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Understanding the complexity of individual developmental pathways: A primer on metaphors, models, and methods to study resilience in development

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Abstract

The modern study of resilience in development is conceptually based on a complex adaptive system ontology in which many (intersystem) factors are involved in the emergence of resilient developmental pathways. However, the methods and models developed to study complex dynamical systems have not been widely adopted, and it has recently been noted this may constitute a problem moving the field forward. In the present paper, I argue that an ontological commitment to complex adaptive systems is not only possible, but highly recommended for the study of resilience in development. Such a commitment, however, also comes with a commitment to a different causal ontology and different research methods. In the first part of the paper, I discuss the extent to which current research on resilience in development conceptually adheres to the complex systems perspective. In the second part, I introduce conceptual tools that may help researchers conceptualize causality in complex systems. The third part discusses idiographic methods that could be used in a research program that embraces the interaction dominant causal ontology and idiosyncratic nature of the dynamics of complex systems. The conclusion is that a strong ontological commitment is warranted, but will require a radical departure from nomothetic science.

Keywords: Complex systems; interaction dominant dynamics; resilience; adaptation; idiographic methods

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Introduction

Psychopathology has recently been reconceptualized from a condition comparable to a disease with a unique etiology of identifiable causes (i.e., the medical disease model), into a phenomenon with a massively multifactorial etiology (Borsboom & Cramer, 2013), best described as "a complex system of contextualized dynamic processes that is nontrivially specific to each individual" (Wright & Woods, 2020). A complex dynamical system consists of many different components (which can also be complex systems), that interact with the internal and external environment of the system, across many different spatial and temporal scales. The behavior of a complex system is often referred to as a self-organized state or pattern which emerges from those multiscale interactions. Conceptualizing psychopathology as a self-organized state of a complex system implies that trying to establish a chain of independent, universal causal factors may be a futile endeavor, because the pattern emerges from the continuous interactions between a myriad of bio-psycho-socio-cultural processes (Hayes et al., 2015; Olthof, Hasselman, Oude Maatman, et al., 2023). Moreover, the onset, course, and persistence of a psychopathological state will be codetermined by a unique history of lived experiences that is unique to an individual patient. Based on this complex system perspective on psychopathology, a vast heterogeneity of symptoms and causal factors is indeed expected. For example, in a sample of 3700 patients diagnosed with Major Depressive Disorder, about 8% of all unique symptom patterns were endorsed by five individuals or less, and the most common pattern had a frequency of occurrence of just 1.8% (Fried & Nesse, 2015). Another example reveals the heterogeneity does not only concern factors that are psychological in nature. Wolfers et al. (2018) describe an attempt to identify structural differences between brain areas in patients with schizophrenia and healthy controls, which was successful at the level of the averaged brains (218 patients vs. 256 healthy control), but found a maximum of 2% overlap in just a few anomalous loci between patients. The authors conclude "the average patient is a noninformative construct in psychiatry that falls apart when mapping abnormalities at the level of the individual patient" (Wolfers et al., 2018, p. 1146).

To the developmental psychologist this complex systems perspective may appear as old ideas parading as new ones: Many of the metaphors and models inspired by complexity science were introduced several decades ago to describe developmental processes as self-organizing, interaction dominant and multicausal (e.g., Cicchetti

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& Tucker, 1994; Lewis, 1995), for example, in the context of the dynamic systems approach to the development of cognition and action (Thelen & Smith, 1994; van Geert, 1991), Ecological Systems Theory (EST; Bronfenbrenner, 1992) and its successors, such as the Phenomenological version of EST (Hall et al., 2022; Spencer et al., 1997). These and other developmental scientists have consistently emphasized the importance of taking the dynamical, multifactorial, and idiosyncratic nature of (the development of) human behavior into account and phenomena such as person–environment interactions, resilience, and feedback loops, are now more generally considered powerful explanatory vehicles in theories of human behavior and cognition (Heino et al., 2021; Masten et al., 2021; van Geert, 2019).

Notwithstanding the emerging theoretical consensus, there are many different opinions on the appropriate research methods and analytical tools that can be used to study these phenomena in a way that respects the importance of their dynamical and person-specific nature. Many researchers default to familiar nomothetic methods, that is, they attempt to infer properties of complexity phenomena based on statistical models fitted to cross-sectional, static, data (e.g., van de Leemput et al., 2014). There is still a dearth of successful examples of personalized statistical time series models (Bringmann, 2021; Ram et al., 2013; Wright & Woods, 2020). Such research programs are based on a *weak complexity* commitment (cf. Hasselman, 2022), in which there is a consensus about the theoretical object of study being a complex dynamical system with many interacting components, without any profound consequences for modal research practices, such as measurement models, study design and data analytic techniques. Even if it is recognized that time series data of human behavior reveal all the hallmarks of complex dynamics, such as non-stationarity, heterogeneity, and long-range temporal correlations (Olthof et al., 2020), these properties are often considered a nuisance factor that should be removed, by design (e.g. a "burst week" to avoid nonstationarity), by data filtering (e.g. time-series detrending), or, by modeling such phenomena as independent components in statistical models, such as time-varying covariates or random effects (Beltz & Gates, 2017; Bringmann et al., 2017). Interestingly, researchers spearheading the symptom network approach to psychopathology recently identified this gap between theory and methods as a potential problem by concluding that certain "methodological and practical challenges hamper moving from theory to clinical research" (Bringmann et al., 2022) and that "network psychometrics may make concessions that make the models used deviate from the complex systems thinking that inspired network theory" (Epskamp & Isvoranu, 2022).

The purpose of the present paper is to demonstrate that an empirical research program based on an ontological commitment to complex adaptive systems (*strong complexity*) is possible, by introducing metaphors, models, and methods that provide a better conceptual fit between theory and data. The paper is divided into three parts, the first part is mainly conceptual, it introduces some of the important features of complex systems after which the multisystem perspective on resilience in development and psychopathology as presented by Masten et al. (2021) will be used as a starting point for a discussion of opportunities to make a strong complexity commitment. The second part concerns the question of how to deal with causality in an ontology in which the assumption is that everything is interacting with everything else. Some conceptual tools will be introduced that may guide the formulation of research questions under a strong complexity commitment. The final part describes a number of idiographic complexity methods that can be used to empirically study multiscale interactions and emergent dynamics, taking hypothetical examples based on PVEST (Spencer et al., 1997) as well as Masten et al. (2021).

Complex adaptive systems: Individual pathways to psychological resilience

A system is an entity that can be described as a composition of components, according to one or more organizing principles. The organizing principles can take many different forms, but essentially, they decide the relationship between parts and wholes, between a micro-scale structure and a macro-scale state. The behavior of a dynamical system is often described as an evolution of states observable at the level of the whole, generated by configurations of the micro-scale structure. The internal structure of the system, as well as the nature of its components determine whether it is evident how micro-scale configurations are related to a macro state, that is, whether it is possible to know which components cause the macro state. In a complex system, this relationship is often unknown. A complex system is an open system with many different parts that can interact with each other and with the environment external to the system, in fact, its parts can be complex systems as well. The sciences that study the behavior of complex dynamical systems refer to the macro states as emerging from the interactions between the many component processes of the system. Complex systems tend to transition between stable (attractor) states under influence of changes in their internal or external environment, a physical process known as self-organization.

A first consequence of a strong complexity commitment would be to adopt a so-called interaction-dominant causal ontology to explain behavior (Ihlen & Vereijken, 2010; Van Orden et al., 2011; Wallot & Kelty-Stephen, 2017), which is profoundly different from the component-dominant dynamics on which current nomothetic, statistical methods are based. Figure 1 is a schematic representation of the differences between the two causal ontologies as they pertain to explaining behavior. For the purpose of the present paper, I discuss three important consequences of adopting interaction dominant dynamics as a causal ontology.

The first consequence can be illustrated by noticing the perfect fit between component-dominant dynamics and statistical models that seek to identify independent components in predictor variables that add up to explain the variance in an outcome variable (i.e., inferential statistics). If the component-dominant ontology is correct, this means statistical models can provide an explanation of phenomena in terms of the specific meaning or function associated with the linear arrangement of components that have been identified to play a role as predictors of the behavior of interest. However, if we are convinced the actual ontology resembles the interaction-dominant case, this is no longer possible, because it is the nature of the interactions between the components, not their specific function, that explains the observed behavior, a feature that may be summarized as *dynamics over content*. Methods that can be used to study the presence of multiscale interactions as well as characterize the nature of these interactions, will likely evidence nonlinear phenomena such as coupled dynamics between many different factors (feedback loops, predator–prey dynamics), or, they may reveal there is no such thing as a characteristic scale at which the dynamics of an observable can be described due to the presence of (multi) fractal scaling phenomena (Gilden et al., 1995; Wallot & Kelty-Stephen, 2017; Wijnants et al., 2009). Which factors are involved in the feedback loop is less important than the knowledge that the structure of the system under study permits such feedback loops to emerge. It is even expected that the elements that constitute such loops will vary between and even within individuals. As many authors have pointed out, attempts to study interaction

