Predicting Resilience Losses in Dyadic Team Performance

Hill, Yannick; den Hartigh, Ruud J. R. ; Cox, Ralf F. A.; de Jonge, Peter; Van Yperen, Nico W.

Published in:
Nonlinear dynamics, psychology, and life sciences

Nonlinear Dynamics, Psychology, and Life Sciences, Vol. 24, No. 3, pp. 327-351.

Predicting Resilience Losses in Dyadic Team Performance

Yannick Hill,[1] Ruud J. R. Den Hartigh, Ralf F. A. Cox, Peter De Jonge, *and* ***Nico W. Van Yperen****, University of Groningen, The Netherlands*

Abstract: *In the current study, we applied the dynamical systems approach to obtain novel insights into resilience losses. Dyads (n = 42) performed a lateral rhythmical pointing (Fitts) task. To induce resilience losses and transitions in performance, dyads were exposed to ascending and descending scoring scenarios. To assess changes in the complexity of the dyadic pointing performance, reflecting their resilience, we performed cross-recurrence quantification analyses. Then, we tested for temporal patterns indicating resilience losses. We applied lag 1 autocorrelations to assess critical slowing down and mean squared successive differences (MSSD) to assess critical fluctuations. Although we did not find evidence that scoring scenarios produce performance transitions across individuals, we did observe transitions in each condition. Contrary to the lag 1 autocorrelations, our results suggest that transitions in human performance are signaled by increases in the MSSD. Specifically, both positive and negative performance transitions were accompanied with increased fluctuations in performance. Furthermore, negative performance transitions were accompanied with increased fluctuations of complexity, signaling resilience losses. On the other hand, complexity remained stable for positive performance transitions. Together, these results suggest that combining information of critical fluctuations in performance and complexity can predict both positive and negative transitions in dyadic team performance.*

Key Words: complexity, critical slowing down, cross-recurrence quantification analysis, dynamical systems, transitions

INTRODUCTION

In virtually any domain in which humans strive for optimal performance, encountering setbacks such as errors, injuries, or being outperformed by others, is unavoidable. These setbacks need to be overcome in order to reach top performance, which means that individuals need to be able to adapt to adverse events in order to be successful. In the psychological literature, this positive adaptation to adverse events is defined as resilience (Fletcher & Sarkar, 2012,

[1] Correspondence address: Yannick Hill, Faculty of Behavioral and Social Sciences – Department of Psychology, Grote Kruisstraat 2/1 9712 TS Groningen, The Netherlands. E-mail: y.hill@rug.nl

2013; Galli & Gonzalez, 2015; Hill, Den Hartigh, Meijer, De Jonge, & Van Yperen, 2018a). In the resilience literature, researchers tend to focus on identifying individual traits and psychological characteristics, which predict whether or not an individual is able to adapt to an adverse event (e.g., Connor & Davidson, 2003; Fletcher & Sarkar, 2013; Galli & Vealey, 2008; Mummery, Schofield, & Perry, 2004; Rutter, 1985). However, several studies have also pointed out that resilience is determined by a dynamic interplay between a person and a changing environment (Egeland, Carlson, & Sroufe, 1993; Fletcher & Sarkar, 2012; Galli & Vealey, 2008). Indeed, resilience is a complex process that cannot be reduced to a single (set of) more or less fixed factor(s) (Davydov, Stewart, Ritchie, & Chaudieu, 2010; Hill 2018a; Pincus & Metten, 2010; Pincus, Kiefer, & Beyer, 2018; Tusaie & Dyer, 2004).

To capture the inherent dynamics of resilience and how it changes over time, a recent target article by Hill and colleagues (2018a) opened the discussion on studying the temporal process of resilience. The authors proposed a dynamical systems approach to map out how individuals adapt after experiencing an adverse event and make temporal predictions about changes in resilience. For instance, when the performance of an individual starts to fluctuate, or an individual takes increasing amounts of time to recover from an adverse event, a negative shift in performance may occur (see also Pincus & Metten, 2010; Scheffer et al., 2012, 2018). Although previous studies have utilized temporal processes to capture resilience in motor behavior, such as changes in electromyography data from vertical jumps following neuromuscular training (Kiefer & Myer, 2015), studies on predicting breakdowns of resilience during human (motor) performance is currently lacking. As a consequence, there is no empirical evidence for patterns in performance that may predict how individuals adapt to adverse events over time. Therefore, we designed an experiment to test how resilience in individuals dynamically changes, and whether a loss of resilience can be predicted by applying analytical tools of the complex dynamical systems approach.

Resilience in Dynamical Systems

Resilience is a complex process, which describes how a dynamical, bio-psychosocial system adapts to perturbations over time (Hill et al., 2018b). In order to understand resilience, it is therefore essential to quantify the iterative states of the system while performing and being perturbed. However, it is impossible to measure all underlying processes of a dynamical system individually. Nevertheless, according to Takens' embedding theorem (1981), a dynamical system's state can be reconstructed from time-serial observations (i.e., dense repeated measurements) of a single variable produced by the system. In this way, by measuring time-serial data of a single representative variable, a researcher can assess the dynamical organization of the system and how it reacts to perturbations.

In line with this, recent research suggests that particular patterns in time-series data can inform about the adaptability of a system (Delignières, Fortes, & Ninot, 2004; Den Hartigh, Cox, Gernigon, Van Yperen, & Van Geert, 2015; Goldberger et al., 2002; Manor et al., 2010). Specifically, it is assumed that a system's complexity reflects an optimal blend of stability and flexibility as can be derived from patterns in time-series (Davids, Glazier, Araújo, & Bartlett, 2003; Delignières & Marmelat, 2012, 2013; Den Hartigh et al., 2015; Kiefer & Myer, 2015; Manor et al., 2010; Pincus & Metten, 2010). The blend of flexibility and stability enables a system to adapt behavioral patterns in response to perturbations (i.e., flexibility), while maintaining its global level of functioning (i.e., stability). This means that when a system becomes too rigid (i.e., too little complexity), it may not be able to develop new behavioral patterns required for optimal adaptation to the environment (Kiefer, Silva, Harrison, & Araújo, 2018; Hill et al. 2020). On the other hand, when a system is too instable (i.e., too much complexity), the system does not attain a usefully stable state, meaning that even a minor perturbation may cause the system to shift into a different (possibly undesired) state. Therefore, the direction of the deviation from a system's complexity does not necessarily indicate a resilience loss. For example, some studies show that a reduction of complexity is associated with negative health outcomes in cardiovascular systems (Goldberger et al., 2002), but increased resilience in human motor systems (Kiefer & Myer, 2015). Similarly, losses of resilience can be associated with both increases and decreases in complexity (Pincus et al., 2014). Instead, the functional interplay of rigidity and stability may determine a system's resilience (Harrison & Stergiou, 2015; Pincus, 2014; Pincus, Cadsky, Berardi, Asuncion, & Wann, 2019). This suggests that resilience in a system, which resides in a desired state, may be reflected by stable levels of its complexity.

Based on this line of research, when (critical) changes in a system's complexity occur, it may indicate a loss of resilience. In other words, the system would lose the ability to positively adapt to adverse events. This can lead to an undesirable transition in the level of functioning, when being exposed to a perturbation (Dai, Vorselen, Korolev, & Gore, 2012; Hill et al., 2018a; Scheffer et al., 2009, 2012; Van de Leemput et al., 2014). Recent research suggests that such transitions typically occur when a system is exposed to a series of perturbations within a relatively short timeframe. For example, in humans, a major depressive episode does not usually follow a major negative life event, but rather develops from a history of many negative events occurring in close temporal proximity. By mapping out the system's states over time, researchers found that prior to a transition (e.g., the onset of a major depression) the system takes increasingly more time to adapt to the series of perturbations (probably reflecting an increased rigidity in the system), a period called "critical slowing down" (Dai et al., 2012; Scheffer et al., 2012, 2018; Van de Leemput et al., 2014). The increase in the amount of time a system needs to adapt to a perturbation reflects a loss of the system's resilience. By deriving the system's complexity from such time-serial data, researchers may be able to explicitly link the loss of resilience to changes of the system's complexity.

