G. (2004). The fractal dynamics of self-esteem and physical self. *Nonlinear Dynamics, Psychology, and Life Sciences, 8*, 479-510.
- Delignières, D., & Torre, K. (2009). Fractal dynamics of human gait: A reassessment of the 1996 data of Hausdorff et al.. *Journal of Applied Physiology, 106*(4), 1272-1279. <https://doi.org/10.1152/jappphysiol.90757.2008>
- Delignières, D., Torre, K., & Lemoine, L. (2009). Long-range correlation in synchronization and syncopation tapping: A linear phase correction model. *PLoS ONE, 4*(11), e7822. <https://doi.org/10.1371/journal.pone.0007822>
- Den Hartigh, R. J. R., Cox, R. F. A., Gernigon, C., Van Yperen, N. W., & van Geert, P. L. C. (2015). Pink noise in rowing ergometer performance and the role of skill level. *Motor Control, 19*(4), 355-369. <https://doi.org/10.1123/mc.2014-0071>
- Den Hartigh, R. J., Cox, R. F., & van Geert, P. L. (2017). Complex versus complicated models of cognition. In L. Magnani & T. Bertolotti (Eds.), *Springer handbook of model-based science* (pp. 657-669). Springer.
- Den Hartigh, R. J. R., Hill, Y., & van Geert, P. L. C. (2018). The development of talent in sports: A dynamic network approach. *Complexity, 2018*(9280154), 1-13. <https://doi.org/10.1155/2018/9280154>
- Den Hartigh, R. J. R., Otten, S., Gruszczynska, Z. M., & Hill, Y. (2021). The relation between complexity and resilient motor performance and the effects of differential learning. *Frontiers in Human Neuroscience, 15*(715375). <https://doi.org/10.3389/fnhum.2021.715375>
- Den Hartigh, R. J. R., van Dijk, M. W. G., Steenbeek, H. W., & van Geert, P. L. C. (2016). A dynamic network model to explain the development of excellent human performance. *Frontiers in Psychology, 7*(532). <https://doi.org/10.3389/fpsyg.2016.00532>
- Den Hartigh, R. J. R., van Geert, P. L. C., Van Yperen, N. W., Cox, R. F. A., & Gernigon, C. (2016). Psychological momentum during and across sports matches: Evidence for interconnected time scales. *Journal of Sport & Exercise Psychology, 38*(1), 82-92. <https://doi.org/10.1123/jsep.2015-0162>
- de Ruiter, N. M. P., Den Hartigh, R. J. R., Cox, R. F. A., Van Geert, P. L. C., & Kunnen, E. S. (2015). The temporal structure of state self-esteem variability during parent-adolescent interactions: More than random fluctuations. *Self and Identity, 14*(3), 314-333. <https://doi.org/10.1080/15298868.2014.994026>
- de Ruiter, N. M. P., Hollenstein, T., van Geert, P. L. C., & Kunnen, E. S. (2018). Self-esteem as a complex dynamic system: Intrinsic and extrinsic microlevel dynamics. *Complexity, 2018*(4781563), 1-19. <https://doi.org/10.1155/2018/4781563>
- Dindar, M., Alikhani, I., Malmberg, J., Järvelä, S., & Seppänen, T. (2019). Examining shared monitoring in collaborative learning: A case of a recurrence quantification analysis approach. *Computers in Human Behavior, 100*, 335-344. <https://doi.org/10.1016/j.chb.2019.03.004>
- Dowe, P. (1992). Wesley Salmon's process theory of causality and the conserved quantity theory. *Philosophy of Science, 59*(2), 195-216. <https://doi.org/10.1086/289662>
- Erlhagen, W., & Schönner, G. (2002). Dynamic field theory of movement preparation. *Psychological Review, 109*(3), 545-572. <https://doi.org/10.1037/0033-295X.109.3.545>
- Eronen, M. I. (2020). Causal discovery and the problem of psychological interventions. *New Ideas in Psychology, 59*(100785). <https://doi.org/10.1016/j.newideapsych.2020.100785>
- Espelage, D. L., Holt, M. K., & Henkel, R. R. (2003). Examination of peer-group contextual effects on aggression during early adolescence. *Child Development, 74*(1), 205-220. <https://doi.org/10.1111/1467-8624.00531>
- Fajen, B. R., & Warren, W. H. (2003). Behavioral dynamics of steering, obstacle avoidance, and route selection. *Journal of Experimental Psychology: Human Perception and Performance, 29*(2), 343-362. <https://doi.org/10.1037/0096-1523.29.2.343>
- Fischer, K. W., & Granott, N. (1995). Beyond one-dimensional change: Parallel, concurrent, socially distributed processes in learning and development. *Human Development, 38*(6), 302-314. <https://doi.org/10.1159/000278336>
- Fisher, A. J., Medaglia, J. D., & Jeronimus, B. F. (2018). Lack of group-to-individual generalizability is a threat to human subjects research. *Proceedings of the National Academy of Sciences, 115*(27), E6106-E6115. <https://doi.org/10.1073/pnas.1711978115>
- Freeman, J. B., & Ambady, N. (2010). MouseTracker: Software for studying real-time mental processing using a computer mouse-tracking method. *Behavior Research Methods, 42*(1), 226-241. <https://doi.org/10.3758/brm.42.1.226>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Freese J., & Kevern J. A. (2013). Types of causes. In S. Morgan (Ed.), *Handbook of causal analysis for social research* (pp. 27-41). Springer.
- Fried, E. I. (2020). Lack of theory building and testing impedes progress in the factor and network literature. *Psychological Inquiry*, 31(4), 271-288. <https://doi.org/10.1080/1047840X.2020.1853461>
- Fried, E. I., Flake, J. K., & Robinaugh, D. J. (2022). Revisiting the theoretical and methodological foundations of depression measurement. *Nature Reviews Psychology*, 1(6), 358-368. <https://doi.org/10.1038/s44159-022-00050-2>
- Gardner, M. (1970). Mathematical games: The fantastic combinations of John Conway's new solitaire game "life". *Scientific American*, 223(4), 120-123. <https://doi.org/10.1038/scientificamerican1070-120>
- Gernigon, C., d'Arripe-Longueville, F., Delignières, D., & Ninot, G. (2004). A dynamical systems perspective on goal involvement states in sport. *Journal of Sport & Exercise Psychology*, 26(4), 572-596. <https://doi.org/10.1123/jsep.26.4.572>
- Gernigon, C., Vallacher, R. R., Nowak, A., & Conroy, D. E. C. (2015). Rethinking approach and avoidance in achievement contexts: The perspective of dynamical systems. *Review of General Psychology*, 19(4), 443-457. <https://doi.org/10.1037/gpr0000055>
- Geveke, C. H., Steenbeek, H. W., Doornenbal, J. M., & van Geert, P. L. C. (2017). Attractor states in teaching and learning processes: A study of out-of-school science education. *Frontiers in Psychology*, 8(299). <https://doi.org/10.3389/fpsyg.2017.00299>
- Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science*, 267(5205), 1837-1839. <https://doi.org/10.1126/science.7892611>
- Goldberg, D. E. (1989). *Genetic algorithms in search, optimization, and machine learning*. Addison-Wesley.