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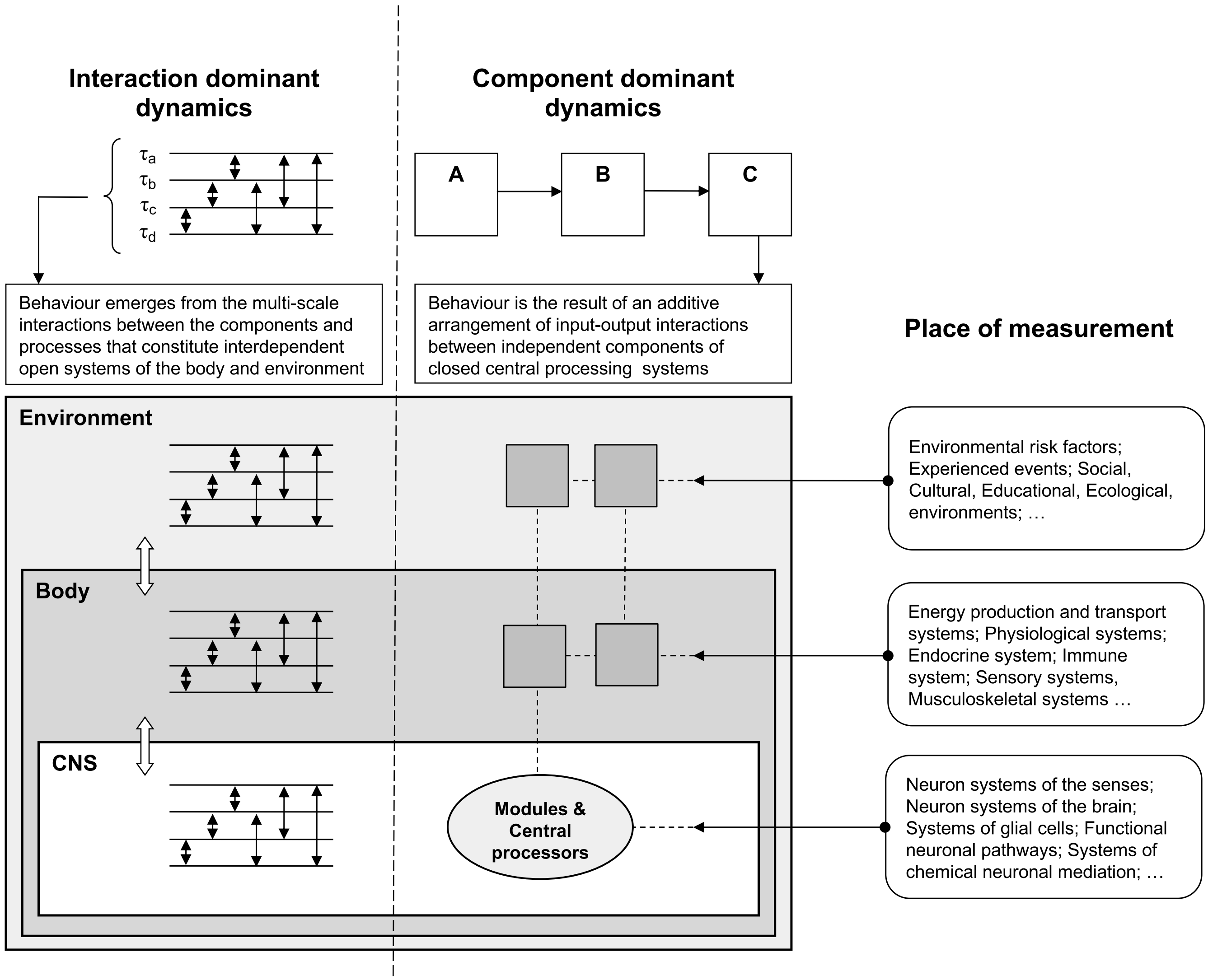

Figure 1. Contrasting two different causal ontologies used to explain behavior of complex systems. On the left, interaction dominant dynamics, on the right component dominant dynamics. See text for details.

dominant dynamics using analytical tools developed to identify independent components may lead to invalid inferences about the underlying causal structure (Van Orden et al., 2005; Wallot & Kelty-Stephen, 2017; Wijnants, Cox, et al., 2012; Wijnants, Hasselman, et al., 2012).

A second important difference is that the scales at which component processes are observed appear to play no role at all in a component-dominant ontology when determining efficient causation. Scales can be thought of in the spatial sense (e.g., the central nervous system, the body, the environment) as well as in the temporal sense (neuronal oscillations, circadian rhythms, developmental change). As will be explained in what follows, in a causal ontology in which interactions dominate the dynamics, the spatial and temporal scales across which interactions take place determine the kind of causal entailment that is possible (see e.g., Van Orden et al., 2012). The choice for a phenomenon of interest will also determine a scale of interest, relative to which other scales are considered slower or faster, smaller or larger (Noble, 2012; van Geert & Fischer, 2009).

A third important difference is that an interaction dominant causal ontology implies an idiographic science (e.g., Molenaar, 2004), in which the goal is to understand the personal histories of individuals through the observation of their social development, mental health, or academic performance over time, and in different contexts of their internal and external environment. In a component dominant ontology, the assumption is often that individual differences, e.g., in developmental trajectories can be understood as deviations from a characteristic, population-level exemplar and as a consequence, that it is possible to explain individual behavior based on knowledge about the population-level exemplar (cf. van Geert, 2019). It is not the case that nomothetic, law-like, information plays no role in a complex systems ontology: Knowledge about universal properties of the dynamics of complex systems guides empirical inquiries, for example, the universal phenomena that occur just before a system transitions from one stable state into another, like the liquid-to-gas transition when boiling water, have also been found in time series of self-reports of human experience. Phenomena such as the occurrence of critical fluctuations and critical slowing down have been shown to function as early warning signals of sudden transitions in symptom severity associated with mood disorders (Olthof, Hasselman, Strunk, et al., 2020; Wichers et al., 2016). As

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expected based on the universality of these phenomena, the early warning signals are naïve to the direction of change, they do not indicate whether symptoms of depression will increase or decrease, they just lawfully indicate that a system is self-organizing into a new stable state.

With these considerations in mind, we can now examine the multisystem perspective on resilience in development and psychopathology as reviewed by Masten et al. (2021) and evaluate the level of ontological commitment to complex dynamical systems in the proposed theoretical conceptualizations and research methods. I will focus on the concepts of resilience, adaptation, and multiscale interactions.

Psychological resilience: To adapt, or to absorb?

One of the earliest definitions of the concept of resilience in the scientific literature is by Holling (1973): "resilience determines the persistence of relationships within a system and is a measure of the ability of these systems to absorb changes of state variables, driving variables, and parameters, and still persist." Hollis was studying ecological systems, but the phenomenon is observed in a wide range of complex systems and reflects the fact that once a system has settled into a stable state, it will resist internal and external perturbations in order to persist the current state into the future. The term resilience has acquired slightly different meanings in different scientific domains, a recent review identified ecological, organizational, engineering, economic, and psychological resilience, which were in turn defined slightly different within each domain (see Table 1 in Fraccascia et al., 2018). Based on the literature of contemporary psychological science, Masten et al. (2021) suggest defining resilience as: "the capacity of a dynamic system to adapt successfully through multisystem processes to challenges that threaten the function, survival, or development of the system."

This definition correctly reflects the way in which the term is used in clinical science, clinical practice, and common language use, that is, the ability to persist a very specific state, one that is considered beneficial to the individual in question, such as a "healthy" physical or mental state, or a developmental trajectory that is "typical." However, formally, resilience refers to the ability of a complex system to persist *any* state in response to perturbation (Cui et al., 2023), irrespective of whether the state is a clinical depression, or represents 10 years of sobriety. In fact, from a complex systems perspective, psychotherapeutic interventions are designed to perturb the psychopathological state, to break down its resilience and destabilize it (Olthof et al., 2019), allowing the system to reorganize itself into a new stable state that is not pathological (Olthof, Hasselman, Oude Maatman, et al., 2023; see also, Schiepek, 2009). As mentioned before, the general principles and processes involved in transitions between stable states in complex systems are the same for "healthy" and "unhealthy" states and measures to determine whether a system is about to transition from one stable state into another, are called "resilience loss indicators" (Hasselman, 2022; Weinans et al., 2021). To avoid any confusion, I will use the term *psychological resilience* to refer to the persistence of states that can be labeled as "healthy," and use qualifications such as "a stable psychopathological state" for the resilience of states that are maladaptive or "unhealthy."

In Holling's (1973) original definition of resilience, the word "absorb" is used in reference to the ability to resist changes that may come from a multitude of sources in the internal or external environment of the system. The definition of psychological resilience uses the term "adaptation" to refer to the same ability, but also adds that adaptation will occur through "multisystem processes". The properties of adaptation and resilience are two related, but separate characteristics of complex systems. Adaptation refers to the ability of a system to reorganize its internal structure in response to changes in the internal or external environment in order to allow the system to continue to perform its general function. The latter is also included in the definition of psychological resilience as "challenges that threaten the function, survival, or development of the system." In the context of learning and development, adaptation will generally increase the complexity of the system, or at least expand the degrees of freedom the system has available to generate its behavior. That is, adaption implies new states will emerge, that can of course vary in their degree of stability, their resilience. If a system would be caught in a state that is extremely resilient, it would, by definition, be very difficult to adapt to any changing demands of the environment, due to the "persistence of relationships within a system," that is, the resistance to change the internal structure is implied by the extreme resilience of the state. This is why the term "absorb" is used to describe the resilience of a state: No adaptation of structure is required; the current state will persist.

From the perspective of a strong complexity commitment, the definition of psychological resilience as provided by Masten et al. (2021) should be considered a mixture of the concepts of resilience and adaptation. Psychological resilience describes the observable phenomenon of the remarkable stability of specific "healthy" states that can absorb all kinds of shocks and perturbations, as well as the ability of a system to reorganize its structure in order to be able to continue producing similar resilient "healthy" states under changing demands of the internal and external environment. Given these annotations, there are no objections to commit to a complex system ontology for studying psychological resilience in development based on interaction dominant dynamics.