Another warning signal for transitions in dynamical systems derived from time-serial data comes from the long line of research related to the HKB model (Haken, Kelso, & Bunz, 1985; Kelso, 1995). This model maintains that repeated perturbations cause the system to lose stability, which results in increasing fluctuations in the order parameter (i.e., a macroscopic variable characterizing the behavior of the system). The emerging critical fluctuations have been shown to precede transitions in a variety of forms of human behavior, such as interlimb coordination (Frank, Peper, Daffertshofer, & Beek, 2006), intermanual coordination (Kelso, Scholz, & Schöner, 1986), and arm curling (Hristovski & Balagué, 2010). However, critical fluctuations do not only signal undesired transitions, such as fatigue in arm curling (Hristovski & Balagué, 2010). Indeed, transitions in human development are also marked by an increase in fluctuations before the system manifests itself in a new (improved) state (Van Geert, 1997). For example, the (positive) effect of therapy for aggressive behavior in children has been shown to be indicated by increases in fluctuations (Lichtwarck-Aschoff, Hasselman, Cox, Depler, & Granic, 2012). Furthermore, dynamical systems are capable of demonstrating transitions to a higher level of functioning after being exposed to perturbations (e.g., Agathokleous, Kitao, & Calabrese, 2018; Calabrese 2005a, 2005b; Kiefer et al., 2018). However, it is important to note that in contrast to undesirable transitions in behavior, these positive transitions to higher levels of functioning are not associated with losses of resilience as indicated by critical changes in complexity. This means that transitions to both more and less desirable states are marked by increases in critical fluctuations in a system's behavior. On the other hand, only undesirable transitions to a lower level of functioning may be accompanied by critical changes in a system's complexity (resilience losses, cf. Pincus, 2014; Pincus et al., 2019), whereas complexity during positive transitions may remain stable.

Time-Series Analyses Techniques for Complex Dynamical Systems

A particular index that has been applied to predict the occurrence of transitions following critical slowing down, is the lag 1 autocorrelation (e.g., Clements & Ozgul, 2016; Dai et al., 2012; Scheffer et al., 2012; Van de Leemput et al., 2014). According to Scheffer and colleagues (2009), the autocorrelation increases before the system reaches the transition point, signaling a "slowing" within the system. An increase in the autocorrelation can therefore be used as an early warning signal of undesirable transitions. However, recent research has shown that this technique may not work as a reliable warning signal in systems that produce high levels of noise (Liu, Chen, Aihara, & Chen, 2015). Such fluctuations in signals are naturally occurring in complex dynamical systems and an important source of information rather than being undesirable noise (Kelso, 2010; Liu et al., 2015). As a consequence, although empirical evidence is still marginal, the autocorrelation may best be suited for systems producing low levels of natural fluctuations.

Critical fluctuations in a time-series are indicated by an increase in instability of subsequent time points within the series. An index that captures the (in)stability of a time-series is the mean square of successive differences (MSSD; Von Neumann, Kent, Bellinson, & Hart, 1941). An increase in the MSSD over time signals an increase in fluctuations in the signal (i.e., an increase in instability). Thus, if a system is approaching a transition preceded by critical fluctuations, the MSSD increases prior to the transition.

In order to test whether transitions in performance can be predicted based on changes in the system's resilience, the complexity of the system needs to be determined. Recurrence quantification analysis (RQA) is a method to assess the complexity of dynamical systems. It captures the presence and absence of recurring patterns in a nonlinear time-series produced by complex dynamical systems (Marwan, Romano, Thiel, & Kurths, 2007), and has been successfully applied to, amongst others, muscle activation dynamics (Kiefer & Myer, 2015), sports performance (Stöckl, 2015; Stöckl et al., 2017), and rhythmical aiming movements (Wijnants, Bosman, Hasselman, Cox, & Van Orden, 2009; Wijnants, Hasselman, Cox, Bosman, & Van Orden, 2012). The recurring patterns are obtained by analyzing time-delayed copies of the time-series within a multidimensional phase space in accordance with Takens' embedding theorem (1981). Based on the resulting recurring structures various measures can be derived. One measure that can be derived from the RQA to assess a system's complexity is the Shannon entropy of the distribution of diagonal lines in the recurrence plot, which is linked to the amount of repetitive information in the signal (Shannon, 1948). This repetitive information determines the underlying complexity of a given system. If a system is low in complexity, subsequent time points in a series do not convey any new information about the system's behavior, yielding an entropy value approaching 0. This would reflect a simple deterministic system, which involves no randomness, and which evolves in a predictable way given certain initial conditions. A random system, which evolves in a completely unpredictable way due to a purely stochastic dynamics, would yield new information with every new time point. The continuous addition of new information would yield maximum entropy values. A complex system resides between these extremes displaying an optimal blend of rigidity and flexibility, also yielding relatively high entropy values (Davids et al., 2003; Delignières & Marmelat, 2012, 2013; Den Hartigh et al., 2015; Kiefer & Myer, 2015; Manor et al., 2010; Pincus & Metten, 2010). Thus, entropy can indicate the complexity of a system by indicating the rigidness and flexibility of the system (Marwan et al., 2007).

RQA can also be extended to studying the temporal organization of two coupled systems (i.e., cross-recurrence quantification analysis, CRQA; Shockley, Butwill, Zbilut, & Webber, 2002) such as dyadic performance. More specifically, the CRQA can assess the complexity of a system that consists of two interacting (or coupled) individuals. However, in order to assess early warning signals like critical fluctuations or critical slowing down in the behavior of a system, a time-series mapping how the entropy within the system changes over a longer time frame needs to be established. To do so, the time-serial data can be split into shorter successive segments (or windows). These segments are then analyzed by the CRQA individually, creating a windowed analysis. The resulting time-series of the windowed analysis thereby maps the changes of the entropy over time, which can be used to assess early warning signals. Specifically, critical fluctuations in the entropy values could signal losses of resilience of the system, which leaves it vulnerable to perturbations, and could in turn lead to potentially lead to undesirable transitions in the system.

The Current Study

The current study provides a first empirical investigation of losses in resilience from a complex dynamical systems perspective in human (motor) performance, using a lateral rhythmical pointing (i.e., Fitts) task. Thereby, we are zooming into the signatures of performance, complexity, critical slowing down, and critical fluctuations while dyads are exposed to externally induced perturbations. Specifically, we examined whether negative transitions in performance are signaled by a loss in a system's resilience, indicated by critical slowing down or critical fluctuations. These undesirable transitions reflect change in a behavioral pattern, which yields lower scores during the lateral pointing task, while a positive performance transition would mark an increase in scoring. We were also interested in whether these negative performance transitions can be provoked by externally imposed perturbations that are induced regularly during the performance. In sports and gaming contexts, scoring scenarios are often used for this purpose, in which an athlete or player gradually moves away from their goal by winning or losing points (cf. Briki, Den Hartigh, Markman, Micallef, & Gernigon, 2013; Den Hartigh & Gernigon, 2018; Den Hartigh, Gernigon, Van Yperen, Marin, & Van Geert, 2014; Den Hartigh, Van der Sluis, & Zaal, 2018; Vallerand, Colavecchio, & Pelletier, 1988). In dyadic rowing performance, Den Hartigh and colleagues (2014) found that such descending scoring scenarios (i.e., falling behind or losing a lead) lead to less stable performance patterns in a dyadic rowing task compared to ascending scoring scenarios (i.e., catching up to an opponent or extending a lead). Furthermore, transitions in performance are especially likely to occur when a system is performing in a relatively unstable state that is difficult to sustain, such as antiphase (i.e., opposite oscillation) relative to in-phase (i.e., same oscillation) coordination patterns (e.g., Cuijpers, Den Hartigh, Zaal, & De Poel, 2019; Cuijpers, Zaal, & De Poel, 2015; Haken et al., 1985; Kelso et al., 1986; Meerhoff & De Poel, 2014; Richardson, Marsh, Isenhower, Goodman, & Schmidt, 2007). Therefore, from a complex dynamical systems perspective, when attempting to perform in a relatively unstable state (such as antiphase coordination), repeated exposure to external perturbations in the form of a descending scoring scenario, may cause transitions to an undesirable state during performance (scoring fewer points than before). In this study, we designed a lateral movement task, during which dyads were instructed to perform in an antiphase coordination pattern, while being exposed to either an ascending or descending scoring scenario.

Hypothesis 1: When performing a dyadic task, negative performance transitions occur more frequently across individuals when being exposed to a series of external perturbations induced by a descending scoring scenario than in an ascending scoring scenario.

When a complex dynamical system loses resilience, it reveals early warning signals indicating that a transition is approached. These warning signals (i.e., critical slowing down and critical fluctuations) are considered as indications that a system is losing complexity and therefore becomes less able to adapt to the induced perturbations. Therefore, a loss of complexity in a system is expected to precede transitions to lower scoring behavior.

Hypothesis 2: Early warning signals of resilience losses within individuals – critical slowing down and critical fluctuations – derived from time-series of performance and system's complexity indicate the occurrence of a negative performance transition in performance.