- Gottman, J., Swanson, C., & Swanson, K. (2002). A general systems theory of marriage: Nonlinear difference equation modeling of marital interaction. *Personality and Social Psychology Review*, 6(4), 326-340. https://doi.org/10.1207/s15327957pspr0604_07
- Gottschalk, A., Bauer, M. S., & Whybrow, P. C. (1995). Evidence of chaotic mood variation in bipolar disorder. *Archives of General Psychiatry*, 52(11), 947-959. <https://doi.org/10.1001/archpsyc.1995.03950230061009>
- Granic, I., Hollenstein, T., Dishion, T., & Patterson, G. R. (2003). Longitudinal analysis of flexibility and reorganization in early adolescence: A dynamic systems study of family interactions. *Developmental Psychology*, 39(3), 606-617. <https://doi.org/10.1037/0012-1649.39.3.606>
- Granic, I., & Patterson, G. R. (2006). Toward a comprehensive model of antisocial development: A dynamic systems approach. *Psychological Review*, 113(1), 101-131. <https://doi.org/10.1037/0033-295x.113.1.101>
- Grossberg, S. (1988). Nonlinear neural networks: Principles, mechanisms, and architectures. *Neural Networks*, 1(1), 17-61. [https://doi.org/10.1016/0893-6080\(88\)90021-4](https://doi.org/10.1016/0893-6080(88)90021-4)
- Guastello, S. J., Koopmans, M., & Pincus, D. (Eds.). (2009). *Chaos and complexity in psychology: The theory of nonlinear dynamical systems*. Cambridge University Press.
- Guastello, S. J., & Liebovitch, L. S. (2009). Introduction to nonlinear dynamics and complexity. In S. J. Guastello, M. Koopmans, & D. Pincus, D. (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 1-40). Cambridge University Press.
- Haken, H. (1992). Synergetics in psychology. In W. Tschacher, G. Schiepek, & E. J. Brunner (Eds.), *Self-organization and clinical psychology. Springer Series in Synergetics* (Vol. 58, pp. 32-54). Springer.
- Haken, H., Kelso, J. A. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. *Biological Cybernetics*, 51(5), 347-356. <https://doi.org/10.1007/BF00336922>
- Hamaker, E. L. (2023). The curious case of the cross-sectional correlation. *Multivariate Behavioral Research*. <https://doi.org/10.1080/00273171.2022.2155930>
- Harmon-Jones, E., & Harmon-Jones, C. (2007). Cognitive dissonance theory after 50 years of development. *Zeitschrift Für Sozialpsychologie*, 38(1), 7-16. <https://doi.org/10.1024/0044-3514.38.1.7>
- Harrison, J. R., Lin, Z., Carroll, G. R., & Carley, K. M. (2007). Simulation modeling in organizational and management research. *Academy of Management Review*, 32(4), 1229-1245. <https://doi.org/10.5465/amr.2007.26586485>
- Haslam, S. A., & Reicher, S. D. (2017). 50 Years of "obedience to authority": From blind conformity to engaged followership. *Annual Review of Law and Social Science*, 13(1), 59-78. <https://doi.org/10.1146/annurev-lawsocsci-110316-113710>
- Hausdorff, J. M., Purdon, P. L., Peng, C. K., Ladin, Z., Wei, J. Y., & Goldberger, A. L. (1996). Fractal dynamics of human gait: Stability of long-range correlations in stride interval fluctuations. *Journal of Applied Physiology*, 80(5), 1448-1457. <https://doi.org/10.1152/jappl.1996.80.5.1448>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Hausman, D. M., & Woodward, J. (1999). Independence, invariance and the causal Markov condition. *The British Journal for the Philosophy of Science*, *50*(4), 521-583. <https://doi.org/10.1093/bjps/50.4.521>
- Hausman, D. M., & Woodward, J. (2004). Manipulation and the causal Markov condition. *Philosophy of Science*, *71*(5), 846-856. <https://doi.org/10.1086/425235>
- Henrich, C. C., Kuperminc, G. P., Sack, A., Blatt, S. J., & Leadbeater, B. J. (2000). Characteristics and homogeneity of early adolescent friendship groups: A comparison of male and female clique and nonclique members. *Applied Developmental Science*, *4*(1), 15-26. https://doi.org/10.1207/s1532480xads0401_2
- Hesp, C., Steenbeek, H. W., & van Geert, P. L. C. (2019). Socio-emotional concern dynamics in a model of real-time dyadic interaction: Parent-child play in autism. *Frontiers in Psychology*, *10*(1635). <https://doi.org/10.3389/fpsyg.2019.01635>
- Hill, Y., Meijer, R. R., Van Yperen, N. W., Michelakakis, G., Barisch, S., & Den Hartigh, R. J. R. (2021). Non-ergodicity in protective factors of resilience in athletes. *Sport, Exercise, and Performance Psychology*, *10*(2), 217-223. <https://doi.org/10.1037/spy0000246>
- Hoeksma, J. B., Oosterlaan, J., Schipper, E., & Koot, H. (2007). Finding the attractor of anger: Bridging the gap between dynamic concepts and empirical data. *Emotion*, *7*(3), 638-648. <https://doi.org/10.1037/1528-3542.7.3.638>
- Hoffman, B. R., Monge, P. R., Chou, C.-P., & Valente, T. W. (2007). Perceived peer influence and peer selection on adolescent smoking. *Addictive Behaviors*, *32*(8), 1546-1554. <https://doi.org/10.1016/j.addbeh.2006.11.016>
- Holden, J. G., Van Orden, G. C., & Turvey, M. T. (2009). Dispersion of response times reveals cognitive dynamics. *Psychological Review*, *116*(2), 318-342. <https://doi.org/10.1037/a0014849>
- Holland, J. H. (1975). *Adaptation in natural and artificial systems*. University of Michigan Press.
- Holland, J. H. (1998). *Emergence: From chaos to order*. Oxford University Press.
- Jackson, J. C., Rand, D., Lewis, K., Norton, M. I., & Gray, K. (2017). Agent-based modeling: A guide for social psychologists. *Social Psychological and Personality Science*, *8*(4), 387-395. <https://doi.org/10.1177/1948550617691100>
- Jager, W., Popping, R., & van de Sande, H. (2001). Clustering and fighting in two-party crowds: Simulating the approach-avoidance conflict. *Journal of Artificial Societies and Social Simulation*, *4*(3). <http://jasss.soc.surrey.ac.uk/4/3/7.html>
- Jenkins, B. N., Hunter, J. F., Richardson, M. J., Conner, T. S., & Pressman, S. D. (2020). Affect variability and predictability: Using recurrence quantification analysis to better understand how the dynamics of affect relate to health. *Emotion*, *20*(3), 391-402. <https://doi.org/10.1037/emo0000556>
- Johnson, J. S., Spencer, J. P., & Schöner, G. (2008). Moving to higher ground: The dynamic field theory and the dynamics of visual cognition. *New Ideas in Psychology*, *26*(2), 227-251. <https://doi.org/10.1016/j.newideapsych.2007.07.007>
- Kameda, T., Takezawa, M., & Hastie, R. (2003). The logic of social sharing: An evolutionary game analysis of adaptive norm development. *Personality and Social Psychology Review*, *7*(1), 2-19. https://doi.org/10.1207/s15327957pspr0701_1