In their review of the models and methods used to study resilience, the authors point out that: "Still missing in cascade models, however, is the dynamic interplay of complex adaptive systems" (Masten et al., 2021, p. 531). The authors proceed to discuss a shortlist of multisystem resilience factors that concern processes that span many different systems (brain, body, family, school, community) and spatiotemporal scales (neurobiological, cognitive, emotional, and cultural processes). Although an important emphasis is placed on the complex, nonlinear dynamics involved in understanding resilience of developmental pathways, virtually all conclusions, suggestions, and recommendations are based on a component-dominant causal ontology in which it is assumed possible to trace the individual contributions of component processes to explain psychological resilience in development. That is, the scales and system boundaries that are acknowledged to exist, appear to play no role in data analysis and causal inference, they appear as additional independent components or mediators in the causal chain. This is also reflected in interventions which are described as functioning as a mediator to amplify (or reduce) the effects of resilience or risk factors (i.e., by "installing" a better component into the chain).

From the perspective of the strong ontological commitment to complexity, resilience should be an emergent property, not an identifiable set of risk factors. Empirical studies would focus on examining the contexts in which resilience emerges and when it does not. It is expected that what is a risk factor to one individual may be a protective factor to another, or, that such factors may even switch roles within an individual, phenomena that are in fact briefly discussed by Masten et al. (2021) in reference to the work of

Rutter (1987). Dealing with causality in complex adaptive systems remains a difficult topic, in the next section several conceptual tools are introduced that may help researchers get a better grip on complexity, by aligning posited causes, cascades, and contexts along spatial and temporal scales.

Dealing with causality in complex systems

Using an interaction dominant causal ontology to explain behavior can become overwhelming when the vast number of potential factors that could be involved present themselves. For example, according to the Complexity Theory of Psychopathology (Olthof, Hasselman, Oude Maatman, et al., 2023), "pathology is not a disorder, but another kind of order" (Bosman, 2017). Differentiating between a stable psychological state that is "healthy" and one that is "pathological" is based on a normative judgement which always exists relative to the social and cultural contexts of a specific time and location. Is it the case that, in order to determine why a certain behavioral pattern displayed by an individual should be called a disordered pattern, we would need to consider causes that may transcend the life span of an individual, for example, the events in a family history that cause an individual to be born at a particular geographical location, in a specific sociocultural environment, in a specific moment in time? These events are no longer present, but their after-effects do play a role in explaining why the behavior of an individual in the here and now is considered "normal," "anti-social," "above average," "pathological," etc. (Olthof, Hasselman, Oude Maatman, et al., 2023). If this is the case, how would we differentiate the effects of these causes from effects of events that lie in an individual's personal history and interact in the present through the memory of their experience?

Permissive and causative structure

In an interaction-dominant causal ontology it makes sense to distinguish between *immediate* causal entailment and entailment that is *mediative* for explaining the behavior of individuals (see Figure 2). The former refers to causes for the current state of affairs whose effects are immediate (e.g., laws of physics, genotype, sociocultural environment, personality), the latter refers to the causes that can be traced as mediators in the realization of the current state of affairs (e.g., age, time of day, quality of sleep last night, current emotional state). The divide between the different types of entailment is an *effect horizon*, its main purpose is to serve as an explanatory vehicle to indicate there is a structure that is *permissive* of the behavior in the present, and a structure that is *causative* (cf. Walker, 1983). The permissive structure appears as a set of constants painted on the horizon representing boundary conditions for the causative structure. The causative structure lies within the horizon and is the set of efficient causes of the behavior under scrutiny in the present. Quantum physical phenomena are permissive of phenomena at larger spatial scales; that is, in most circumstances it will not be sensible to declare quantum phenomena as the efficient causes for the macro-scale structure of biological systems, although there is no doubt that the macro state could not manifest itself without the immediate entailment of those quantum phenomena. The same holds for speciation by natural selection: The genome is permissive of the structure and function of organisms belonging to a specific species, for example flight in birds. It is not wrong, but also not very informative, to suggest that the behavior of an individual organism, such as a bird flying away upon sensing danger, was caused by an ancient event in their evolutionary history. This ancient event does however permit the bird to fly away.

In cases in which the time scale of interest corresponds roughly to the time scale of daily experiences, the permissive structure will contain variables related to socio-cultural processes and facts from history of nations that may be labelled as "systemic," these effects are always present and immediate. It is expected that these systemic effects will result in adaptation in the sense of changes to the internal structure of the system. An example is given by Spencer et al. (1997) of the recursive self-appraisal processes in African-American adolescent males who will likely experience the immediate presence of stereotypes and biases as they become aware of their family, community and cultural history. These effects (protective, promoting, or random destabilizing shocks) can interact across time scales as multiplicative cascades which can have catastrophic effects (e.g. producing bi-modal outcomes as described by the cusp catastrophe; Brummitt et al., 2015), that will depend on the particulars of an individual's unique history of experiences. Indeed, Spencer et al., (1997, p. 818) write: "In the context of such a culture, youth having similar experiences can exhibit either resiliency, or psychopathology."

Upward and downward causation

The effect horizon represents a divide between spatial and/or temporal scales, which could emerge naturally due to the study design or the variables of interest, however, in principle its placement is completely arbitrary. For example, suppose a researcher is only interested in explaining the behavior of a sample of participants during a laboratory experiment. All characteristics and experiences of the participant before the start of the experiment are considered immediate effects, static parameters. The experimental manipulations are considered the causal structure that mediates a participants' behavior. As is often the case in sample-based laboratory experiments, some aspects of the permissive structure may be quantified with the purpose of examining the extent of their role in explaining the behavior observed during the experiment, such as their age or educational background, whereas other factors are "controlled for" by random sampling or random assignment of participants to design cells. The causative structure in this case is narrow in the sense that there is not a lot of room to detect any effects of factors that mediate the behavior of interest, which is of course intended by the design. Any effects of variables other than the experimental manipulation must be inferred from between individual differences in values sampled from the immediate causal factors. The causative structure is also shallow, in the sense that it is common to look at just one type of outcome variable at one scale of observation, it's either response latencies or brain activity or heart rate, or eye movements, but rarely all of those at once.

As a contrast, consider an experience sampling study about mood dynamics, in which participants for 2 months provide daily self-reports about experienced emotions, perceived stress and physical fitness and wear an electronic device which registers heart rate and electrodermal activity. The permissive structure consists of all the things that do not change during the period of observation, such as personality traits, academic achievement, ethnicity. The causative structure covers a much wider range of time scales compared to the laboratory experiment. Factors that are mediative of mood dynamics may concern stress, quality of sleep, but also self-reported mood of the previous week, or month and perhaps an increased heart rate only moments before a mood change. Due to the long observation time, we may expect

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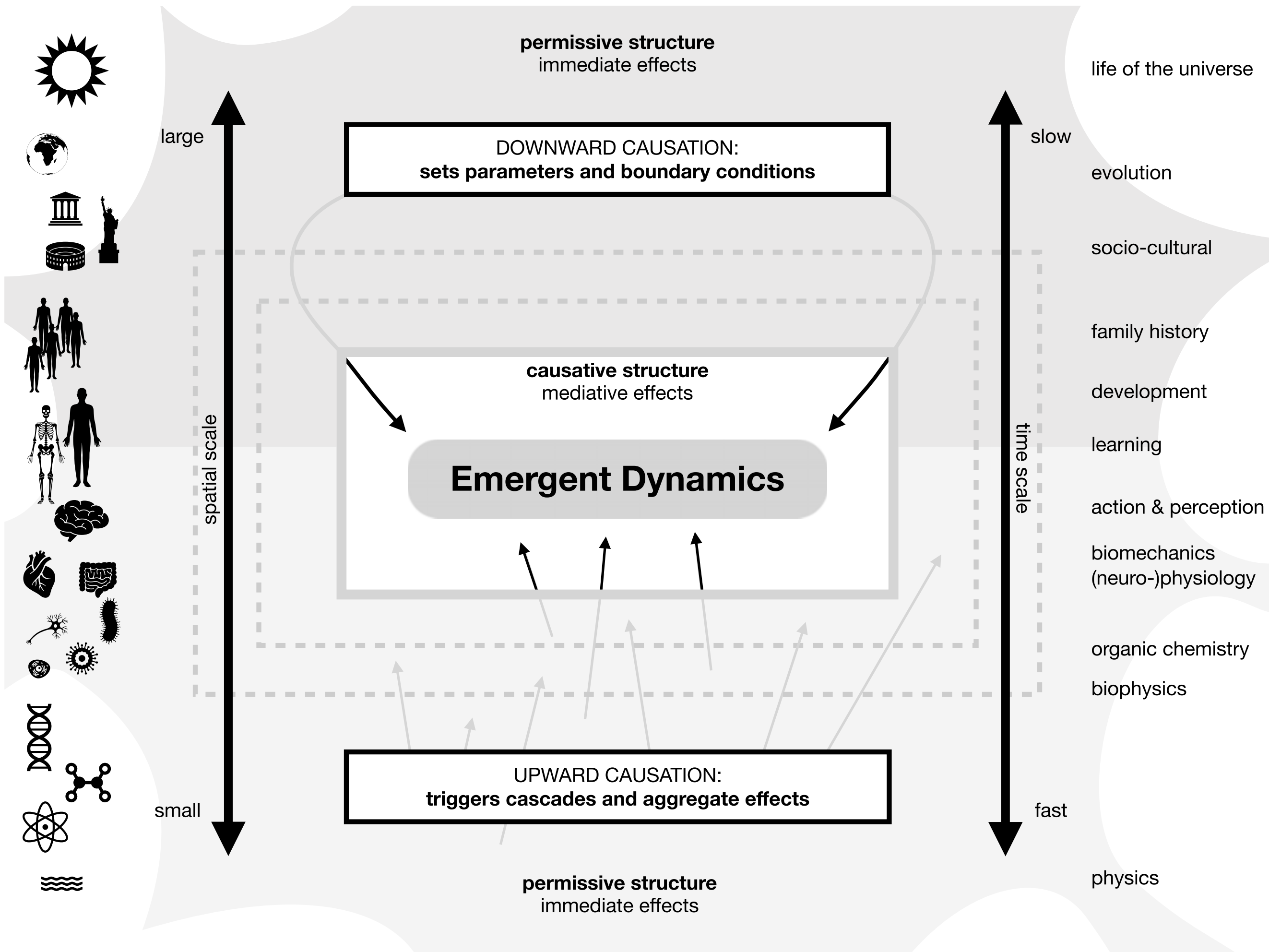

Figure 2. The gray boxes represent different effect horizons that can be placed at an arbitrary divide between spatial and temporal scales to separate immediate and mediative effects into permissive and causative structures, respectively. In addition, this illustration shows that upward causation involves structures and processes that have cascading or aggregate effects relative to higher scales. Downward causation involves structures and processes that set parameters and boundary conditions for lower scales.

interactions with the environment like the weather or random events that can be considered external shocks or perturbations, such as the loss of a loved one. The causative structure is also less shallow than the laboratory experiment because of the simultaneous observation of psychological as well as physiological processes, which allows for the determination of coupling strength between the different scales of observation as well as the direction of their coupling.