Complex dynamical systems can also undergo positive transitions in performance due to external perturbations (e.g., Agathokleous et al., 2018; Calabrese 2005a, 2005b; Kiefer et al., 2018). Such positive transitions are also marked by periods of instability (i.e., critical fluctuations) in performance (cf. Van Geert, 1997; Lichtwark-Aschoff et al., 2012). As these transitions are not due to a loss in resilience, it is likely that the system does not lose complexity prior to their occurrence. Therefore, critical fluctuations in system's performance as such may not yield a reliable early warning signal for undesirable transitions, because they also indicate positive transitions.

Hypothesis 3: Positive transitions in a system's performance are preceded by critical fluctuations in performance while complexity remains stable prior to positive transitions.

If all three hypotheses are supported, we conclude that negative and positive performance transitions follow similar "warning signals" at the behavioral level, but can be distinguished on fluctuations in the complexity of the system, which reflects its resilience. Specifically, resilience losses as indicated by critical changes in the system's complexity (Pincus, 2014; Pincus et al., 2014; Pincus et al., 2019) would be indicative of negative performance transitions, whereas stable levels of complexity (and therefore stable levels of resilience) would be indicative of positive or the absence of performance transitions.

METHOD

Participants

Our sample consisted of 84 international first year psychology students (29 male, 55 female; 40.48% Dutch, 39.29% German, and 20.24% other nationalities), who were randomly sorted into a total of 46 dyads. The mean age of the participants was 20.2 years (*SD* = 2.4) and the dyads consisted of male-male (7), female-female (20), and male-female (15) dyads.

Experimental Design & Procedure

After receiving the approval of the local ethical committee of Psychology, the study was conducted within the research facilities of the University. Upon entering the room, the participants were asked to fill in the informed consent sheet. Following the completion of the questionnaires, the participants completed a computerized Fitts task. The task involved two Nintendo Wii remotes that were connected via Bluetooth to a computer, which ran the software displaying the Fitts task on a large (1080 x 1920 pixels) television screen. The targets of the Fitts task were two static bars (300 pixels in size) located close to both the left- and right-hand side (1100 pixels distance) of the screen (see Fig. 1). Each participant was able to move one out of two cursors (50 pixels in size) projected on the screen using the Wii remote. The motion sensor for the Nintendo Wii remotes, tracking the cursor positions by pixel at a frequency of 100 Hz, was attached to the bottom of the screen. The index of difficulty (Fitts & Peterson, 1964) determined by the following formula:

$$\mathrm{ID} = \log_2 (2D / W)$$

where D corresponds to the distance between targets and W to the targets' widths, yielded 3.22.

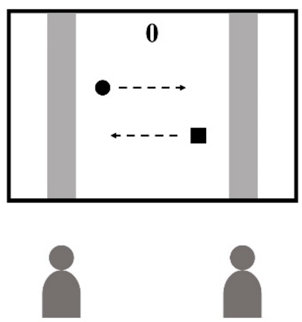

Fig. 1. Figure of the computerized Fitts task. The grey areas at the left-hand side and the right-hand sand of the screen (black rectangle) represent the targets. The participants, facing the screen while sitting next to each other, controlled either a (green) circle or a (purple) square as the cursor. The current score was indicated by an orange number appearing in the top center of the screen.

Practice Trials

Before the actual data collection, each participant received a total of three practice trials. For every trial and the final assessment, the participants were asked take a seat on a table standing on a fixed position, marked on the floor in order to control for the possible confound of the distance to the motion sensor of the Nintendo Wii. Thereby, the two participants were sitting right next to each other facing and operating on the same screen. The first practice trial involved a visual search task lasting 180 seconds to become familiar with the sensitivity of the Wii remote. During the second practice trail each participant practiced the Fitts task on their own for another 180 seconds. In the final practice trial, the dyad practiced the Fitts task together with the instruction not to verbally communicate with each other during the task. For this trial, the participants were instructed to create an antiphase movement pattern (oscillating in the opposite direction) as this was the aim for the final task. This means that when person A hits the target on the right-hand side of the screen, person B should hit the left-hand side. Then, the pattern reverses as A moves to the left and B to the right.

Competitive Fitts Task

After the practice was completed, the actual data collection began. The participants were told that their performance (i.e., amount of accurate, coordinated hits in a given time) was compared to the performance of their peer norm group as predicted by Fitts law. An accurate hit was achieved when the cursors hit the opposite targets on the screen at the same time (i.e., minimally one point in the time-series of the position data during which the cursors resided in the opposite targets), alternating their movements from side to side (antiphase coordination). Therefore, points could only be collected if the participants maintained their coordination structure. Furthermore, the participants were asked not to verbally communicate with each other during the task, and they were told that their score was compared to the norm value at a 20 second interval. If they collected more accurate hits, they would win a point and if they achieved fewer, they would lose a point. The competition was set to end if the dyad was either 10 points ahead, 10 points behind, or a total of 10 minutes had passed. The scores were manipulated to induce either ascending or descending scoring sequence (see Table 1) and appeared in the middle of the screen (cf. Den Hartigh et al., 2014, Den Hartigh et al., 2018; Den Hartigh, Van Geert, Van Yperen, Cox, & Gernigon, 2016). After the competitive Fitts task was completed, the participants filled in a final questionnaire consisting of the assessment of demographics, the Brief Resilience Scale (Smith et al., 2008), the manipulation check assessing how hard the participants tried to win the competition, and other possible confounding variables, such as experience of video games.

Table 1. Standardized Feedback in the Positive and Negative Scoring Conditions.

	Positive PM	*Negative PM*
Neutral Phase	1 0 -1 0	1 0 -1 0
Starting Phase	-1 -2 -3 -4 -5 -6 -7 -8	1 2 3 4 5 6 7 8
Phase Under Study	-7 -6 -5 -4 -3 -2 -1 0 1 2 3 4 5 6 7 8 9 10	7 6 5 4 3 2 1 0 -1 -2 -3 -4 -5 -6 -7 -8 -9 -10

Measures

Position Data

The position of each cursor was quantified for horizontal movements along an x-axis. Numerical values correspond to the number of the pixel of the screen where the center of the cursor is currently located. These positions were assessed 100 times per second (100 Hz), yielding a continuous time-series of the participants' behavioral output. The oscillation movement of the participants translate into continuous cyclic movement data, which unfolded over time resemble a sinusoid (wave-like) function.

Data Analysis

In the first step of the analysis, we computed the running outcome measures for complexity based on the x-axis position data of the dyads. Complexity was determined by the entropy measure of the CRQA, carried out using the crp-toolbox (Marwan et al., 2007). The details of the mathematical underpinnings of the CRQA are discussed elaborately elsewhere (e.g., Marwan et al., 2007; Riley & Van Orden, 2005; Shockley et al., 2002; Webber & Zbilut, 2005; Wijnants et al., 2012). Because the CRQA for continuous data analyzes recurring patterns in a time-series with delayed copies of itself in a multidimensional phase space, three parameters need to be determined.

First, in order to conduct the necessary phase space reconstruction, the embedding delay (*tau*) for the copies of the time-series is established. In the current study, the choice for the embedding delay for each dyad was based on the average mutual information function. The mutual information indicates the predictability of $X(t+x)$ given the time-series $X(t)$ over a range of possible delay choices (Fraser & Swinney, 1986). The smaller the values of the average mutual information function, the more new information is provided about the dynamics at the according delay. The optimal delay allows for the analysis of the most information, thus representing the smallest value in the mutual information function. In this particular case, as the optimal delay in a cyclic movement pattern represents 1/4 of the movement cycle, it strongly depends on the movement frequency (i.e., oscillation speed) of each dyad (Richardson, Schmidt, & Kay, 2007). Therefore, the optimal delay is unique for each dyad, so we computed *tau* for each dyad rather than choosing a common value for the entire dataset.

Second, the embedding dimension (m), specifying the number of dimensions necessary for the phase space reconstruction, was determined by global False Nearest Neighbors analyses for each dyad based on their embedding delay (Kennel, Brown, & Abarbanel, 1992). Furthermore, the global False Nearest Neighbor analyses were based on the Euclidean distance norms. Moving the time-series to a higher dimensional space serves to account for the "false recurrence" that may be observed in lower dimensional spaces by recreating the system's attractor in the appropriate space. The majority of dyads (n = 26) in our study yielded an optimal embedding of 6 dimensions. However, some dyads (n = 16) required an additional dimension to be added in order to reduce the assessment of false recurrence. The use of higher dimensional spaces is not a drawback as the higher the number of dimensions the more conservative the analysis becomes by reducing the amount of false recurrence (Wijnants et al., 2012).

Third, the recurrence threshold or radius (ε) determines which distance two time-points in the m-dimensional reconstructed phase space may maximally display in order to be considered as recurring. Thus, the higher the radius, the more points will be considered recurrent. Upon inspection of the recurrence plots, ε was set to 2 using the Euclidean norm for all dyads.