- Kello, C. T., Anderson, G., Holden, J., & Van Orden, G. (2008). The pervasiveness of 1/f scaling in speech reflects the metastable basis of cognition. *Cognitive Science: A Multidisciplinary Journal*, *32*(7), 1217-1231. <https://doi.org/10.1080/03640210801944898>
- Kello, C. T., Beltz, B. C., Holden, J. H., & Van Orden, G. C. (2007). The emergent coordination of cognitive function. *Journal of Experimental Psychology: General*, *136*(4), 551-568. <https://doi.org/10.1037/0096-3445.136.4.551>
- Kello, C. T., Brown, G. D. A., Ferrer-i-Cancho, R., Holden, J. G., Linkenkaer-Hansen, K., Rhodes, T., & Van Orden, G. C. (2010). Scaling laws in cognitive sciences. *Trends in Cognitive Sciences*, *14*(5), 223-232. <https://doi.org/10.1016/j.tics.2010.02.005>
- Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. MIT Press.
- Kelty-Stephen, D. G., & Mangalam, M. (2022). Fractal and multifractal descriptors restore ergodicity broken by non-Gaussianity in time series. *Chaos, Solitons & Fractals*, *163*(112568). <https://doi.org/10.1016/j.chaos.2022.112568>
- Kernis, M. H., & Waschull, S. B. (1995). The interactive roles of stability and level of self-esteem: Research and theory. *Advances in Experimental Social Psychology*, *27*, 93-141. [https://doi.org/10.1016/s0065-2601\(08\)60404-9](https://doi.org/10.1016/s0065-2601(08)60404-9)
- Kim, M. P., & Rosenberg, S. (1980). Comparison of two structural models of implicit personality theory. *Journal of Personality and Social Psychology*, *38*(3), 375-389. <https://doi.org/10.1037/0022-3514.38.3.375>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Kunnen, E. S., de Ruiter, N. M. P., Jeronimus, B. F., & van der Gaag, M. A. E. (Eds.). (2019). *Psychosocial development in adolescence: Insights from the dynamic systems approach*. Routledge.
- Laplace, P.-S. de (1814). *A philosophical essay on probabilities*. Translated into English from the original French 6th ed. by F. W. Truscott and F. L. Emory (1902). John Wiley & Sons.
- Lichtwarck-Aschoff, A., van Geert, P., Bosma, H., & Kunnen, S. (2008). Time and identity: A framework for research and theory formation. *Developmental Review, 28*(3), 370-400.
<https://doi.org/10.1016/j.dr.2008.04.001>
- Lickliter, R., & Witherington, D. C. (2017). Towards a truly developmental epigenetics. *Human Development, 60*(2-3), 124-138. <https://doi.org/10.1159/000477996>
- Linville, P. W. (1987). Self-complexity as a cognitive buffer against stress-related illness and depression. *Journal of Personality and Social Psychology, 52*(4), 663-676. <https://doi.org/10.1037/0022-3514.52.4.663>
- Liu, Y.-T., Mayer-Kress, G., & Newell, K. M. (2006). Qualitative and quantitative change in the dynamics of motor learning. *Journal of Experimental Psychology: Human Perception and Performance, 32*(2), 380-393.
<https://doi.org/10.1037/0096-1523.32.2.380>
- Lowie, W., Plat, R., & de Bot, K. (2014). Pink noise in language production: A nonlinear approach to the multilingual lexicon. *Ecological Psychology, 26*(3), 216-228.
<https://doi.org/10.1080/10407413.2014.929479>
- Luhmann, C. C., & Rajaram, S. (2015). Memory transmission in small groups and large networks. *Psychological Science, 26*(12), 1909-1917. <https://doi.org/10.1177/0956797615605798>
- Marsh, K. L., Johnston, L., Richardson, M. J., & Schmidt, R. C. (2009). Toward a radically embodied, embedded social psychology. *European Journal of Social Psychology, 39*(7), 1217-1225.
<https://doi.org/10.1002/ejsp.666>
- Maylor, E. A., Chater, N., & Brown, G. D. A. (2001). Scale invariance in the retrieval of retrospective and prospective memories. *Psychonomic Bulletin & Review, 8*(1), 162-167.
<https://doi.org/10.3758/BF03196153>
- McHugh, K. A., Yammarino, F. J., Dionne, S. D., Serban, A., Sayama, H., & Chatterjee, S. (2016). Collective decision making, leadership, and collective intelligence: Tests with agent-based simulations and a field study. *The Leadership Quarterly, 27*(2), 218-241. <https://doi.org/10.1016/j.leaqua.2016.01.001>
- Meinecke, A. L., Handke, L., Mueller-Frommeyer, L. C., & Kauffeld, S. (2020). Capturing non-linear temporally embedded processes in organizations using recurrence quantification analysis. *European Journal of Work and Organizational Psychology, 29*(4), 483-500. <https://doi.org/10.1080/1359432X.2019.1658624>
- Menninga, A., van Geert, P., van Vondel, S., Steenbeek, H., & van Dijk, M. (2022). Teacher-student interaction patterns change during an early science teaching intervention. *Research in Science Education, 52*(5), 1497-1523. <https://doi.org/10.1007/s11165-021-09997-3>
- Merlone, U., Panchuk, A., & van Geert, P. (2019). Modeling learning and teaching interaction by a map with vanishing denominators: Fixed points stability and bifurcations. *Chaos, Solitons & Fractals, 126*, 235-265.
<https://doi.org/10.1016/j.chaos.2019.06.008>
- Merrick, K. E., & Shafi, K. (2013). A game theoretic framework for incentive-based models of intrinsic motivation in artificial systems. *Frontiers in Psychology, 4*(791). <https://doi.org/10.3389/fpsyg.2013.00791>
- Messick, D. M., & Liebrand, W. B. G. (1995). Individual heuristics and the dynamics of cooperation in large groups. *Psychological Review, 102*(1), 131-145. <https://doi.org/10.1037/0033-295X.102.1.131>
- Mischel, W., & Shoda, Y. (1995). A cognitive-affective system theory of personality: Reconceptualizing situations, dispositions, dynamics, and invariance in personality structure. *Psychological Review, 102*(2), 246-268.
<https://doi.org/10.1037/0033-295X.102.2.246>
- Mischel, W., & Shoda, Y. (1998). Reconciling processing dynamics and personality dispositions. *Annual Review of Psychology, 49*, 229-258. <https://doi.org/10.1146/annurev.psych.49.1.229>
- Molenaar, P. C. M., & Campbell, C. G. (2009). The new person-specific paradigm in psychology. *Current Directions in Psychological Science, 18*(2), 112-117. <https://doi.org/10.1111/j.1467-8721.2009.01619.x>
- Molenaar, P. C. M., Sinclair, K. O., Rovine, M. J., Ram, N., & Corneal, S. E. (2009). Analyzing developmental processes on an individual level using nonstationary time series modeling. *Developmental Psychology, 45*(1), 260-271. <https://doi.org/10.1037/a0014170>
- Monroe, B. M., & Read, S. J. (2008). A general connectionist model of attitude structure and change: The ACS (Attitudes as Constraint Satisfaction) model. *Psychological Review, 115*(3), 733-759.