These examples reveal that there is *no privileged scale* at which causality resides in complex systems. The phenomena of interest, more specifically, the measurement context chosen to study those phenomena, involves a choice for a specific range of spatiotemporal scales at which mediative causes may be observed. These choices have consequences for causal inference, that is, relative to a scale of interest, the directionality of the causal entailment of other factors is important (see Figure 3). To understand these effects, one can imagine that from the perspective of the scale of interest, slower and faster changing processes have to be "resampled" in order to evaluate their effects, which is commonly referred to as coarse graining (Flack, 2017).[1] In general, fast processes evolving at shorter time scales can be said to be responsible for bottom-up, aggregate effects (e.g. "mean field" cascading effects), whereas processes at slower scales are more likely to have top-down effects setting boundary conditions for the faster changing processes (Noble, 2012; Noble et al., 2019). By ordering the factors that make up the causative structure relative to a temporal scale of interest, the presence of phenomena such as feedback loops that span multiple scales (referred to as circular, bi-directional, or delayed-feedback causation) can be studied. These and other interesting phenomena (such as scale-invariance) remain invisible, or, are considered logically impossible, if multiscale dynamics are ignored, of there is no commitment to interaction dominant dynamics (Runge, Nowack, et al., 2019).

Applying these concepts to understand the factors involved in psychological resilience in development as discussed by Masten et al. (2021) would start with the question of where to place the effect horizon. This will be determined by the phenomenon of interest, obviously, if the purpose is to study life-span resilience, the permissive and causative structures would include different variables compared to a study in which resilience to real-life experienced perturbations (random shocks, systemic stressors) is observed. It is unlikely that the dynamics (and effect magnitudes) at one scale of observation easily translate to other (coarse-grained)

[1]The method for examining dynamics at different contiguous scales is more complex than suggested here and concerns the renormalization group approach to study a system under different scale transformations.

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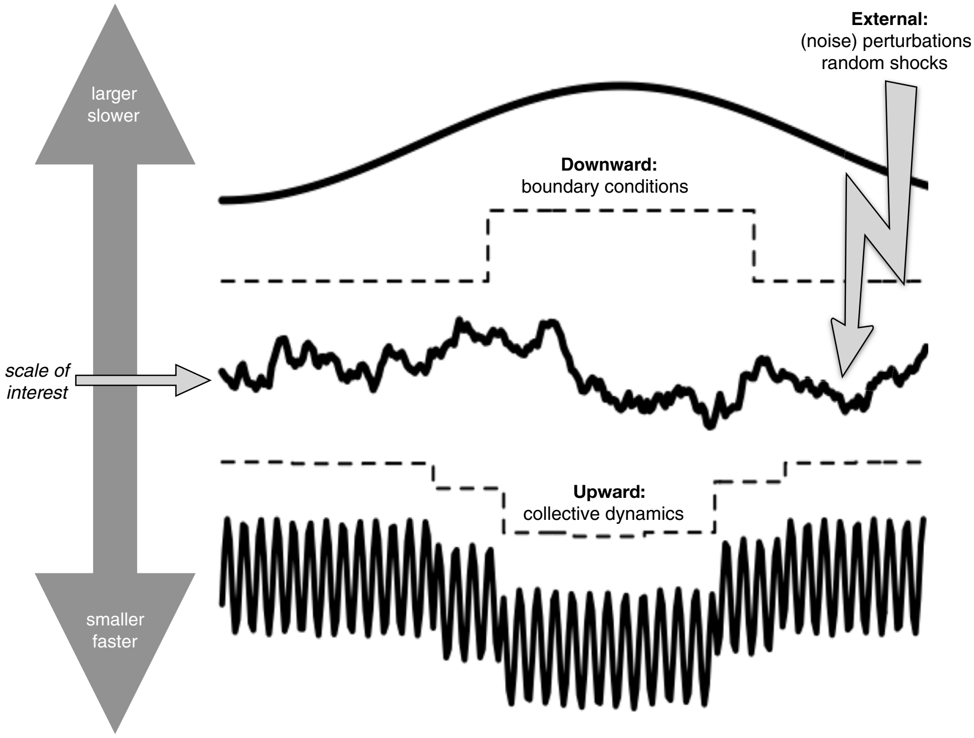

Figure 3. The figure displays how, relative to a scale of interest, coarse-graining of slower time scales (upper dashed line) can be understood as changes in parameters that remain constant for longer periods of time, whereas coarse-graining of faster time scales (lower dashed line) can be understood as changes in control parameters that affect the dynamics at the scale of interest. External perturbations (gray arrow) can affect boundary conditions as well as dynamics. Not shown are the downward, boundary setting effects from the scale of interest to the faster time scale and the upward collective dynamics form the scale of interest to the slower time scale.

scales, something which is for example not accounted for in the cascading model, or any other statistical model for that matter. Cascading effects (effects crossing scale and system boundaries) will often be multiplicative in nature (Kelty-Stephen et al., 2013), or represent mean-field catastrophic effects (Brummitt et al., 2015), but they will unlikely be of the linear additive kind as assumed in a path cascading models. Such models are also unlikely to be able to capture phenomena such as feedback loops, or, be cast as idiographic models (however, see e.g. Bringmann, 2021; Ram et al., 2013 for potential solutions)

To summarize, studying causality in complex systems will not yield a neat list of independent efficient causes to explain the dynamics of a phenomenon of interest (cf. Runge, Bathiany, et al., 2019), instead, a system of coupled processes may be uncovered, whose contributions can be evaluated relative to an effect horizon. The effect horizon separates coupled processes into a permissive and a causative structure and the choice to focus on a particular scale of interest determines the kind of causal role (top-down, bottom-up, immediate, mediative) factors can play in explaining the dynamics of the phenomenon of interest. Committing to an interaction dominant causal ontology as described here will have profound consequences for the design of diagnostic tools and intervention methods as well as the evaluation of the current empirical record (see e.g., Hardeman et al., 2019; Lichtwarck-Aschoff et al., 2012; Nahum-Shani et al., 2017; Olthof et al., 2019; Schiepek, Aichhorn, et al., 2016). For example, research based on inferring linear associations between independent components based on cross-sectional samples of many individuals, may have uncovered statistically reliable dependencies between risk and protective factors, however, the complex system ontology presented here would predict that these associations represent coarse-grained dynamics that exist only at the chosen scale of interest (i.e., the sample aggregate). There are no guarantees that these associations will generalize from the group level to explain behavior at the level of the individual (see e.g., Fisher et al., 2018; Wolfers et al., 2018). Nomothetic sample based studies may have identified boundary conditions that can inform studies that focus on the individual, because if the dynamics of interest can be observed at the level of daily experience of an individual, then that should be the scales of interest for scientific scrutiny.

Idiographic complexity methods

Several authors have stressed the importance of including an individual's unique history of experienced events into explanations of complex developmental pathways, for example: "The point is that self-organization is determined not only by context (e.g. home, school, community) but by the phenomenological experience of race, gender, physical status, and many other potential factors" (Spencer et al., 1997, p. 820). From the perspective of a research program based on the strong complexity assumption, such factors should be studied using idiographic methods, or a small data paradigm (Hekler et al., 2019). In the most general sense, idiographic methods study the dynamics of the observables of a particular system, which can be an individual, a school, a company, or a country. Of course, multiple cases can be studied and compared, even statistically, but essential is that any inferences made are not based on aggregates of the individual dynamics, rather, the individual dynamics are first quantified before they are aggregated, hence the dictum: "first analyze, then aggregate!" (Peter Molenaar quoted in Rose, 2016, p. 1). To illustrate how idiographic methods can be used to study complex developmental pathways in context, we'll use the etiology of negative learning attitudes used by Spencer et al. (1997) to argue for the importance of extending the ecological systems approach with a phenomenological perspective, by studying the school experiences of African American adolescents. A negative learning attitude can be considered a self-organized emergent attractor state of a complex system that is undesirable, in the sense that it will negatively affect the individual who is "stuck" in this state. Spencer et al. (1997)