To assess the change of recurring patterns within the systems over time, a windowed CRQA was applied. The windowed analysis requires the specification of the window size (*WS*; i.e., amount of data points to be analyzed) and the window step (*SS*; i.e., distance between starting values of each analysis). As for the phase space reconstruction the amount of data points should be at least larger than *m* times *tau*, we chose for this minimal amount of data points for the analysis and added one full movement cycle (4 times *tau*) to provide a proper amount of data points for the analysis to be carried out. Therefore, the window size (*WS*) is determined by

$$WS = m * tau + 4 * tau = (m + 4) * tau$$

For the window step (*SS*), we decided to move from one full cycle to the next full cycle, thus yielding

$$SS = 4 * tau$$

For each window the amount of recurring points minimally required to yield a diagonal line, which serves as the basis for the entropy calculation was set to 1/4 movement cycle (i.e., *tau*).

In the second step of the analysis, we calculated performance of the dyads also in windows to determine the change in performance over time based on the position data. Performance of the dyads was quantified as the amount of accurate hits they produced in antiphase coordination. As explained to the participants an accurate hit was achieved when the two cursors were present in the target areas at the opposite end at the same time. Therefore, when dyads deviated strongly from the antiphase coordination pattern, they were unable to collect any accurate hits.

In order to optimize comparisons between the two outcome variables of complexity and performance, the window sizes and the according window steps for the performance analysis were matched to the values used for CRQA. Therefore, both performance and CRQA were calculated from the same raw data and yield time-series of the exact same length.

After the outcome measure time-series of performance and complexity were established, we examined the performance time-series of each dyad for transition points. These were located by assessing the point in time where differences between the mean of the time-series up until this point and the mean of the time-series following this point was the largest (see Table 2). This was obtained by calculating the largest absolute difference between every pair of means prior and following a given time-point, while including a minimum of 25 data points for a mean calculation on both sides of the change point. The resulting transitions were then categorized into positive and negative performance transitions based on the direction of change in the means prior to the change point and following it. A positive performance transition represented a positive change in means following a change point and a negative performance transition represented a negative change in means. For the group-level analysis of whether negative performance transitions occurred more frequently in descending scoring scenarios (Hypothesis 1), we conducted a chi-square test assessing whether the distribution of transitions was randomly distributed across the different scoring scenarios.

Table 2. Calculation Table for Largest Change in Means for a Performance Scores Time-Series of Length *i* and a Minimum of 25 Data Points for Each Mean.

Time Point	*Mean1 Range*	*Mean 2 Range*	*Change Direction*	*Change Strength*
25	$[n_1, n_{25}]$	$[n_{26}, n_i]$	Sign (M1 – M2)	| M1 – M2 |
26	$[n_1, n_{26}]$	$[n_{27}, n_i]$	Sign (M1 – M2)	| M1 – M2 |
…	…	…	…	…
n-26	$[n_1, n_{i-26}]$	$[n_{i-25}, n_i]$	Sign (M1 – M2)	| M1 – M2 |

To test for the early warning signals of negative (Hypothesis 2) and positive performance transitions (Hypothesis 3), the time-series were further analyzed on an individual level. As the change point analysis requires at least 25 data points following the transition point to be calculated, the warning signal patterns were assessed in a similar window of 25 data points prior to and following the change point. All dyads were analyzed for early warning signals around their respective transition point. Dyads with a negative performance transition (Hypothesis 2) were assessed for both critical slowing down and critical fluctuations in the time-series for both outcome measures, performance (i.e., accurate hits) and complexity (i.e., entropy). Critical slowing down was assessed by applying a running lag 1 autocorrelation, while critical fluctuations were assessed by a running MSSD (*window size* = 25, *window step* = 1 for both running measures). Dyads demonstrating a positive transition (Hypothesis 3) were assessed for critical fluctuations, using a running MSSD (*window size* = 25, *window step* = 1) only. The resulting running measures were plotted and inspected for increases around the transition point in a window of 25 data points in each direction. Finally, the proportion of dyads exhibiting the expected patterns were tested against the proportion of dyads exhibiting different patterns around the transition points. We used a chi-square test in order to assess whether the patterns in positive and negative transitions are due to chance alone.

RESULTS

Preliminary Analyses

Prior to the analyses, we tested for significant differences in potentially confounding variables between the two conditions: Competitiveness, resilience, experience in video games, cooperation, and whether or not the participants used to engage in team sports. No significant differences were found between the groups (*ps* > .21). Furthermore, the participants indicated they did their best to win the competition (*M* = 4.05 on a 5-point Likert scale).

Effect of Repeated External Perturbations

The chi-square test for the frequency distribution of positive and negative performance transitions did not yield a significant effect (X^2 (1, N = 42) = 0.429, p = .513, ϕ = 0.101). Therefore, we did not find a significant association between scoring scenarios and transitions in performance.

Warning Signals for Negative Performance Transitions in Team Performance

Fourteen dyads in total demonstrated a negative transition in performance. In order to test for critical slowing down prior to transitions, we computed the lag 1 autocorrelation for performance (i.e., accurate hits) and complexity (i.e., entropy). However, the expected pattern of a steady increase in the autocorrelation when a system is approaching a negative performance transition was found in either entropy or accurate hits in three of the dyads only (see Fig. 2, for an example). Therefore, in this study, the lag 1 autocorrelation does not reflect a reliable early warning signal for negative performance transitions in dyadic task performance.

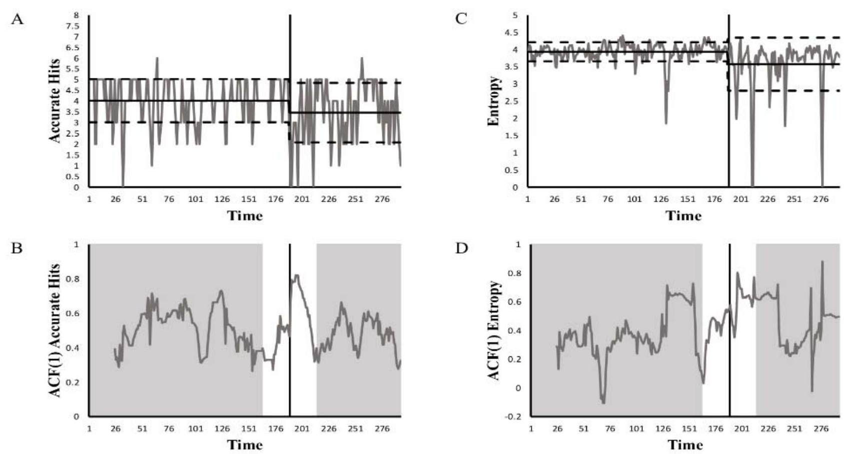

Fig. 2. A dyad's produced amount of accurate hits (A) and entropy (C) over time and their according lag 1 autocorrelation (B and D respectively). The horizontal black line (A and C) represents the mean of the time-series alongside the standard deviation indicated by the dotted lines. The vertical black line represents the time point where the change of mean in the accurate hits time-series is the largest (i.e., transition point in performance). The white areas surrounding the orange line in B and D represent the area inspected for increases in warning signals. The example dyad demonstrates a negative transition in performance accompanied by increases in lag 1 autocorrelations in both accurate hits and entropy.

The test for critical fluctuations as an early warning signals assessed the changes of stability in the in the performance and entropy measures using a running MSSD. Similar to the lag 1 autocorrelation, we expected an increase in fluctuations (i.e., increase in MSSD) around the transition in performance. Indeed, we found that 78.6% (11 out of 14) of the dyads demonstrated increases in fluctuations surrounding the transition point in both accurate hits and entropy (see Fig. 3 for a representative example). The chi-square test for the frequency distribution of accurate and inaccurate predictions yielded a significant effect with a large effect size (X^2 (1, N = 14) = 4.571, p = .033, ϕ = 0.583). Of the three dyads that did not exhibit the expected patterns, one dyad demonstrated no increase in fluctuations in performance, one dyad demonstrated no increase in entropy fluctuations, and one dyad demonstrated no increase in either performance or entropy fluctuations around the transition point. This supports that transitions in performance are preceded by increases in fluctuations.