<https://doi.org/10.1037/0033-295x.115.3.733>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Newcomb, A. F., Bukowski, W. M., & Pattee, L. (1993). Children's peer relations: A meta-analytic review of popular, rejected, neglected, controversial, and average sociometric status. *Psychological Bulletin*, *113*(1), 99-128. <https://doi.org/10.1037/0033-2909.113.1.99>
- Newell, K. M., Liu, Y.-T., & Mayer-Kress, G. (2001). Time scales in motor learning and development. *Psychological Review*, *108*(1), 57-82. <https://doi.org/10.1037/0033-295x.108.1.57>
- Nosek, B. A., Hardwicke, T. E., Moshontz, H., Allard, A., Corker, K. S., Dreber, A., Fidler, F., Hilgard, J., Kline Struhl, M., Nuijten, M., Rohrer, J., Romero, F., Scheel, A., Scherer, L., Schönbrodt, F., & Vazire, S. (2022). Replicability, robustness, and reproducibility in psychological science. *Annual Review of Psychology*, *73*, 719-748. <https://doi.org/10.1146/annurev-psych-020821-114157>
- Nosek, B. A., Spies, J. R., & Motyl, M. (2012). Scientific utopia: II. Restructuring incentives and practices to promote truth over publishability. *Perspectives on Psychological Science*, *7*(6), 615-631. <https://doi.org/10.1177/1745691612459058>
- Nourrit-Lucas, D., Tossa, A. O., Zélic, G., & Delignières, D. (2015). Learning, motor skill, and long-range correlations. *Journal of Motor Behavior*, *47*(3), 182-189. <https://doi.org/10.1080/00222895.2014.967655>
- Nowak, A. (2004). Dynamical minimalism: Why less is more in psychology. *Personality and Social Psychology Review*, *8*(2), 183-192. https://doi.org/10.1207/s15327957pspr0802_12
- Nowak, A., Gelfand, M. J., Borkowski, W., Cohen, D., & Hernandez, I. (2015). The evolutionary basis of honor cultures. *Psychological Science*, *27*(1), 12-24. <https://doi.org/10.1177/0956797615602860>
- Nowak, A., Szamrej, J., & Latané, B. (1990). From private attitude to public opinion: A dynamic theory of social impact. *Psychological Review*, *97*(3), 362-376. <https://doi.org/10.1037/0033-295X.97.3.362>
- Nowak, A., & Vallacher, R. R. (1998). *Dynamical social psychology*. Guilford Press.
- Nowak, A., & Vallacher, R. R. (2019). Nonlinear societal change: The perspective of dynamical systems. *British Journal of Social Psychology*, *58*(1), 105-128. <https://doi.org/10.1111/bjso.12271>
- Nowak, A., & Vallacher, R. R., Bartkowski, W., & Olson, L. (2023). Integration and expression: The complementary functions of self-reflection. *Journal of Personality*. <https://doi.org/10.1111/jopy.12730>
- Nowak, A., Vallacher, R. R., Tesser, A., & Borkowski, W. (2000). Society of self: The emergence of collective properties in self-structure. *Psychological Review*, *107*(1), 39-61. <https://doi.org/10.1037/0033-295X.107.1.39>
- Nowak, A., Vallacher, R. R., & Zochowski, M. (2005). The emergence of personality: Dynamic foundations of individual variation. *Developmental Review*, *25*(3-4), 351-385. <https://doi.org/10.1016/j.dr.2005.10.004>
- Nowak, A., Vallacher, R. R., Zochowski, M., & Rychwalska, A. (2017). Functional synchronization: The emergence of coordinated activity in human systems. *Frontiers in Psychology*, *8*(94). <https://doi.org/10.3389/fpsyg.2017.00945>
- Olthof, M., Hasselman, F., & Lichtwarck-Aschoff, A. (2020). Complexity in psychological self-ratings: Implications for research and practice. *BMC Medicine*, *18*(317). <https://doi.org/10.1186/s12916-020-01727-2>
- Olthof, M., Hasselman, F., Strunk, G., van Rooij, M., Aas, B., Helmich, M. A., Schiepek, G., & Lichtwarck-Aschoff, A. (2020). Critical fluctuations as an early-warning signal for sudden gains and losses in patients receiving psychotherapy for mood disorders. *Clinical Psychological Science*, *8*(1), 25-35. <https://doi.org/10.1177/2167702619865969>
- Open Science Collaboration (2015). Estimating the reproducibility of psychological science. *Science*, *349*(6251), aac4716-aac4716. <https://doi.org/10.1126/science.aac4716>
- Pearl, J. (2009). *Causality: Models, reasoning, and inference* (2nd ed.). Cambridge University Press.
- Peng, C.-K., Mietus, J., Hausdorff, J. M., Havlin, S., Stanley, H. E., & Goldberger, A. L. (1993). Long-range anticorrelations and non-Gaussian behavior of the heartbeat. *Physical Review Letters*, *70*(9), 1343-1346. <https://doi.org/10.1103/physrevlett.70.1343>
- Reutlinger, A. (2013). *A theory of causation in the social and biological sciences*. Palgrave Macmillan.
- Richardson, M. J., Dale, R., & Marsh, K. L. (2014). Complex dynamical systems in social and personality psychology: Theory, modeling, and analysis. In H. T. Reis & C. M. Judd (Eds.), *Handbook of research methods in social and personality psychology* (2nd ed., pp. 253-282). Cambridge University Press.
- Richardson, M. J., Marsh, K. L., & Schmidt, R. C. (2005). Effects of visual and verbal interaction on unintentional interpersonal coordination. *Journal of Experimental Psychology: Human Perception and Performance*, *31*(1), 62-79. <https://doi.org/10.1037/0096-1523.31.1.62>
- Rosenhead, J., Franco, L. A., Grint, K., & Friedland, B. (2019). Complexity theory and leadership practice: A review, a critique, and some recommendations. *The Leadership Quarterly*, *30*(5), 101304. <https://doi.org/10.1016/j.leaqua.2019.07.002>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Rozin, P. (2001). Social psychology and science: Some lessons from Solomon Asch. *Personality and Social Psychology Review*, 5(1), 2-14. https://doi.org/10.1207/s15327957pspr0501_1
- Samuelson, L. K., Kucker, S. C., & Spencer, J. P. (2017). Moving word learning to a novel space: A dynamic systems view of referent selection and retention. *Cognitive Science*, 41(S1), 52-72. <https://doi.org/10.1111/cogs.12369>
- Samuelson, L. K., Schutte, A. R., & Horst, J. S. (2009). The dynamic nature of knowledge: Insights from a dynamic field model of children's novel noun generalization. *Cognition*, 110(3), 322-345. <https://doi.org/10.1016/j.cognition.2008.10.017>
- Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., Held, H., van Nes, E. H., Rietkerk, M., & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature*, 461(7260), 53-59. <https://doi.org/10.1038/nature08227>
- Schein, C., Jackson, J. C., Frasca, T., & Gray, K. (2020). Praise-many, blame-fewer: A common (and successful) strategy for attributing responsibility in groups. *Journal of Experimental Psychology: General*, 149(5), 855-869. <https://doi.org/10.1037/xge0000683>
- Schöner, G., Spencer, J. P., and the DFT Research Group (2015). *Dynamic thinking: A primer on dynamic field theory*. Oxford University Press.