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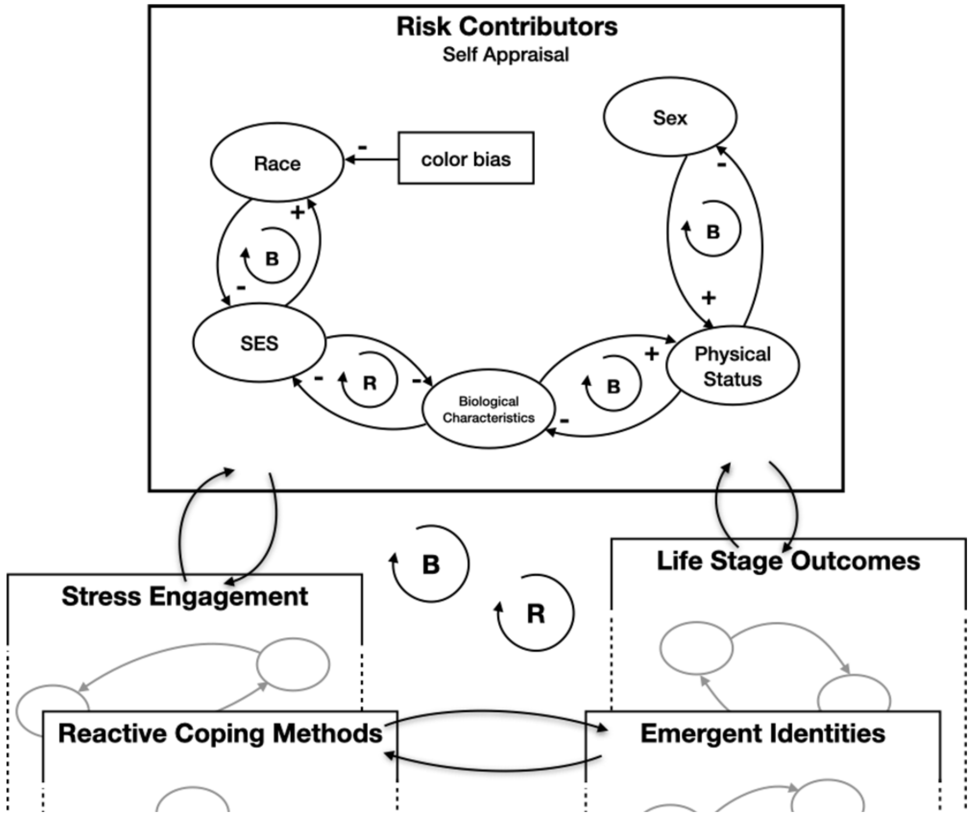

Figure 4. A fictive annotated, multiscale Causal Loop Diagram based on Figure 1 in Spencer et al. (1997). The diagram shown here schematically represents the micro-level associations between important risk contributors in self-appraisal in response to stereotypes and biases. The annotations + and – indicate the direction of a hypothetical effect. Whenever loops emerge, they may be labeled as reinforcing (R, +|+ or –|–), or balancing (B, +|– or –|+). In practice, this model would be constructed based on Group Model Building by domain experts as well as the scientific literature. These diagrams can also be created for the other domains as well as the interactions between the domains (macro-level).

review many different factors and processes that may be causally entailed in the emergence and persistence of the state and provide graphical representations of the way these factors are interrelated. However, taking personal biographies of experienced events into account remains more a theoretical goal, as the suggested relationships between variables are inferred from aggregate, cross-sectional data. A first step to make the conceptual model more idiographic could be to use the method of group model building to create causal loop diagrams (Rouwette, 2016).

Causal loop diagrams

A Causal Loop Diagram (CLD) is a visual representation the of dependencies of all factors involved in explaining a phenomenon that can be understood as an emergent, self-organized state of a complex system (Crielaard et al., 2022). It is constructed through a process called Group Model Building (Rouwette, 2016), in which domain experts and stakeholders collaborate to identify the important causal structures. The associations in CLDs can be annotated (indication of direction of effect or nature of feedback loops) based on the empirical record. CLDs can also represent dynamics on multiple scales, which is very similar to the notion of course grained, or emergent dynamics. Although the schematic representation can be helpful, ultimately the goal is to translate the diagram into a so-called System Dynamics Model (SDM) which is a computational version of the CLD, a set of coupled differential equations. The advantage of turning the graphical model into a computational one is that it is possible to simulate "what if" scenarios. For example, an SDM was used study how diabetes may be reduced in three countries in the Caribbean. The SDMs were successfully used to inform health policy decisions (Guariguata et al., 2016). CLDs can become very complex, for example, an attempt to map the multicausality of Alzheimer's disease (Uleman et al., 2021), resulted in 38 variables and 150 connections between them interacting across 3 different scales.

Figure 4 represents a (fictitious) annotated, multiscale CLD, based on Figure 1 from Spencer et al. (1997). In the original figure, a notion of scale within and between the different domains was already present. Constructing a CLD may further specify the complex interactions within and between the domains. For example, Spencer et al. (1997) report their data was collected in a southeastern metropolitan area of the US. One could use the Group Building Method to build a CLD using experts (scientists, healthcare providers) and stakeholders (policy makers, educators, community members) from the metropolitan area, local experts. The CLD can be annotated and adjusted based on a review of the scientific literature. The CLD would be an idiographic model because it describes the complex dynamics of a particular case, it is unlikely that it would generalize to a northwestern metropolitan area. It would represent "a reflection of the knowledge and assumptions held by a person or group—a shared mental model" (Crielaard et al., 2022, p. 7), meaning that it might also change if a completely different group of experts were invited, however, procedures and tests have been developed to evaluate the reliability and validity of the models (Crielaard et al., 2022 is an excellent review).

Suppose a multiscale annotated CLD has been made for all domains and underlying variables in Figure 4 (Figure 1 in Spencer et al., 1997), what would resilience refer to in the sense of the general stability of a state? An unhealthy macro-state could represent a situation in which most African American adolescents in this southeastern metropolitan area of the US develop some degree of negative learning attitudes. The emergent sate would be called resilient, if it persists for a longer period of time, the development of the negative learning attitudes can likely be regarded as a maladaptive process, permitted by a set of immediate (systemic) factors related to US culture and history, personality, and gender, mediated by the lived experience of negative events that involve stereotypes and biases. We have now used the terms resilience and adaptation to describe the emergence of an "unhealthy" state which reflects their universality and explanatory power in describing complex dynamics. Within the context of psychological resilience, which was reserved for the emergence and persistence of "healthy" states, one would need to define another set of terms that describe the emergence of stable, "unhealthy" states (see Lunansky et al., 2022), which seems redundant if they are governed by the same mechanisms as is assumed in the complex systems perspective.

Now suppose an SDM has been created that can be used to simulate different "what if" scenarios. To simulate what may be required to transition to a resilient state in which learning attitudes are predominantly positive, the focus would be on mediative factors that could be changed in reality, which may inform the design of interventions or policies. Different scenarios can be simulated and this is in fact what has been successfully applied to inform complex policy decisions (cf. Rouwette, 2016). However, there are no technical objections to change the permissive structure to simulate what happens if for example the immediate effects due to culture and history are reduced or removed. Assuming the result would be positive, this can be a tool to argue for the necessity of more profound cultural changes.

Idiographic System Modeling

Idiographic system modeling can be described as creating a CLD for an individual, to gain insight in the factors that determine what may worsen or ameliorate experienced symptoms of psychopathology (Schiepek, Stöger-Schmidinger, et al., 2016). This mixed-method consists of a three-hour co-creative session before treatment starts in which a network is created that represents connections between different factors, very similar to the annotated CLD. The next step is to translate the factors and relationships identified in the network into questions that can be administered on a daily basis (personalized process monitoring), to gain insights into how these factors change over time. During the therapy the data generated by the patient will be used to inform the therapy. This method capitalizes on *dynamics over content*, the idea is that personalized rather than standardized questionnaires provide an optimal window into the mental, emotional, and physiological states that underly the experienced psychopathological symptoms. Studying the dynamics of these states will reveal information about the stability and interactions of the systems involved. Consequently, personalized questions may be meaningful to the patient, but difficult to interpret for an outsider, for example, in a study of the feasibility of applying personalized process monitoring methods in youth with mild intellectual disability and borderline intellectual functioning, a participant came up with the question "Did your bucket empty by smoking weed?" (Hulsmans et al., 2023). We do not exactly know what this means, but one can imagine that daily self-reports of these and other personalized questions carry unique information about the mental, emotional, and physical states of this particular participant. The personalized items function as collective variables that tap into underlying dynamics, often the goal is to infer periods of destabilization (loss of resilience) to inform intervention strategies (Fartacek et al., 2016; Olthof, Hasselman, Strunk, et al., 2020).

In order to empirically support the claim *dynamics over content*, it is necessary to show that aspects of the dynamics of personalized questionnaires (dynamical invariants) are associated to outcome measures across different individuals. Olthof et al. (2022) studied 404 patients who were treated at an inpatient clinic that uses Idiographic System Modelling, to answer the question whether there is information at the level of the dynamics of these personalized questionnaires that generalizes across patients. The questionnaires consisted of 13 items on average, with an average time series length of 36 days. For each multivariate time series of personalized items, a principal component analysis (PCA) was performed, which was used to create one univariate time series for each patient by projecting only the first principal component. This timeseries represents the primary dimension in which the system changes, it is an abstract representation of the multivariate dynamics and if a transition occurs it is expected to be registered in this component (Lever et al., 2020). The results revealed characteristic change patterns in the projected time series (no shift, gradual change, one shift, reversed shift, multiple shifts) that were associated to treatment effects. Patients that experienced no shift, or a reverse shift, showed the least improvement. This study shows empirically that the traditional focus on finding general factors of stable pathological or healthy states, may not be representative of the highly idiosyncratic nature of the processes involved in their emergence.

This method can of course also be used to study the emergence of negative learning attitudes in African American adolescents in the southeastern metropolitan area of the US. It would require idiographic system modeling of each participant to gain insight in what kind of factors affect their behavior and self-appraisal. This could already be very informative without personalized process monitoring: Is it the case that all participants will identify the expected immediate causes permissive of developing negative attitudes? Do participants report the same coping mechanisms, how do they express experiencing chronic, or resilient states using their own vocabulary? Personalized process monitoring would also reveal how often participants are exposed to biases and stereotypes during a day and also directly observe how this affects their daily experience of the world. Initially, one might conduct multiple case studies to evaluate the feasibility of daily measurements, as well as the study duration, which should be long enough to be able to register interesting phenomena. The methods described in Olthof et al. (2022) can be used to study larger groups with the purpose of identifying associations between the dynamics and outcome variables. The results would be based on the personal experiences of individual participants, which is exactly what PVEST identifies as essential for understanding complex developmental pathways.