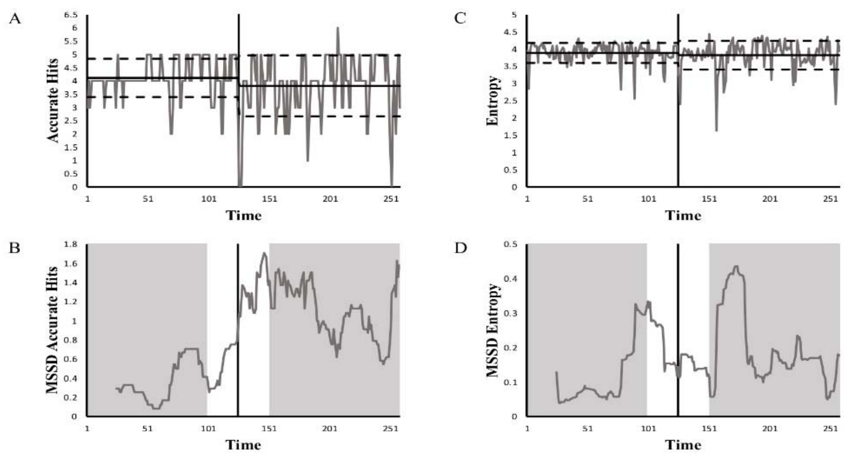

Fig. 3. A dyad's produced amount of accurate hits (A) and entropy (C) over time and their windowed (n = 25) MSSDs (B and D respectively). The horizontal black line (A and C) represent the mean of the time-series alongside the standard deviation indicated by the dotted lines. The vertical black line represents the time point where the change of mean in the accurate hits time-series is the largest (i.e., transition point in performance). The white areas surrounding the vertical black line in B and D represent the area inspected for increases in warning signals.

Predicting Positive Transitions in Performance

The change point analysis yielded a total of 28 dyads demonstrating a positive transition. We found that positive transitions in performance in 19 of the 28 (67.9%) dyads were accompanied by increases in the running MSSD of accurate hits, while entropy remained stable (see Fig. 4 for a representative example). The chi-square test for the frequency distribution of accurate and inaccurate predictions approached significance and yielded a medium effect size (X^2 (1, N = 28) = 3.571, p = .059, ϕ = 0.357). Of the remaining nine dyads that did not exhibit the expected patterns, two dyads demonstrated only slight increases of fluctuations in accurate hits while stable entropy. Six dyads showed an increase in fluctuations of both accurate hits and entropy, and one dyad demonstrated no increases in either performance or entropy fluctuations. Taken together, negative transitions in system's performance appear to be preceded by an increase in instability of both performance and complexity, whereas positive transitions are indicated by increases in instability of performance only. However, some dyads demonstrating a positive transition (21.4%) resembled the expected patterns of negative transitions. The analyses for both positive and negative performance transitions were also conducted with percent determinism (i.e., an alternative measure from CRQA related to the predictability of the system) and yield highly similar results.

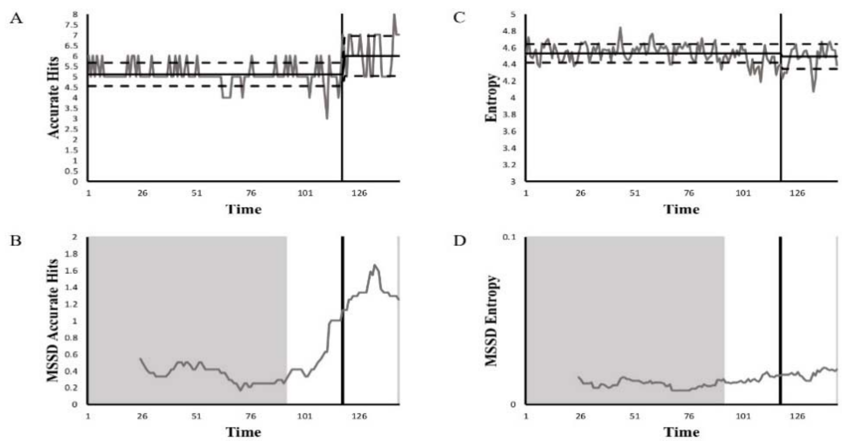

Fig. 4. Example of a dyad displaying a positive transition in performance. The amount of accurate hits (A) and entropy (C) over time with their corresponding running MSSD (B and D, respectively). The horizontal black line (A and C) represent the mean of the time-series alongside the standard deviation indicated by the dotted lines. The vertical black line represents the time point where the change of mean in the accurate hits time-series is the largest (i.e., transition point in performance). The white areas surrounding the vertical black line in B and D represent the area inspected for increases in warning signals.

The previous analyses revealed two issues in the pattern identification. First, it may be difficult to identify meaningful patterns of change when a change point occurs very early in the time-series because of an absent baseline stability level (the running MSSD and lag 1 autocorrelation were based on bins of 25 data points, cf. Cabrieto, Tuerlinckx, Kuppens, Bobála, & Ceulemans, 2018). This means that early changes can lead to misinterpretations due to the scaling of the running statistics. For example, a system may demonstrate high levels of variability prior to a transition and low levels of variability following the transition. Without sufficient information about the system prior to the transition point, a high level of variability may be interpreted as an indication of critical fluctuations. However, it cannot be determined whether these fluctuations are a result of the system's prior state or whether they truly reflect critical fluctuations. Second, dyads that demonstrate high levels of noise throughout the time-serial data may cause fluctuation changes to be interpreted as meaningful patterns, when they actually reflect random variation. Thus, random noise may be misinterpreted as meaningful indications of transitions. Therefore, we conducted a follow-up analysis for early warning signals (i.e., Hypothesis 2 and Hypothesis 3), in which we excluded all dyads demonstrating the transition very early ($n < 100$ data points, see Figure 5A for example) and high levels of noise throughout the entire time-series (overall MSSD > 0.4, see Fig. 5B for example).

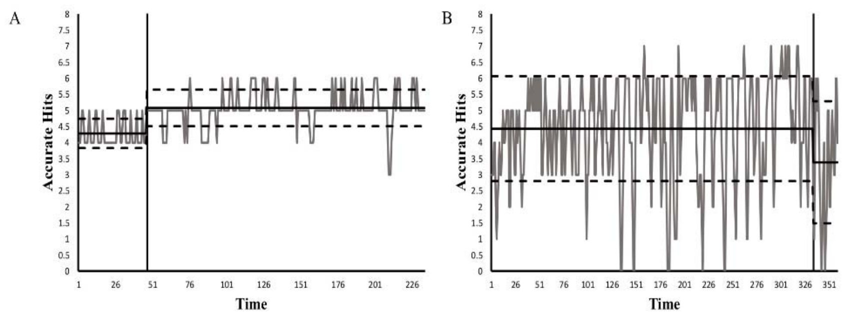

Fig. 5. Example of a time-series demonstrating an early transition indicated by the black, vertical line (A) and high levels of overall noise (B), which were excluded from further analyses. The horizontal, black line represents the mean of the time-series in the individual sections and the dashed lines the according standard deviation.

Follow-up Analysis

Of the 14 dyads demonstrating negative performance transitions four (28.6%) met the eligibility criteria. Of these four, only one dyad demonstrated increase in the lag 1 autocorrelations for performance and entropy. However, all four demonstrated increases in fluctuations in both entropy and performance in proximity to the transition point. For dyads demonstrating positive transitions, twelve out of 28 (42.9%) met the eligibility criteria. In these twelve dyads, nine transitions (75%) were accompanied by increases in the running MSSD of accurate hits, while entropy remained stable (see Fig. 5 for a representative example). One dyad demonstrated only slight increases of fluctuations in accurate hits while stable entropy. The other two dyads deviating from the common pattern showed an increase in fluctuations of both accurate hits and entropy. Taken together, the follow-up analyses strengthened the initial findings that both positive and negative transitions are indicated by fluctuations in performance, but only negative transitions are associated with fluctuations in complexity, while complexity remains stable in positive transitions.

DISCUSSION

The basic assumption of the present research is that resilience is a complex process that cannot be reduced to a single (set of) factor(s) (e.g., Davydov et al., 2010; Hill, 2018a; Pincus & Metten, 2010; Pincus et al., 2018; Tusaie & Dyer, 2004). To capture this complexity, Hill and colleagues (2018a, 2018b) suggested to study how the process of resilience unfolds over time applying a dynamical systems approach. The aim of the current study was to provide a first empirical investigation of changes in resilience during human (motor) performance from a complex dynamical systems perspective, using a lateral rhythmical pointing (i.e., Fitts) task. That is, we examined whether time-serial patterns, such as critical slowing down and critical fluctuations, can predict resilience losses within a system leading to negative transitions in performance (Dai et al., 2012; Kelso, 2010; Scheffer et al., 2009, 2012, 2018; Van de Leemput et al., 2014), or predict positive transitions to higher performance (e.g., Agathokleous et al., 2018; Calabrese 2005a, 2005b; Kiefer et al., 2018). In order to trigger transitions, we induced external perturbations while the dyads were performing. To test whether repeated external perturbations lead to negative transitions in performance, we compared dyadic performance in a Fitts task in descending scoring scenarios to performance in ascending scoring scenarios. Unexpectedly, the results indicate no significant differences in the amount of negative performance transitions in ascending and descending scoring sequences. Thus, we did not find evidence to support the notion that repeated perturbations cause undesired transitions in systems (Dai et al., 2012, Scheffer et al., 2012, 2018; Van de Leemput et al., 2014).