- Schuhmacher, N., Ballato, L., & van Geert, P. (2014). Using an agent-based model to simulate the development of risk behaviors during adolescence. *Journal of Artificial Societies and Social Simulation*, 17(3). <https://doi.org/10.18564/jasss.2485>
- Schutte, A. R., Spencer, J. P., & Schöner, G. (2003). Testing the dynamic field theory: Working memory for locations becomes more spatially precise over development. *Child development*, 74(5), 1393-1417. <https://doi.org/10.1111/1467-8624.00614>
- Serban, A., Yammarino, F. J., Dionne, S. D., Kahai, S. S., Hao, C., McHugh, K. A., Lee Sotak, K., Mushore, A. B. R., Friedrich, T. L., & Peterson, D. R. (2015). Leadership emergence in face-to-face and virtual teams: A multi-level model with agent-based simulations, quasi-experimental and experimental tests. *The Leadership Quarterly*, 26(3), 402-418. <https://doi.org/10.1016/j.leaqua.2015.02.006>
- Shockley, K., & Turvey, M. T. (2005). Encoding and retrieval during bimanual rhythmic coordination. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 31(5), 980-990. doi:10.1037/0278-7393.31.5.980
- Shoda, Y., LeeTiernan, S., & Mischel, W. (2002). Personality as a dynamical system: Emergence of stability and distinctiveness from intra and interpersonal interactions. *Personality and Social Psychology Review*, 6(4), 316-325. https://doi.org/10.1207/s15327957pspr0604_06
- Shoda, Y., Wilson, N. L., Whitsett, D. D., Lee-Dussud, J., & Zayas, V. (2015). The person as a cognitive-affective processing system: Quantitative idiography as an integral component of cumulative science. In M. Mikulincer & P. R. Shaver, M. L. (Eds.), *APA handbook of personality and social psychology, Vol. 4, Personality processes and individual differences* (pp. 491-523). American Psychological Association.
- Showers, C. (1992). Compartmentalization of positive and negative self-knowledge: Keeping bad apples out of the bunch. *Journal of Personality and Social Psychology*, 62(6), 1036-1049. <https://doi.org/10.1037/0022-3514.62.6.1036>
- Simmons, J. P., Nelson, L. D., & Simonsohn, U. (2011). False-positive psychology: Undisclosed flexibility in data collection and analysis allows presenting anything as significant. *Psychological Science*, 22(11), 1359-1366. <https://doi.org/10.1177/0956797611417632>
- Simons, D. J., Shoda, Y., & Lindsay, D. S. (2017). Constraints on Generality (COG): A proposed addition to all empirical papers. *Perspectives on Psychological Science*, 12(6), 1123-1128. <https://doi.org/10.1177/1745691617708630>
- Smaldino, P. E., Calanchini, J., & Pickett, C. L. (2015). Theory development with agent-based models. *Organizational Psychology Review*, 5(4), 300-317. <https://doi.org/10.1177/2041386614546944>
- Smith, E. R., & Conrey, F. R. (2007). Agent-based modeling: A new approach for theory building in social psychology. *Personality and Social Psychology Review*, 11(1), 87-104. <https://doi.org/10.1177/1088868306294789>
- Sparrow, W. A., & Newell, K. M. (1998). Metabolic energy expenditure and the regulation of movement economy. *Psychonomic Bulletin & Review*, 5(2), 173-196. <https://doi.org/10.3758/bf03212943>
- Spencer, J. P., Smith, L. B., & Thelen, E. (2001). Tests of a dynamic systems account of the A-not-B error: The influence of prior experience on the spatial memory abilities of two-year-olds. *Child Development*, 72(5), 1327-1346. <https://doi.org/10.1111/1467-8624.00351>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Spivey, M. J., & Dale, R. (2006). Continuous dynamics in real-time cognition. *Current Directions in Psychological Science*, 15(5), 207-211. <https://doi.org/10.1111/j.1467-8721.2006.00437.x>
- Steele, J. S., Ferrer, E., & Nesselroade, J. R. (2013). An idiographic approach to estimating models of dyadic interactions with differential equations. *Psychometrika*, 79(4), 675-700. <https://doi.org/10.1007/s11336-013-9366-9>
- Steels, L., & Belpaeme, T. (2005). Coordinating perceptually grounded categories through language: A case study for colour. *Behavioral and Brain Sciences*, 28(4), 469-489. <https://doi.org/10.1017/s0140525x05000087>
- Steenbeek, H., & van Geert, P. (2008). The empirical validation of a dynamic systems model of interaction: Do children of different sociometric statuses differ in their dyadic play interactions? *Developmental Science*, 11(2), 253-218. <https://doi.org/10.1111/j.1467-7687.2007.00655.x>
- Strogatz, S. (2003). *Sync: The emerging science of spontaneous order*. Hyperion Books.
- Swann, W. B., Jr. (2012). Self-verification theory. In P. A. M. Van Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), *Handbook of theories of social psychology* (Vol. 2, pp. 23-42). Guilford Press.
- Szucs, D., & Ioannidis, J. P. A. (2017). Empirical assessment of published effect sizes and power in the recent cognitive neuroscience and psychology literature. *PLoS Biology*, 15(3), e2000797. <https://doi.org/10.1371/journal.pbio.2000797>
- Tesser, A. (1988). Toward a self-evaluation maintenance model of social behavior. *Advances in Experimental Social Psychology*, 21, 181-227. [https://doi.org/10.1016/s0065-2601\(08\)60227-0](https://doi.org/10.1016/s0065-2601(08)60227-0)
- Thagard, P., & Nerb, J. (2002). Emotional gestalts: appraisal, change, and the dynamics of affect. *Personality and Social Psychology Review*, 6(4), 274-282. https://doi.org/10.1207/s15327957pspr0604_02
- Thelen, E., Corbetta, D., Kamm, K., Spencer, J. P., Schneider, K., & Zernicke, R. F. (1993). The transition to reaching: Mapping intention and intrinsic dynamics. *Child Development*, 64(4), 1058-1098. <https://doi.org/10.1111/j.1467-8624.1993.tb04188.x>
- Thelen, E., Schöner, G., Scheier, C., & Smith, L. (2001). The dynamics of embodiment: A field theory of infant perseverative reaching. *Behavioral and Brain Sciences*, 24(1), 1-34. <https://doi.org/10.1017/S0140525X01003910>
- Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. MIT press.
- Thelen, E., & Ulrich, B. D. (1991). Hidden skills: A dynamic systems analysis of treadmill stepping during the first year. *Monographs of the Society for Research in Child Development*, 56(1, Serial No. 223), i-103. <https://doi.org/10.2307/1166099>
- Tognoli, E., & Kelso, J. A. S. (2014). The metastable brain. *Neuron*, 81(1), 35-48. <https://doi.org/10.1016/j.neuron.2013.12.022>
- Tognoli, E., Zhang, M., Fuchs, A., Beetle, C., & Kelso, J. A. S. (2020). Coordination dynamics: A foundation for understanding social behavior. *Frontiers in Human Neuroscience*, 14(317). <https://doi.org/10.3389/fnhum.2020.00317>