Multilayer networks

So far, we have not addressed the multisystemic nature of different factors associated with psychological resilience. To study different systems that are interacting, multilayer networks can be used. Figure 5 displays three different types of multilayer networks, that can be used to represent different types of multiscale interactions. The bottom row displays the "monolayer" version of the network, the question for each situation is whether the interlayer associations displayed as dashed lines in the top row should be treated differently from the association within each layer (solid lines). The *interconnected graph* (first column) treats variables clustered at a layer as relatively independent entities, for example, layers may represent associations between a group of psychological

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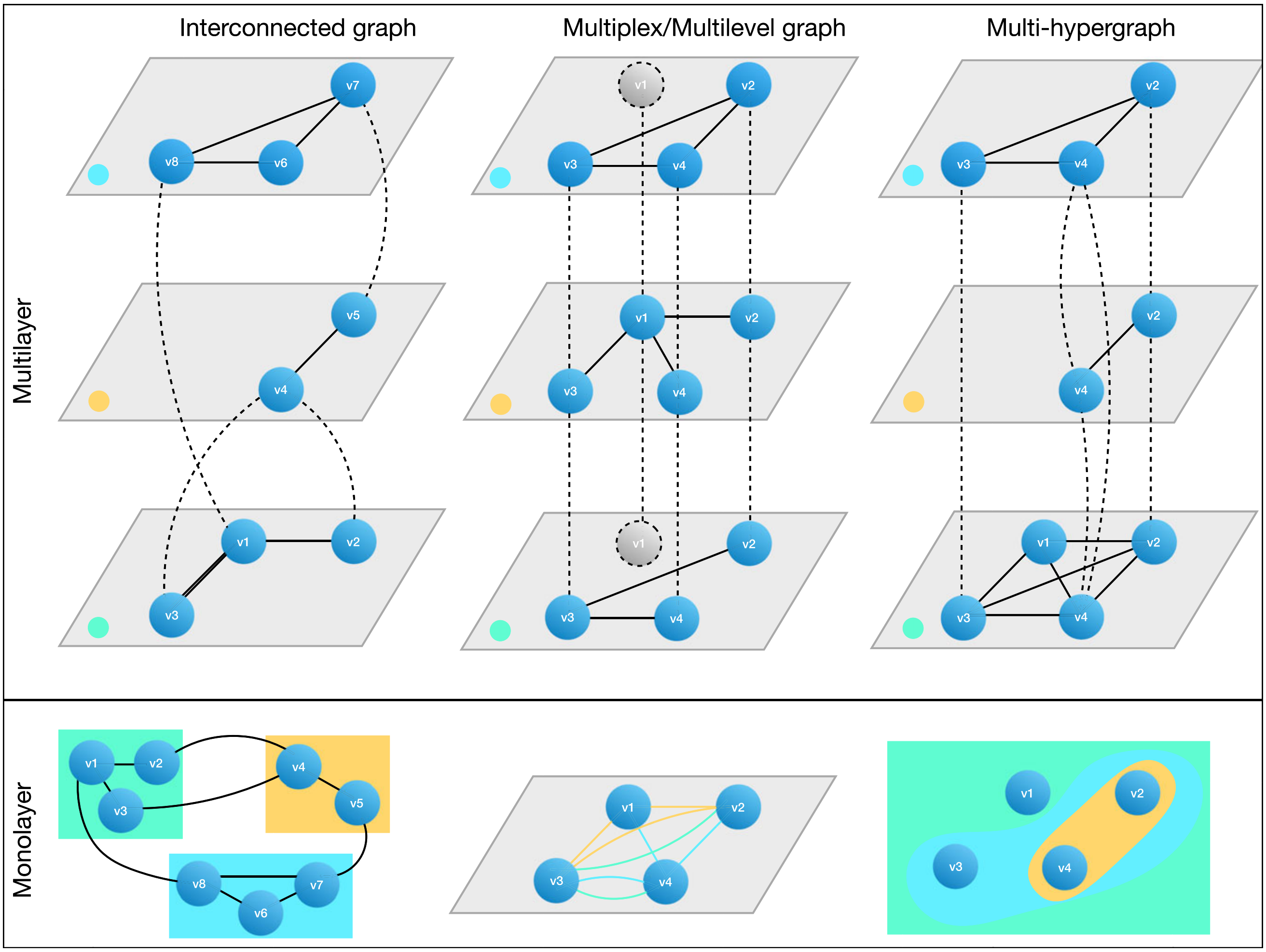

Figure 5. Examples of different options for constructing multilayer networks. See text for details.

variables e.g., treating the domains in Figure 4 as relatively independent. The *multiplex graph* is a multilayer network in which all variables (nodes) are present at all layers (a *multilevel graph* does allow some nodes to be missing, e.g., the node v1 in Figure 5). Recurrence networks are multiplex graphs in which each node represents a point in time at which a value was observed. Different network layers can represent different groups of variables, physiological, psychological, and endocrine variables measured simultaneously in a multivariate time series (Hasselman & Bosman, 2020; Hasselman, 2022; Zou et al., 2019). To construct a network in which the domains in Figure 4 are layers in the multiplex, a rather intensive study would be required in which all relevant factors are queried at least every day. There are examples of such studies, in which one participant provided about 45 responses per day for a period of 239 consecutive days (Wichers et al., 2016), enough data to construct a multiplex recurrence network with 6 different layers (see Hasselman, 2022). In a *hypergraph*, edges can connect to more than one node, so a node can belong to different subsets that represent different types of associations or states. Recently, hypergraphs have been applied to model psychological data (Marinazzo et al., 2022). In a *multi-hypergraph*, the different edge types are placed on separate layers.

Suppose the personalised studies suggested in the previous sections would have been conducted, and multivariate time series data were available representing the idiographic systems of adolescents as they pertain to negative learning attitudes, a multiplex recurrence network could be constructed for each individual. The structure of these networks can be characterized using different network measures that express for example the accessibility of certain states (probability of occurrence), but can also be used to quantify the structural similarities between the different layers in the network (see Hasselman, 2022). Other layers could represent family members also participating in the study, or more abstract, a network representing a family-level network of relevant variables which interacts with the individual network through course-grained dynamics can be constructed. Network measures, such as the (cross-)clustering coefficient can be used to determine coupling dynamics between different layers (Donges et al., 2011; Feldhoff et al., 2012). Such measures can be used in statistical analyses to examine moderation, group differences etc., the main difference to traditional studies being that the data at its highest resolution would represent summaries of the dynamics of the personal experiences of an individual, not estimates inferred from the averaged dynamics of many individuals: "first analyze, then aggregate!".

Discussion

The purpose of the present paper was to demonstrate a research program to study resilience in development based on a strong

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complexity commitment is possible. Strong complexity refers to the fact that if the theoretical complexity perspective is taken seriously, the modal research practices of the social sciences, which are predominantly nomothetic and statistical in nature, will have to be (partially) abandoned and replaced with idiographic methods (Bringmann, 2021; Molenaar, 2004; Wright & Woods, 2020). The most important reason for this change is the profound difference in causal inference. Nomothetic methods based on statistical inference imply a component dominant causal ontology, in which independent components can be identified that add up to explain the variance in a variable of interest. A strong complexity commitment implies an interaction dominant causal ontology in which behavior emerges from the multiscale interactions between the many different components of a complex system.

In the first part of the paper, some conceptual differences between the definitions of psychological resilience and resilience as the stability of an emergent state were resolved and it was concluded that there should be no objections for the field to make a strong ontological commitment. In the second part of the paper, conceptual tools were introduced that should facilitate thinking about causality in the context of interaction dominant dynamics. The first step is to separate causal factors into immediate and mediative effects. Doing so will orient the factors according to spatial and temporal scales and this allows for a characterization of causal entailment in terms of upward, or aggregate effects, and downward, or boundary effects. Doing so will reveal that there is no privileged scale at which causality resides, effects are generally evaluated relative to a scale of interest, which can change depending on the phenomena studied.

In the third part, several methods and models were introduced that are idiographic in nature and could constitute the basis for a research program based on a strong complexity commitment. These methods have in common that they take a "case" approach, characterized by the idea that studying the interaction dynamics between relevant factors is more important than interpreting what these factors actually represent (dynamics over content). As a consequence, many methods make use of a partial or completely personalized questionnaires to optimally tap into the state dynamics that are relevant to the individual. Even in the case of completely personalized data, it is still possible to identify characteristic dynamics shared between individuals (Olthof et al., 2022).

To conclude, it is possible to start an empirical research program based on idiographic methods and models to study resilience in development. However, this will require embracing an interaction-dominant causal ontology, in which chains of unique, additive, component causes, are no longer available as explanations of observed behavior.