The absence of a clear indication that the resulting transitions were induced externally may be due to the fact that systems do not only change in response to external events. Indeed, systems are constantly undergoing change as a result of the dynamic interactions among the components that constitute a system. Theoretically speaking, a system develops future states based on its current states through a self-organizing iterative process (e.g., Den Hartigh, Van Dijk, Steenbeek, & Van Geert, 2016; Gernigon, Vallacher, Nowak, & Conroy, 2015; Nowak & Vallacher, 1998; Vallacher, Van Geert, & Nowak, 2015; Van Geert, 1991, 2009). These internal processes can also lead to nonlinear changes or transitions, both positive and negative, to a new state where the system stabilizes (Nowak & Vallacher, 1998; Van Geert, 1997). For example, Richardson, Marsh, and colleagues (2007) demonstrated that movement patterns in dyads become rhythmically coupled without verbal communication due to self-organizing processes within the system. In other words, the new state of the system (i.e., rhythmic coordination) emerged from the ongoing interactions between the two actors. Therefore, the failure of the manipulation of the study to induce transitions may be due to the fact that they were not sufficiently stressful to override the natural changes occurring by intrinsic dynamics of the system.

On an individual dyadic level, we examined when the dyads demonstrated the largest change in performance and whether the change was positive or negative. Dyads demonstrating a negative performance transition were tested for critical slowing down and critical fluctuations around the transition point. The results yielded that critical slowing down as indicated by the lag 1 autocorrelation did not signal the occurrence of negative performance transitions. The absence of the expected pattern in the time-series may be due to the high ratio of noise compared to the signal length, which interferes with the results from the autocorrelations (Clements, Drake, Griffiths, & Ozgul, 2015; Clements, McCarthy, & Blanchard, 2019; Hastings & Wysham, 2010; Liu et al., 2015). However, note that the absence of the expected patterns does not indicate an absence of critical slowing down in the system, but merely that the statistical analysis does not detect it. The results of the critical fluctuation analyses revealed that negative performance transitions were indeed accompanied by increased fluctuations in both performance and complexity. As anticipated, this suggests that negative performance transitions follow a loss of resilience within the system, indicated by critical fluctuations in complexity.

The notion that critical fluctuations in complexity indicate negative performance transitions is further supported by the pattern of fluctuations in positive transitions. We found a tendency that positive transitions were marked by increases in fluctuations of performance only, while the system's complexity remained stable over time. Therefore, critical fluctuations in performance accompanied by losses of resilience are associated with undesirable transitions in performance, whereas positive transitions are not marked by resilience losses. An interesting observation was that six dyads exhibited the expected warning signals of negative transitions while experiencing a positive transition. That is, the dyads showed instabilities in their performance accompanied with instabilities in their complexity. Because the complexity measure in this study is derived from the temporal patterns of the movements by the dyads, it could be concluded that resilience losses are associated with breakdowns in the system's structural organization. It may be speculated that these dyads have been approaching a negative transition, but that the structural changes in the system's organization allowed it to adapt positively, instead (Pincus & Metten, 2010; Kiefer et al., 2018). This might be an explanation for why the expected signs of structural breakdowns in the systems did not indicate negative transitions in each case. However, more research is needed to specifically address this type of transition.

The observed patterns of critical fluctuations are in line with the HKB model, which maintains that variability is an essential source of flexibility and adaptability, rather than a source of undesirable noise (Kelso, 2010). According to the HKB model, internal and external perturbations cause a system to lose stability, which in turn leads to increasing fluctuations when being exposed to perturbations (Kelso et al., 1986). Therefore, transitions are inherently marked by increasing noise (i.e., fluctuations). The presented findings suggest that both positive and negative performance transitions are marked by increasing fluctuations in performance. However, only negative performance transitions result from a loss in resilience marked by increasing fluctuations in complexity. As increasing noise levels have been shown to interfere with the analysis techniques for critical slowing down (Clements et al., 2015, 2019; Hastings & Wysham, 2010; Liu et al., 2015), the current findings suggest that critical fluctuations may be a more reliable indicator of transitions in human performance than critical slowing down.

LIMITATIONS AND FUTURE DIRECTIONS

The results of the current study need to be interpreted with caution due to the relatively small sample size. Although the dynamical systems approach places an emphasis on individual-level analyses, the observed patterns need to be validated on a larger scale using a variety of tasks, measures, and individuals. Furthermore, the current findings are based on a lab study utilizing a rather artificial task design. In order to generalize the current findings to natural human performance scenarios, the observed patterns preceding positive and negative performance transitions need to be replicated with research designs high in ecological validity (cf., Davids, Araújo, Vilar, Renshaw, & Pinder, 2013). This means that study designs should reflect the real-world performance as closely as possible and capture the information in the environment to which humans constantly need to attune. For example, to test resilience losses in soccer matches, an ideal design would include natural (moving) teammates and opponents, instead of static obstacles on the field.

Another limitation of the current study that we did not manipulate the index of difficulty of the Fitts task (Fitts & Peterson, 1964). The index of difficulty we chose may not have been sufficiently and equally challenging for every dyad. Kiefer and colleagues (2018) point out that performers, who reach the same maximum performance level, may adapt differently to varying task-demands. Therefore, the manipulation of the changing scoring patterns may not have produced the desired effects because the task was not sufficiently challenging for some participants. In line with this, previous research has shown that the movement dynamics change when the index of difficulty is systematically varied during a Fitts paradigm (Huys, Knol, Sleimen-Malkoun, Temprado, & Jirsa, 2015). This means that transitions in performance may be evoked by systematic manipulation of the index of difficulty. Although such manipulations were beyond the scope of the present study, we recommend that future studies utilizing this paradigm should (also) include systematic variations in the task difficulty.

Finally, because the current study did not find a significant relationship between the induced external perturbations and the resulting transitions in performance, future research should focus on the circumstances under which external perturbations can lead to resilience losses for different individuals. A promising approach for optimizing performance in response to perturbations, in line with the complex dynamical systems approach, comes from research on complex biological systems. In toxicology, the concept of hormesis describes that low doses of perturbations (i.e., chemical and physical agents in toxicology) induce beneficial outcomes of a system, while drastic negative effects occur when a certain threshold in dosage is exceeded. According to Kiefer and colleagues (2018), these principles can be applied to human (athletic) performance as well, using time-serial performance data. In response to being exposed to (controlled) increasing amount of environmental perturbations this time-serial data can inform about the optimal perturbation load an athlete should be exposed to for optimal growth. Thereby, specific predictions about the impact of perturbations can be tailored to the individual-level.

CONCLUSION

In conclusion, the current study provides a first empirical account on the complexity of the temporal resilience process in human performance. We applied a complex dynamical systems approach to analyze time-series of dyadic performance and derive the system's complexity. Given that we found that negative performance transitions occur when performance and complexity both demonstrate increases in fluctuations, whereas positive transitions appeared to be marked by stable levels of complexity within the system, we conclude that complexity is a likely indicator of a system's adaptability in response to perturbations (cf., Davids et al., 2003; Delignières & Marmelat, 2012, 2013; Den Hartigh, et al., 2015; Kiefer & Myer, 2015; Manor et al., 2010; Pincus & Metten, 2010). This supports the assumption that a stable blend between stability and flexibility (i.e., complexity) within a system causes a system to be able to adapt to perturbations while maintain its overall level of functioning. Therefore, combining information on critical fluctuations in both performance and complexity potentially provides a reliable tool to predict both positive and negative performance transitions, and prevent the latter from occurring.