- Usher, M., Stemmler, M., & Olami, Z. (1995). Dynamic pattern formation leads to 1/f noise in neural populations. *Physical Review Letters*, 74(2), 326-329. doi:10.1103/physrevlett.74.326
- Vallacher, R. R., & Fennell, E. (2021). Rapid social change and the emergence of populism. In J. P. Forgas, W. D. Crano, & K. Fiedler (Eds.), *The psychology of populism: The tribal challenge to liberal democracy* (pp. 332-347). Routledge/Taylor & Francis.
- Vallacher, R. R., Nowak, A., Froehlich, M., & Rockloff, M. (2002). The dynamics of self-evaluation. *Personality and Social Psychology Review*, 6(4), 370-379. https://doi.org/10.1207/S15327957PSPR0604_11
- Vallacher, R. R., Read, S. J., & Nowak, A. (Eds.). (2017). *Computational social psychology*. Routledge/Taylor & Francis.
- Vallacher, R. R., van Geert, P., & Nowak, A. (2015). The intrinsic dynamics of psychological process. *Current Directions in Psychological Science*, 24(1), 58-64. <https://doi.org/10.1177/0963721414551571>
- Vallacher, R. R., & Wegner, D. M. (1989). Levels of personal agency: Individual variation in action identification. *Journal of Personality and Social Psychology*, 57(4), 660-671. <https://doi.org/10.1037/0022-3514.57.4.660>
- van de Leemput, I. A., Wichers, M., Cramer, A. O. J., Borsboom, D., Tuerlinckx, F., Kuppens, P., van Nes, E. H., Viechtbauer, W., Giltay, E. J., Aggen, S. H., Derom, C., Jacobs, N., Kendler, K. S., van der Maas, H. L. J., Neale, M. C., Peeters, F., Thiery, E., Zachar, P., & Scheffer, M. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences*, 111(1), 87-92. <https://doi.org/10.1073/pnas.1312114110>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Van der Maas, H. L. J., Dolan, C. V., Grasman, R. P. P. P., Wicherts, J. M., Huizenga, H. M., & Raijmakers, M. E. J. (2006). A dynamical model of general intelligence: The positive manifold of intelligence by mutualism. *Psychological Review*, *113*(4), 842-861. <https://doi.org/10.1037/0033-295X.113.4.842>
- van Dijk, M., van Geert, P., Korecky-Kröll, K., Maillochon, I., Laaha, S., Dressler, W. U., & Bassano, D. (2013). Dynamic adaptation in child–adult language interaction. *Language Learning*, *63*(2), 243-270. <https://doi.org/10.1111/lang.12002>
- van Geert, P. (1991). A dynamic systems model of cognitive and language growth. *Psychological Review*, *98*(1), 3-53. <https://doi.org/10.1037/0033-295X.98.1.3>
- van Geert, P. (1994). *Dynamic systems of development: Change between complexity and chaos*. Harvester Wheatsheaf.
- van Geert, P. (1998). A dynamic systems model of basic developmental mechanisms: Piaget, Vygotsky, and beyond. *Psychological Review*, *105*(4), 634-677. <https://doi.org/10.1037/0033-295x.105.4.634-677>
- van Geert, P. (2014a). Dynamic modeling for development and education: From concepts to numbers. *Mind, Brain, and Education*, *8*(2), 57-73. <https://doi.org/10.1111/mbe.12046>
- van Geert, P. (2014b). Group versus individual data in a dynamic systems approach to development. *Enfance*, *3*(3), 283-312. <https://doi.org/10.3917/enf1.143.0283>
- van Geert, P., & de Ruiter, N. (Eds.). (2022). *Toward a process approach in psychology: Stepping into Heraclitus' River*. Cambridge University Press.
- van Geert, P., & Steenbeek, H. (2005). Explaining after by before. Basic aspects of a dynamic systems approach to the study of development. *Developmental Review*, *25*(3-4), 408-442. <https://doi.org/10.1016/j.dr.2005.10.003>
- van Gelder, T., & Port, R. (1995). It's about time: An overview of the dynamical approach to cognition. In R. Port & T. van Gelder (Ed.), *Mind as motion: Explorations in the dynamics of cognition* (pp. 1-43). MIT Press.
- Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2003). Self-organization of cognitive performance. *Journal of Experimental Psychology: General*, *132*(3), 331-350. <https://doi.org/10.1037/0096-3445.132.3.331>
- Varela, F. J., Thompson, E., & Rosch, E. (1991). *The embodied mind: Cognitive science and human experience*. The MIT Press.
- Wagenmakers, E.-J., Farrell, S., & Ratcliff, R. (2005). Human cognition and a pile of sand: A discussion on serial correlations and self-organized criticality. *Journal of Experimental Psychology: General*, *134*(1), 108-116. <https://doi.org/10.1037/0096-3445.134.1.108>
- Wagenmakers, E.-J., Sarafoglou, A., Aarts, S., Albers, C., Algermissen, J., Bahník, Š., van Dongen, N., Hoekstra, R., Moreau, D., van Ravenzwaaij, D., Sluga, A., Stanke, F., Tendeiro, J., & Aczel, B. (2021). Seven steps toward more transparency in statistical practice. *Nature Human Behaviour*, *5*, 1473-1480. <https://doi.org/10.1038/s41562-021-01211-8>
- Wagenmakers, E.-J., van der Maas, H. L. J., & Farrell, S. (2012). Abstract concepts require concrete models: Why cognitive scientists have not yet embraced nonlinearly coupled, dynamical, self-organized critical, synergistic, scale-free, exquisitely context-sensitive, interaction-dominant, multifractal, interdependent brain-body-niche systems. *Topics in Cognitive Science*, *4*(1), 87-93. <https://doi.org/10.1111/j.1756-8765.2011.01164.x>
- Wagenmakers, E.-J., Wetzels, R., Borsboom, D., van der Maas, H. L. J., & Kievit, R. A. (2012). An agenda for purely confirmatory research. *Perspectives on Psychological Science*, *7*(6), 632-638. <https://doi.org/10.1177/1745691612463078>
- Wallot, S., & Kelty-Stephen, D. G. (2018). Interaction-dominant causation in mind and brain, and its implication for questions of generalization and replication. *Minds and Machines*, *28*(2), 353-374. <https://doi.org/10.1007/s11023-017-9455-0>
- Ward, L. M. (2002). *Dynamical cognitive science*. MIT Press.
- Warren, W. H. (2006). The dynamics of perception and action. *Psychological Review*, *113*(2), 358-389. <https://doi.org/10.1037/0033-295X.113.2.358>
- Westaby, J. D., Pfaff, D. L., & Redding, N. (2014). Psychology and social networks: A dynamic network theory perspective. *American Psychologist*, *69*(3), 269-284. <https://doi.org/10.1037/a0036106>
- Westaby, J. D., Woods, N., & Pfaff, D. L. (2016). Extending dynamic network theory to group and social interaction analysis. *Organizational Psychology Review*, *6*(1), 34-62. <https://doi.org/10.1177/2041386614551319>
- Weston, S. J., Gladstone, J. J., Graham, E. K., Mroczek, D. K., & Condon, D. M. (2019). Who are the scrooges? Personality predictors of holiday spending. *Social Psychological and Personality Science*, *10*(6), 775-782. <https://doi.org/10.1177/1948550618792883>