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References

Beltz, A. M., & Gates, K. M. (2017). Network mapping with GIMME. *Multivariate Behavioral Research*, *52*(6), 789–804. https://doi.org/10.1080/00273171.2017.1373014

Borsboom, D., & Cramer, A. O. (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

Bosman, A. M. T. (2017). Disorders are reduced normativity emerging from the relationship between organisms and their environment. In K. Hens, D. Cutas, & D. Horstkötter (Eds.), *Parental responsibility in the context of neuroscience and genetics* (pp. 35–54). Springer International Publishing. https://doi.org/10.1007/978-3-319-42834-5_3

Bringmann, L. F. (2021). Person-specific networks in psychopathology: Past, present, and future. *Current Opinion in Psychology*, *41*, 59–64. https://doi.org/10.1016/j.copsyc.2021.03.004

Bringmann, L. F., Albers, C., Bockting, C., Borsboom, D., Ceulemans, E., Cramer, A., Epskamp, S., Eronen, M. I., Hamaker, E., Kuppens, P., Lutz, W., McNally, R. J., Molenaar, P., Tio, P., Voelkle, M. C., & Wichers, M. (2022). Psychopathological networks: Theory, methods and practice. *Behaviour Research and Therapy*, *149*, 104011. https://doi.org/10.1016/j.brat.2021.104011

Bringmann, L. F., Hamaker, E. L., Vigo, D. E., Aubert, A., Borsboom, D., & Tuerlinckx, F. (2017). Changing dynamics: Time-varying autoregressive models using generalized additive modeling. *Psychological Methods*, *22*(3), 409–425. https://doi.org/10.1037/met0000085

Bronfenbrenner, U. (1992). Ecological systems theory. In *Six theories of child development: Revised formulations and current issues* (pp. 187–249). Jessica Kingsley Publishers.

Brummitt, C. D., Barnett, G., & D'Souza, R. M. (2015). Coupled catastrophes: Sudden shifts cascade and hop among interdependent systems. *Journal of The Royal Society Interface*, *12*(112), 20150712. https://doi.org/10.1098/rsif.2015.0712

Cicchetti, D., & Tucker, D. (1994). Development and self-regulatory structures of the mind. *Development and Psychopathology*, *6*(4), 533–549. https://doi.org/10.1017/S0954579400004673

Crielaard, L., Uleman, J. F., Châtel, B. D. L., Epskamp, S., Sloot, P. M. A., & Quax, R. (2022). Refining the causal loop diagram: A tutorial for maximizing the contribution of domain expertise in computational system dynamics modeling. *Psychological Methods*. Advance online publication. https://dx.doi.org/10.1037/met0000484

Cui, J., Lichtwarck-Aschoff, A., Olthof, M., Li, T., & Hasselman, F. (2023). From metaphor to computation: Constructing the potential landscape for multivariate psychological formal models. *Multivariate Behavioral Research*, *58*(4), 743–761. https://doi.org/10.1080/00273171.2022.2119927

Donges, J. F., Schultz, H. C. H., Marwan, N., Zou, Y., & Kurths, J. (2011). Investigating the topology of interacting networks. *The European Physical Journal B*, *84*(4), 635–651. https://doi.org/10.1140/epjb/e2011-10795-8

Epskamp, S., & Isvoranu, A.-M. (2022). New trends in network modeling of psychopathology. *World Psychiatry*, *21*(3), 463–464. https://doi.org/10.1002/wps.21017

Fartacek, C., Schiepek, G., Kunrath, S., Fartacek, R., & Plöderl, M. (2016). Real-time monitoring of non-linear suicidal dynamics: Methodology and a demonstrative case report. *Frontiers in Psychology*, *7*, 130. https://doi.org/10.3389/fpsyg.2016.00130

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 of the United States of America*, *115*(27), E6106–E6115. https://doi.org/10.1073/pnas.1711978115

Flack, J. C. (2017). Coarse-graining as a downward causation mechanism. *Philosophical Transactions. Series A, Mathematical, Physical, and Engineering Sciences*, *375*(2109), 20160338. https://doi.org/10.1098/rsta.2016.0338

Fraccascia, L., Giannoccaro, I., & Albino, V. (2018). Resilience of complex systems: State of the art and directions for future research. *Complexity*, *2018*, e3421529–44. https://doi.org/10.1155/2018/3421529

Fried, E. I., & Nesse, R. M. (2015). Depression is not a consistent syndrome: An investigation of unique symptom patterns in the STAR*D study. *Journal of Affective Disorders*, *172*, 96–102. https://doi.org/10.1016/j.jad.2014.10.010

Gilden, D. L., Thornton, T., & Mallon, M. W. (1995). 1/f noise in human cognition. *Science (New York, N.Y.)*, *267*(5205), 1837–1839. https://doi.org/10.1126/science.7892611

Guariguata, L., Guell, C., Samuels, T. A., Rouwette, E. A., Woodcock, J., Hambleton, I. R., & Unwin, N. (2016). Systems Science for Caribbean Health: The development and piloting of a model for guiding policy on diabetes in the Caribbean. *Health Research Policy and Systems*, *14*(1), 79. https://doi.org/10.1186/s12961-016-0150-z

Hall, J., Nichols Lodato, B., & Beale Spencer, M. (2022). Du Boisian contributions to phenomenological variant of ecological systems theory: Interrogating thriving efforts and barbed-wire paths to black resiliency. In A. Morris, W. Allen, C. Johnson-Odim, D. S. Green, M. Hunter, K. Brown, & M. Schwartz (Eds.), *The Oxford handbook of W.E.B. Du Bois* (p. 0). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780190062767.013.33

Hardeman, W., Houghton, J., Lane, K., Jones, A., & Naughton, F. (2019). A systematic review of just-in-time adaptive interventions (JITAIs) to promote physical activity. *International Journal of Behavioral Nutrition and Physical Activity*, *16*(1), 31. https://doi.org/10.1186/s12966-019-0792-7

Hasselman, F. (2022). Early warning signals in phase space: Geometric resilience loss indicators from multiplex cumulative recurrence networks. *Frontiers in Physiology*, *13*, 859127. https://doi.org/10.3389/fphys.2022.859127

Hasselman, F., & Bosman, A. M. T. (2020). Studying complex adaptive systems with internal states: A recurrence network approach to the analysis of multivariate time-series data representing self-reports of human experience. *Frontiers in Applied Mathematics and Statistics*, *6*, 9. https://doi.org/10.3389/fams.2020.00009

Hayes, A. M., Yasinski, C., Ben Barnes, J., & Bockting, C. L. H. (2015). Network destabilization and transition in depression: New methods for studying the dynamics of therapeutic change. *Clinical Psychology Review*, *41*, 27–39. https://doi.org/10.1016/j.cpr.2015.06.007

Heino, M. T. J., Knittle, K., Noone, C., Hasselman, F., & Hankonen, N. (2021). Studying behaviour change mechanisms under complexity. *Behavioral Sciences*, *11*(5), 77. https://doi.org/10.3390/bs11050077

Hekler, E. B., Klasnja, P., Chevance, G., Golaszewski, N. M., Lewis, D., & Sim, I. (2019). Why we need a small data paradigm. *BMC Medicine*, *17*(1), 133. https://doi.org/10.1186/s12916-019-1366-x

Holling, C. S. (1973). Resilience and stability of ecological systems. *Annual Review of Ecology and Systematics*, *4*(1), 1–23. https://doi.org/10.1146/annurev.es.04.110173.000245

Hulsmans, D. H. G., Poelen, E. A. P., Lichtwarck-Aschoff, A., & Otten, R. (2023). The feasibility of daily monitoring in adolescents and young adults with mild intellectual disability or borderline intellectual functioning. *Journal of Applied Research in Intellectual Disabilities*, *36*(4), 847–858. https://doi.org/10.1111/jar.13102

Ihlen, E. A. F., & Vereijken, B. (2010). Interaction-dominant dynamics in human cognition: Beyond 1/f(alpha) fluctuation. *Journal of Experimental Psychology: General*, *139*(3), 436–463. https://doi.org/10.1037/a0019098

Kelty-Stephen, D. G., Palatinus, K., Saltzman, E., & Dixon, J. A. (2013). A tutorial on multifractality, cascades, and interactivity for empirical time series in ecological science. *Ecological Psychology*, *25*(1), 1–62.

Lever, J. J., van de Leemput, I. A., Weinans, E., Quax, R., Dakos, V., van Nes, E. H., Bascompte, J., & Scheffer, M. (2020). Foreseeing the future of mutualistic communities beyond collapse. *Ecology Letters*, *23*(1), 2–15. https://doi.org/10.1111/ele.13401

Lewis, M. D. (1995). Cognition-emotion feedback and the self-organization of developmental paths. *Human Development*, *38*(2), 71–102. https://doi.org/10.1159/000278302

Lichtwarck-Aschoff, A., Hasselman, F., Cox, R., Pepler, D., & Granic, I. (2012). A characteristic destabilization profile in parent-child interactions associated with treatment efficacy for aggressive children. *Nonlinear Dynamics, Psychology, and Life Sciences*, *16*(3), 353–379.