REFERENCES

Agathokleous, E., Kitao, M., & Calabrese, E. J. (2018). Environmental hormesis and its fundamental biological basis: rewriting the history of toxicology. *Environmental Research, 165*, 274-278. 10.1016/j.envres.2018.04.034

Briki, W., Den Hartigh, R. J., Markman, K. D., Micallef, J. P., & Gernigon, C. (2013). How psychological momentum changes in athletes during a sport competetion. *Psychology of Sport and Exercise, 14*, 389-396. doi: 10.1016/ j.psychsport.2012.11.009

Cabrieto J, Adolf J, Tuerlinckx F, Kuppens P, & Ceulemans E. (2019). An objective, comprehensive and flexible statistical framework for detecting early warning signs of mental health problems. *Psychotherapy and Psychosomatics, 88*, 184-186. doi: 10.1159/000494356

Calabrese, E. J. (2005a). Hormetic dose-response relationships in immunology: Occurrence, quantitative features of the dose response, mechanistic foundations, and clinical implications. *Critical Reviews in Toxicology, 35*, 89–295. doi: 10.1080/10408440590917044

Calabrese, E. J. (2005b). Paradigm lost, paradigm found: The re-emergence of hormesis as a fundamental dose response model in the toxicological sciences. *Environmental Pollution, 138*, 379–411. doi: 10.1016/j.envpol.2004.10.001

Clements, C. F., Drake, J. M., Griffiths, J. I., & Ozgul, A. (2015). Factors influencing the detectability of early warning signals of population collapse. *The American Naturalist, 186*, 50-58. doi: 10.1086/681573

Clements, C. F., McCarthy, M. A., & Blanchard, J. L. (2019). Early warning signals of recovery in complex systems. *Nature Communications, 10*, 1681. doi:

10.1038/s41467-019-09684-y
Clements, C. F., & Ozgul, A. (2016). Including trait-based early warning signals helps predict population collapse. *Nature Communications, 7*, 10984. doi: 10.1038/ncomms10984
Connor, K. M., & Davidson, J. R. T. (2003). Development of a new resilience scale: The Connor-Davidson resilience scale (CD-RISC). *Depression and Anxiety, 18*, 76–82. doi:10.1002/da.10113
Cuijpers, L. S., Den Hartigh, R. J., Zaal, F. T., & de Poel, H. J. (2019). Rowing together: Interpersonal coordination dynamics with and without mechanical coupling. *Human Movement Science, 64*, 38-46. doi: 10.1016/j.humov.2018.12.008
Cuijpers, L. S., Zaal, F. T., & de Poel, H. J. (2015). Rowing crew coordination dynamics at increasing stroke rates. *PloS One, 10*, e0133527. doi: 10.1371/ journal.pone.0133527
Dai, L., Vorselen D., Korolev K. S., & Gore., J. (2012). Generic indicators for loss of resilience before a tipping point leading to population collapse. *Science, 336*, 1175- 1177. doi: 10.1126/science.1219805
Davids, K., Araújo, D., Vilar, L., Renshaw, I., & Pinder, R. (2013). An ecological dynamics approach to skill acquisition: Implications for development of talent in sport. *Talent Development and Excellence, 5*, 21-34.
Davids, K., Glazier, P., Araújo, D., & Bartlett R. (2003). Movement systems as dynamical systems: The functional role of variability and its implications for sports medicine. *Sports Medicine, 33*, 245-260. doi: 10.2165/00007256-200333040-00001
Davydov, D. M., Stewart, R., Ritchie, K., & Chaudieu, I. (2010). Resilience and mental health. *Clinical Psychology Review, 30*, 479-495. doi: 10.1016/j.cpr.2010.03.003
Delignières, D., Fortes, M., & Ninot, G. (2004). The fractal dynamics of self- esteem and physical self. *Nonlinear Dynamics in Psychology and Life Sciences, 8*, 479-510.
Delignières, D., & Marmelat, V. (2012). Fractal fluctuations and complexity: Current debates and future challenges. *Critical Reviews in Biomedical Engineering, 40*, 485–500.
Delignières, D., & Marmelat, V. (2013). Degeneracy and long-range correlations. *Chaos: An Interdisciplinary Journal of Nonlinear Science, 23*, 043109. doi: 10.1063/1.4825250
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*, 355-369. doi: 10.1123/mc.2014-0071
Den Hartigh, R. J., & Gernigon, C. (2018). Time-out! How psychological momentum builds up and breaks down in table tennis. *Journal of Sports Sciences, 36*, 2732-2737. doi: 10.1080/02640414.2018.1477419
Den Hartigh, R. J., Gernigon, C., Van Yperen, N. W., Marin, L., & Van Geert, P. L. (2014). How psychological and behavioral team states change during positive and negative momentum. *PloS One, 9*, e97887. doi: 10.1371/journal.pone.0097887
Den Hartigh, R. J., Van der Sluis, J. K., & Zaal, F. T. (2018). Perceiving affordances in sports through a momentum lens. *Human Movement Science, 62*, 124-133. doi: 10.1016/j.humov.2018.10.009
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*. doi: 10.3389/fpsyg.2016.00532
Den Hartigh, R. J., Van Geert, P. L., Van Yperen, N. W., Cox, R. F., & Gernigon, C. (2016). Psychological momentum during and across sports matches: Evidence for interconnected time scales. *Journal of Sport & Exercise Psychology, 38*, 82-92. doi: 10.1123/jsep.2015-0162

Egeland, B., Carlson, E., & Sroufe, L. A. (1993). Resilience as process. *Development and Psychopathology, 5*, 517-528. doi: 10.1017/S0954579400006131
Fitts, P. M., & Peterson, J. R. (1964). Information capacity of discrete motor responses. *Journal of Experimental Psychology, 67*, 103. doi: 10.1037/h0045689
Fletcher, D., & Sarkar, M. (2012). A grounded theory of psychological resilience in Olympic champions. *Psychology of Sport and Exercise, 13*, 669–678. doi: 10.1016/j.psychsport.2012.04.007
Fletcher, D., & Sarkar, M. (2013). Psychological resilience: A review and critique of definitions, concepts and theory. *European Psychologist, 18*, 12-23. doi: 10.1027/1016-9040/a000124
Frank, T. D., Peper, C. E., Daffertshofer, A., & Beek, P. J. (2006). Variability of brain activity during rhythmic unimanual finger movements. In K. Davids, S. Bennett, & K. Newell (Eds.), *Movement system variability* (pp. 271-305). Champaign, IL: Human Kinetics.
Fraser, A. M., & Swinney, H. L. (1986). Independent coordinates for strange attractors from mutual information. *Physical Review A, 33*, 1134. doi: 10.1103/PhysRevA.33.1134
Galli, N., & Gonzalez, S. P. (2015). Psychological resilience in sport: A review of the literature and implications for research and practice. *International Journal of Sport and Exercise Psychology, 13,* 243-257. doi: 10.1080/ 1612197X.2014.946947
Galli, N., & Vealey, R. S. (2008). "Bouncing back" from adversity: Athletes' experiences of resilience. *The Sport Psychologist, 22*, 316-335. doi: 10.1123/tsp.22.3.316
Gernigon, C., Vallacher, R. R., Nowak, A., & Conroy, D. E. (2015). Rethinking approach and avoidance in achievement contexts: The perspective of dynamical systems. *Review of General Psychology, 19*, 443. doi: 10.1037/gpr0000055
Goldberger, A. L., Amaral, L. A., Hausdorff, J. M., Ivanov, P. C., Peng, C. K., & Stanley, H. E. (2002). Fractal dynamics in physiology: alterations with disease and aging. *Proceedings of the National Academy of Sciences, 99*, 2466-2472. doi: 10.1073/pnas.012579499
Haken, H., Kelso, J. S., & Bunz, H. (1985). A theoretical model of phase transitions in human hand movements. *Biological Cybernetics, 51*, 347-356.
Harrison, S. J., & Stergiou, N. (2015). Complex adaptive behavior and dexterous action. *Nonlinear Dynamics, Psychology, and Life Sciences, 19*, 345-394.
Hastings, A., & Wysham, D. B. (2010). Regime shifts in ecological systems can occur with no warning. *Ecology Letters, 13*, 464-472. doi: 10.1111/j.1461-0248.2010.01439.x
Hill, Y., Den Hartigh, R. J. R., Meijer, R. R., De Jonge, P., & Van Yperen, N. W. (2018a). Resilience in sports from a dynamical perspective. *Sport, Exercise, and Performance Psychology, 7*, 333-341. doi: 10.1037/spy0000118
Hill, Y., Den Hartigh, R. J. R., Meijer, R. R., De Jonge, P., & Van Yperen, N. W. (2018b). The temporal process of resilience. *Sport, Exercise, and Performance Psychology, 7*, 363-370. doi: 10.1037/spy0000143
Hill, Y. et al. (2020). Antifragility in climbing: determining optimal stress loads for athletic performance training. *Frontiers in Psychology, 11*. doi: 10.3389/fpsyg.2020.00272
Hristovski, R., & Balagué, N. (2010). Fatigue-induced spontaneous termination point: Nonequilibrium phase transitions and critical behavior in quasi-isometric exertion. *Human Movement Science, 29*, 483-493. 10.1016/j.humov.2010.05.004
Huys, R., Knol, H., Sleimen-Malkoun, R., Temprado, J. J., & Jirsa, V. K. (2015). Does changing Fitts' index of difficulty evoke transitions in movement dynamics? EPJ *Nonlinear Biomedical Physics, 3*, 8. doi: 10.1140/epjnbp/s40366-015-0022-4