COMPLEXITY OF PSYCHOLOGICAL PROCESSES AND REPRODUCIBILITY ISSUE

- Wichers, M., Groot, P. C., Psychosystems, ESM Group, & EWS Group (2016). Critical slowing down as a personalized early warning signal for depression. *Psychotherapy and Psychosomatics*, 85(2), 114-116. <https://doi.org/10.1159/000441458>
- Wilensky, U. (1999). *NetLogo*. Evanston, IL: Northwestern University, Center for Connected Learning and Computer-Based Modeling. <http://ccl.northwestern.edu/netlogo>
- Witherington, D. C. (2011). Taking emergence seriously: The centrality of circular causality for dynamic systems approaches to development. *Human Development*, 54(2), 66-92. <https://doi.org/10.1159/000326814>
- Wolfram, S. (2002). *A new kind of science*. Wolfram Media.
- Wong, A. E., Vallacher, R. R., & Nowak, A. (2016). Intrinsic dynamics of self-evaluation: The role of self-concept clarity. *Personality and Individual Differences*, 100, 167-172. <https://doi.org/10.1016/j.paid.2016.05.024>
- Woodward, J. (2016). Causation and manipulability. In E. N. Zalta (Ed.), *The Stanford Encyclopedia of Philosophy*. <https://plato.stanford.edu/archives/win2016/entries/causation-mani>
- Zanone, P. G., & Kelso, J. A. (1992). Evolution of behavioral attractors with learning: Nonequilibrium phase transitions. *Journal of Experimental Psychology: Human Perception and Performance*, 18(2), 403-421. <https://doi.org/10.1037/0096-1523.18.2.403>
- Zbilut, J. P., & Webber Jr., C. L. (1992). Embeddings and delays as derived from quantification of recurrence plots. *Physics Letters A*, 171(3-4), 199-203. [https://doi.org/10.1016/0375-9601\(92\)90426-M](https://doi.org/10.1016/0375-9601(92)90426-M)
- Zwaan, R. A., Etz, A., Lucas, R. E., & Donnellan, M. B. (2018). Making replication mainstream. *Behavioral and Brain Sciences*, 41, e120. <https://doi.org/10.1017/s0140525x17001972>

Glossary

** Terms the definitions of which can also be found in main text of this article*

Attractor. A region of the space of possible states of a CDS that has the property of stabilizing the system's behavior. The strength of an attractor determines its resistance to perturbation (e.g., Haken et al., 1985). In psychology, a strong attractor corresponds to psychological states or patterns of psychological states that are stabilized and therefore more easily reproducible empirically. In dynamical terms, the quest for reproducibility in mainstream psychology research could be described as a quest for strong attractors. However, stabilized psychological patterns are far from being the most common, which may explain much of the non-reproducibility of the effects reported in this field.

***Causality.** Traditionally, determinism according to which any phenomenon can be explained by previous events and conditions as combined with the laws of nature. For our purpose, two forms of causality are contrasted: *interventionist causality* and *process causality*.

According to interventionist or manipulationist causality, nature or humans can intervene in processes and/or manipulate causes to intervene in processes (Reutlinger, 2013; Woodward, 2016). In mainstream psychological science, this type of causality is represented through separate and additive statistical structures of causal relationships that are generally revealed by nomothetic studies. Today, these statistical structures appear insufficiently reproducible, probably because they cannot account for the complex, dynamic and idiosyncratic features of psychological phenomena (see *Complexity, Intrinsic Dynamics, and Ergodicity*).