Lunansky, G., van Borkulo, C., Blanken, T., Cramer, A. O. J., & Borsboom, D. (2022). Bouncing back from life's perturbations: Formalizing psychological resilience from a complex systems perspective. PsyArXiv. https://doi.org/10.31234/osf.io/ftx4j

Marinazzo, D., Van Roozendaal, J., Rosas, F. E., Stella, M., Comolatti, R., Colenbier, N., Stramaglia, S., & Rosseel, Y. (2022). An information-theoretic approach to hypergraph psychometrics, arXiv:2205.01035. https://doi.org/10.48550/arXiv.2205.01035

Feldhoff, J. H., Donner, R. V., Donges, J. F., Marwan, N., & Kurths, J. (2012). Geometric detection of coupling directions by means of inter-system recurrence networks. *Physics Letters A*, *376*(46), 3504–3513. http://dx.doi.org/10.1016/j.physleta.2012.10.008

Masten, A. S., Lucke, C. M., Nelson, K. M., & Stallworthy, I. C. (2021). Resilience in development and psychopathology: Multisystem perspectives. *Annual Review of Clinical Psychology*, *17*(1), 521–549. https://doi.org/10.1146/annurev-clinpsy-081219-120307

Molenaar, P. C. M. (2004). A manifesto on psychology as idiographic science: Bringing the person back into scientific psychology, this time forever. *Measurement: Interdisciplinary Research & Perspective*, *2*(4), 201–218. https://doi.org/10.1207/s15366359mea0204_1

Nahum-Shani, I., Smith, S. N., Spring, B. J., Collins, L. M., Witkiewitz, K., Tewari, A., & Murphy, S. A. (2017). Just-in-Time Adaptive Interventions (JITAIs) in mobile health: Key components and design principles for ongoing health behavior support. *Annals of Behavioral Medicine: A Publication of the Society of Behavioral Medicine*, *52*(6), 446–462. https://doi.org/10.1007/s12160-016-9830-8

Noble, D. (2012). A theory of biological relativity: No privileged level of causation. *Interface Focus*, *2*(1), 55–64. https://doi.org/10.1098/rsfs.2011.0067

Noble, R., Tasaki, K., Noble, P. J., & Noble, D. (2019). Biological relativity requires circular causality but not symmetry of causation: So, where, what and when are the boundaries? *Frontiers in Physiology*, *10*, 827. https://www.frontiersin.org/article/10.3389/fphys.2019.00827

Olthof, M., Hasselman, F., Aas, B., Lamoth, D., Scholz, S., Daniels-Wredenhagen, N., Goldbeck, F., Weinans, E., Strunk, G., Schiepek, G., Bosman, A. M. T., & Lichtwarck-Aschoff, A. (2022). The best of both worlds? General principles of psychopathology in personalized assessment. *Journal of Psychopathology and Clinical Science*, (accepted). https://doi.org/10.31234/osf.io/jqp7g

Olthof, M., Hasselman, F., & Lichtwarck-Aschoff, A. (2020). Complexity in psychological self-ratings: Implications for research and practice. *BMC Medicine*, *18*(1), 1–16. https://doi.org/10.1186/s12916-020-01727-2

Olthof, M., Hasselman, F., Oude Maatman, F., Bosman, A. M. T., & Lichtwarck-Aschoff, A. (2023). Complexity theory of psychopathology. *Journal of Psychopathology and Clinical Science*, *132*(3), 314–323. https://doi.org/10.1037/abn0000740

Olthof, M., Hasselman, F., Strunk, G., Aas, B., Schiepek, G., & Lichtwarck-Aschoff, A. (2019). Destabilization in self-ratings of the psychotherapeutic process is associated with better treatment outcome in patients with mood disorders. *Psychotherapy Research: Journal of the Society for Psychotherapy Research*, *30*(4), 520–531. https://doi.org/10.1080/10503307.2019.1633484

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

Ram, N., Brose, A., & Molenaar, P. C. M. (2013). Dynamic factor analysis: Modeling person-specific process. In T. D. Little (Eds.), *The Oxford handbook of quantitative methods in psychology: Vol. 2: Statistical analysis* (p. 0). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780199934898.013.0021

Rose, T. (2016). *The end of average: How we succeed in a world that values sameness*. HarperCollins. https://books.google.nl/books?id=0gxXrgEACAAJ

Rouwette, E. The impact of group model building on behavior (2016). https://www.semanticscholar.org/paper/The-Impact-of-Group-Model-Building-on-Behavior-Rouwette/1531d66f3b558bba3fb49947c9423ac6ca046353

Runge, J., Bathiany, S., Bollt, E., Camps-Valls, G., Coumou, D., Deyle, E., Glymour, C., Kretschmer, M., Mahecha, M. D., Muñoz-Marí, J., van Nes, E. H., Peters, J., Quax, R., Reichstein, M., Scheffer, M., Schölkopf, B., Spirtes, P., Sugihara, G., Sun, J., . . . , Zscheischler, J. (2019). Inferring causation from time series in Earth system sciences. *Nature Communications*, *10*(1). https://doi.org/10.1038/s41467-019-10105-3

Runge, J., Nowack, P., Kretschmer, M., Flaxman, S., & Sejdinovic, D. (2019). Detecting and quantifying causal associations in large nonlinear time series datasets. *Science Advances*, *5*(11), eaau4996. https://doi.org/10.1126/sciadv.aau4996

Rutter, M. (1987). Psychosocial resilience and protective mechanisms. *The American Journal of Orthopsychiatry*, *57*(3), 316–331. https://doi.org/10.1111/j.1939-0025.1987.tb03541.x

Schiepek, G. (2009). Complexity and nonlinear dynamics in psychotherapy. *European Review*, *17*(2), 331–356. https://doi.org/10.1017/S1062798709000763

Schiepek, G., Aichhorn, W., Gruber, M., Strunk, G., Bachler, E., & Aas, B. (2016). Real-time monitoring of psychotherapeutic processes: Concept and compliance. *Frontiers in Psychology*, *7*, 604. https://doi.org/10.3389/fpsyg.2016.00604

Schiepek, G., Stöger-Schmidinger, B., Aichhorn, W., Schöller, H., & Aas, B. (2016). Systemic case formulation, individualized process monitoring, and state dynamics in a case of dissociative identity disorder. *Frontiers in Psychology*, *7*, 1545. https://doi.org/10.3389/fpsyg.2016.01545

Spencer, M. B., Dupree, D., & Hartmann, T. (1997). A Phenomenological Variant of Ecological Systems Theory (PVEST): A self-organization perspective in context. *Development and Psychopathology*, *9*(4), 817–833. https://doi.org/10.1017/S0954579497001454

Thelen, E., & Smith, L. B. (1994). *A dynamic systems approach to the development of cognition and action*. MIT Press.

Uleman, J. F., Melis, R. J. F., Quax, R., van der Zee, E. A., Thijssen, D., Dresler, M., van de Rest, O., van der Velpen, I. F., Adams, H. H. H., Schmand, B., de Kok, I. M. C. M., de Bresser, J., Richard, E., Verbeek, M., Hoekstra, A. G., Rouwette, E. A. J. A., & Olde Rikkert, M. G. M. (2021). Mapping the multicausality of Alzheimer's disease through group model building. *GeroScience*, *43*(2), 829–843. https://doi.org/10.1007/s11357-020-00228-7

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 of The United States of America*, *111*(1), 87–92. https://doi.org/10.1073/pnas.1312114110

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. (2019). Dynamic systems, process and development. *Human Development*, *63*(Suppl. 3-4), 153–179. https://doi.org/10.1159/000503825

van Geert, P., & Fischer, K. W. (2009). Dynamic systems and the quest for individual-based models of change and development. In J. P. Spencer, M. S. C. Thomas, & J. McClelland (Eds.), *Toward a new grand theory of development? Connectionism and dynamic systems theory reconsidered* (pp. 313–336). Oxford University Press.

Van Orden, G. C., Holden, J. G., & Turvey, M. T. (2005). Human cognition and 1/f scaling. *Journal of Experimental Psychology. General*, *134*(1), 117–123. https://doi.org/10.1037/0096-3445.134.1.117

Van Orden, G. C., Hollis, G., & Wallot, S. (2012). The blue-collar brain. *Frontiers in Physiology*, *3*(June), 1–12. https://doi.org/10.3389/fphys.2012.00207

Van Orden, G. C., Kloos, H., & Wallot, S. (2011). Living in the pink: Intentionality, wellbeing, and complexity. In C. Hooker (Ed.), *Philosophy of Complex Systems* (Vol. 10, pp. 629–672). North-Holland. https://doi.org/10.1016/B978-0-444-52076-0.50022-5

Walker, I. (1983). Complex-irreversibility and evolution. *Experientia*, *39*(8), 806–813. https://doi.org/10.1007/BF01990396

Wallot, S., & Kelty-Stephen, D. G. (2017). 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

Weinans, E., Quax, R., van Nes, E. H., & Leemput, I. A. (2021). Evaluating the performance of multivariate indicators of resilience loss. *Scientific Reports*, *11*(1), 9148. https://doi.org/10.1038/s41598-021-87839-y

Wichers, M., Groot, P. C., & Psychosystems, E. S. M. G. E. W. S. G. (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

Wijnants, M. L., Bosman, A. M. T., Hasselman, F., Cox, R. F. A., & Van Orden, G. C. (2009). 1/f scaling in movement time changes with practice in precision aiming. *Nonlinear Dynamics, Psychology, and Life Sciences*, *13*(1), 79–98.

Wijnants, M. L., Cox, R. F., Hasselman, F., Bosman, A. M., & Van Orden, G. (2012). A trade-off study revealing nested timescales of constraint. *Frontiers in Physiology*, *3*, 116. https://doi.org/10.3389/fphys.2012.00116

Wijnants, M. L., Hasselman, F., Cox, R. F., Bosman, M. T., & van Orden, G. (2012). An interaction-dominant perspective on reading fluency and dyslexia. *Annals of Dyslexia*, *62*(2), 100–119. https://doi.org/10.1007/s11881-012-0067-3

Wolfers, T., Doan, N. T., Kaufmann, T., Alnaes, D., Moberget, T., Agartz, I., Buitelaar, J. K., Ueland, T., Melle, I., Franke, B., Andreassen, O. A., Beckmann, C. F., Westlye, L. T., & Marquand, A. F. (2018). Mapping the heterogeneous phenotype of schizophrenia and bipolar disorder using normative models. *JAMA Psychiatry*, *75*(11), 1146–1155. https://doi.org/10.1001/jamapsychiatry.2018.2467

Wright, A. G. C., & Woods, W. C. (2020). Personalized models of psychopathology. *Annual Review of Clinical Psychology*, *16*(1), 49–74. https://doi.org/10.1146/annurev-clinpsy-102419-125032

Zou, Y., Donner, R. V., Marwan, N., Donges, J. F., & Kurths, J. (2019). Complex network approaches to nonlinear time series analysis. *Physics Reports*, *787*, 1–97. https://doi.org/10.1016/j.physrep.2018.10.005