According to process causality, phenomena emerge from processes that are both complex (see *Complexity*) and dynamic (see *Intrinsic dynamics*). Therefore, the CDS approach is well suited to shed light on process causality in psychology (van Geert & de Ruiter, 2022), especially through the development and testing of formal models of psychological dynamics, which can be implemented by computer simulation.

Complexity. Property of a system reflecting the mutual and continuous influences among its components, which give rise to global states of the system that in turn constrain the states and interactions of its components (see *Intrinsic dynamics*). Complexity thus defines a process, not a quantity of components or a degree of sophistication of their interactions. As computer simulations can show, very few components and very simple rules of influence are sufficient to make complex behaviors emerge.

Complex is often confused with complicated (e.g., Den Hartigh et al., 2017). According to a reductionist approach, it is possible to identify in a clock the role of each wheel, gear, spring, etc., and reliably deduce the behavior of the system thus composed. In mainstream psychology, this reductionist approach consists in identifying the roles of supposed determinants of psychological phenomena, adding them and combining them in a relatively simple multiplicative way in models of supposedly causal relationships. However, these models explain limited proportions of the variance of the phenomena studied and remain insufficiently reproducible. Unlike a clock, which is a complicated mechanism, the psychological system is complex because its behavior cannot be directly deduced from the knowledge of its components and their relationships (see *Self-organization*).

Critical Slowing Down. Slower return of a system to its previous state resulting from a loss of attractor strength under the effect of strong and/or repeated perturbations. If the stability of a CDS is perturbed, for example by an event or series of events that are not congruent with the system's state, this state will momentarily change, oscillate, and then recover stability. The return time to stability—also called relaxation time—will be shorter the stronger the perturbed attractor is. However, strong and/or repeated perturbations reduce the restoring force of this attractor, which entails an increase in the relaxation time. A critical level of slowing down is a precursor of a shift in attractors, i.e., the adoption of a new stable state by the system. In psychology, this nonlinear behavioral dynamics (see *Non-linearity*), which the traditional approach cannot account for, enables the prediction of when a new stable state is about to be adopted. For example, the critical slowing down of emotional fluctuations has been shown to be an early warning signal of the onset and termination of depressive episodes (van de Leemput et al., 2014; Wichers et al., 2016).

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***Ergodicity.** Statistical property of a process, according to which a statistical model meets *homogeneity* and *stationarity* criteria. A process is homogeneous if its statistical model as deduced from the analyses conducted at the group level is confirmed by the analyses of individual level. The process is stationary if the statistical parameters of its data (mean, variance, saturation coefficients, etc.) do not vary over time. Satisfying the two conditions of homogeneity and stationarity is extremely rare in psychology, where the dynamics of processes imply changes in their statistical features in an idiosyncratic way (Fisher et al., 2018; Hamaker, 2023; Molenaar & Campbell, 2009). Ergodicity is even largely ignored in mainstream research. By making it possible to generalize from idiosyncratic dynamics, the CDS approach conserves the ergodicity of the psychological processes.

***Intrinsic dynamics.** Process of change according to which the state of a system at Time 1 determines, to a certain degree, the state of the system at Time 2. This process follows evolutionary rules that can be expressed mathematically in the form of equations of change such as iterative functions and differential or difference equations (e.g., Vallacher et al., 2015). The intrinsic dynamics of a CDS results from self-organization processes that develop over time in the form of iterative mutual interactions between system components, as well as between these components and the global state of the system (see *Complexity* and *Self-organization*). The investigation of intrinsic dynamics is central to the CDS approach to psychology, whereas it is omitted in a traditional science in search of structures of causal relations.

Metastability. CDSs' self-sustained states resulting from attractor dynamics are sometimes poised in weak attractors (see *Attractor*). This metastability provides CDSs with the capability to rapidly shift towards a variety of coexisting stronger latent attractors (Usher et al., 1995). This provides systems a certain sensitivity to the slightest perturbation that enables their rapid adaptation to novelty and environmental changes (see *Self-organized Criticality*). As a consequence, metastability is a specific stance of attractor dynamics that makes CDSs' behavior difficult to predict and empirically reproduce. Although metastable dynamics could account for the brain's dynamic cognitive, behavioral, and social functions (Tognoli & Kelso, 2014), metastability remains generally understudied, and ignored by mainstream psychological science.

Non-linearity. Lack of proportionality between the quantity or the magnitude of putative causes and the variations of the psychological phenomenon under study. When self-maintaining stable states emerge, systems actively counteract a wide range of perturbations. But during transitory episodes between attractors or when systems' states are metastable, any minor or insignificant influence can entail abrupt shifts in attractors (Haken et al., 1985; Kelso, 1995). This lack of proportionality makes psychological phenomena hardly predictable and hardly reproducible by the general linear model, except when these phenomena are self-sustained in strong attractors (see *Attractor*).

1/f Power-law Distribution. Temporal fluctuations of systems' states, the frequencies of which remain invariant across timescales and obey typical 1/f power-law distributions also called 1/f noise or pink noise. In these distributions, the frequency of a particular magnitude of fluctuation is inversely proportional to this magnitude. 1/f noise characterizes time series with long-range temporal correlations, i.e., time series with lagged autocorrelations that decay slowly, as an inverse power of lag (e.g., Gilden et al., 1995). This typical signature of complexity has been revealed, for example, in the temporal structure of self-esteem variability, which was not random but rather exhibited invariance across different time scales (de Ruiter et al., 2015). 1/f noise has also been found in other psychological phenomena concerning human cognition and motor behavior.

Self-organization. Process by which the internal organization of a system automatically increases without being directed by an external source. This process consists of iterative loops involving (1) changes in the states of the system's components as a result of their previous states and their mutual interactions, (2) the emergence of a global state of the system resulting from its components' evolution, and (3) the constraints exerted by this global state on the system's components and their relationships (see *Complexity* and *Intrinsic Dynamics*). Some bottom-up processes sometimes envisaged in mainstream approaches might be seen as close to the idea of self-organization. However, these processes are considered in terms of interventionist causality that is hardly compatible with the central ideas of complexity and intrinsic dynamics inherent in the process causality perspective (see *Causality*).

***Self-organized Criticality.** A special kind of self-organization that drives the system to critical states that are optimally poised in temporarily stable weak attractors located in the vicinity of stronger attractors. This

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fragile stability—prevalent in natural phenomena—provides systems with flexibility by enabling them to sustain an appropriate state while being ready to adapt quickly to unforeseen circumstances (Bak, 1996, see also *Metastability*). Hence, systems in such a state are very sensitive to the slightest perturbation, which makes their behavior difficult to predict and to reproduce empirically. While ignored by mainstream psychological science, self-organized criticality has been identified within the CDS paradigm in several psychological phenomena such as self-esteem, various types of cognitive performance, and motor behavior.