Kennel, M. B., Brown, R., & Abarbanel, H. D. (1992). Determining embedding dimension for phase-space reconstruction using a geometrical construction. *Physical Review A, 45,* 3403. doi: doi.org/10.1103/PhysRevA.45.3403
Kelso, J. A. S. (1995). *Dynamic patterns: The self-organization of brain and behavior*. Cambridge, MA: MIT Press.
Kelso J. A. (2010). Instabilities and phase transitions in human brain and behavior. *Frontiers in Human Neuroscience, 4,* 23. doi:10.3389/fnhum.2010.00023.
Kelso, J. A. S., Scholz, J. P., & Schöner, G. (1986). Nonequilibrium phase transitions in coordinated biological motion: critical fluctuations. *Physics Letters A, 118*, 279-284. doi: 10.1016/0375-9601(86)90359-2
Kiefer, A. W., & Myer, G. D. (2015). Training the antifragile athlete: A preliminary analysis of neuromuscular training effects on muscle activation dynamics. *Nonlinear Dynamics, Psychology, and Life Sciences, 19*, 489-510.
Kiefer, A. W., Silva, P. L., Harrison, H. S., & Araújo, D. (2018). Antifragility in sport: Leveraging adversity to enhance performance. *Sport, Exercise, and Performance Psychology, 7*, 342-350. doi: 10.1037/spy0000130
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*, 353-379.
Liu, R., Chen, P., Aihara, K., & Chen, L. (2015). Identifying early-warning signals of critical transitions with strong noise by dynamical network markers. *Scientific Reports, 5*, 17501. doi: 10.1038/srep17501
Manor, B., Costa, M. D., Hu, K., Newton, E., Starobinets, O., ... & Lipsitz, L. A. (2010). Physiological complexity and system adaptability: evidence from postural control dynamics of older adults. *Journal of Applied Physiology, 109*, 1786-1791. doi: 10.1152/japplphysiol.00390.2010
Marwan, N., Romano, M. C., Thiel, M., & Kurths, J. (2007). Recurrence plots for the analysis of complex systems. *Physics Reports, 438*, 237-329. doi: 10.1016/j.physrep.2006.11.001
Meerhoff, L. R. A., & De Poel, H. J. (2014). Asymmetric interpersonal coupling in a cyclic sports-related movement task. *Human Movement Science, 35*, 66-79. 10.1016/j.humov.2014.04.003
Mummery, W. K., Schofield, G., & Perry, C. (2004). Bouncing back: The role of coping style, social support and self-concept in resilience of sport performance. *Athletic Insight, 6*, 1-15.
Nowak, A., & Vallacher, R. R. (1998). *Dynamical social psychology*. New York, NY: Guilford Press.
Pincus, D. (2014). One bad apple: Experimental effects of psychological conflict on social resilience. *Interface Focus, 4*. doi: 10.1098/rsfs.2014.0003
Pincus, D., Cadsky, O., Berardi, V., Asuncion, C. M., & Wann, K. (2019). Fractal self structure and psychological resilience. *Nonlinear Dynamics, Psychology, and Life Sciences, 23*, 57-78.
Pincus, D., Eberle, K., Walder, C. S., Kemp, A. S., Lenjav, M., & Sandman, C. A. (2014). The role of self-injury in behavioral flexibility and resilience. *Nonlinear Dynamics, Psychology, and Life Sciences, 18*, 277-296.
Pincus, D., Kiefer, A. W., & Beyer, J. I. (2018). Nonlinear dynamical systems and humanistic psychology. *Journal of Humanistic Psychology, 58*, 343-366. doi: 10.1177/0022167817741784
Pincus, D., & Metten, A. (2010). Nonlinear dynamics in biopsychosocial resilience. *Nonlinear Dynamics, Psychology, and Life Sciences, 14*, 353-380.
Richardson, M. J., Marsh, K. L., Isenhower, R. W., Goodman, J. R., & Schmidt, R. C.

(2007). Rocking together: Dynamics of intentional and unintentional interpersonal coordination. *Human Movement Science, 26*, 867-891. doi: 10.1016/j.humov.2007.07.002

Richardson, M. J., Schmidt, R. C., & Kay, B. A. (2007). Distinguishing the noise and attractor strength of coordinated limb movements using recurrence analysis. *Biological Cybernetics, 96*, 59-78. doi: 10.1007/s00422-006-0104-6

Riley, M. A., & Van Orden, G. C. (2005). *Tutorials in contemporary nonlinear methods for the behavioral sciences*. National Science Foundation.

Rutter, M. (1985). Resilience in the face of adversity: Protective factors and resistance to psychiatric dis- order. *British Journal of Psychiatry, 147*, 598–611. doi:10.1192/bjp.147.6.598

Scheffer, M., Bascompte, J., Brock, W. A., Brovkin, V., Carpenter, S. R., Dakos, V., ... & Sugihara, G. (2009). Early-warning signals for critical transitions. *Nature, 461*, 53. doi: 10.1038/nature08227

Scheffer, M., Bolhuis, J. E., Borsboom, D., Buchman, T. G., Gijzel, S. M., Goulson, D., ... & Martin, C. M. (2018). Quantifying resilience of humans and other animals. *Proceedings of the National Academy of Sciences, 115*, 11883-11890. doi: 10.1073/pnas.1810630115

Scheffer, M., Carpenter, S. R., Lenton, T. M., Bascompte, J., Brock, W., Dakos, V., ... Vandermeer, J. (2012). Anticipating critical transitions. *Science, 338*, 344-348. doi: 10.1126/science.1225244

Shannon, C. E. (1948). A mathematical theory of communication. *Bell System Technical Journal, 27*, 379-423.

Shockley, K., Butwill, M., Zbilut, J. P., & Webber Jr., C. L. (2002). Cross-recurrence quantification of coupled oscillators. *Physics Letters A, 305*, 59-69. doi: 10.1016/S0375-9601(02)01411-1

Smith, B. W., Dalen, J., Wiggins, K., Tooley, E., Christopher, P., & Bernard, J. (2008). The brief resilience scale: assessing the ability to bounce back. *International Journal of Behavioral Medicine, 15*, 194-200.

Stöckl, M., Plück, D., & Lames, M. (2017). Modelling game sports as complex systems application of recurrence analysis to golf and soccer. *Mathematical and Computer Modelling of Dynamical Systems, 23*, 399-415. doi: 10.1080/13873954.2017.1336635

Stöckl, M. (2015). Recurrence Analysis of golfers' performances on the PGA TOUR. *IFAC PapersOnLine, 48*, 786-787. doi: 10.1016/j.ifacol.2015.05.142

Takens F. (1981). Detecting strange attractors in turbulence. In D. Rand, & L. S. Young (Eds.), *Dynamical Systems and Turbulence, Warwick 1980* (pp. 366-381). Springer, Berlin. doi: 10.1007/
BFb0091924

Tusaie, K., & Dyer, J. (2004). Resilience: A historical review of the construct. *Holistic Nursing Practice, 18*, 3-10.

Vallacher, R. R., Van Geert, P., & Nowak, A. (2015). The intrinsic dynamics of psychological process. *Current Directions in Psychological Science, 24*, 58-64. doi: 10.1177/0963721414551571

Vallerand, R. J., Colavecchio, P. G., & Pelletier, L. G. (1988). Psychological momentum and performance inferences: A preliminary test of the antecedents-consequences psychological momentum model. *Journal of Sport & Exercise Psychology, 10*, 92-108.

Van de Leemput, I. A., Wichers, M., Cramer, A. O., Borsboom, D., Tuerlinckx, F., Kuppens, P., ... & Derom, C. (2014). Critical slowing down as early warning for the onset and termination of depression. *Proceedings of the National Academy of Sciences, 111*, 87-92. doi: 10.1073/pnas.1312114110

Van Geert, P. (1991). A dynamic systems model of cognitive and language growth. *Psychological Review, 98*, 3-53. doi: 10.1037/0033-295X.98.1.3

Van Geert, P. (1997). Variability and fluctuations: A dynamic view. In E. Amsel & K. A. Renninger (Eds.), *Change and development: Issues of theory, method, and application* (pp. 193-212). Mahwah, NJ: Erlbaum.

Van Geert, P. (2009). Nonlinear complex dynamical systems in developmental psychology. In S. J. Guastello, M. Koopmans, & D. Pincus (Eds.), *Chaos and complexity in psychology: The theory of nonlinear dynamical systems* (pp. 242-281). New York, NY: Cambridge University Press.

Von Neumann, J., Kent, R. H., Bellinson, H. R., & Hart, B. T. (1941). The mean square successive difference. *The Annals of Mathematical Statistics, 12*, 153-162.

Webber Jr., C. L. & Zbilut, J. P., 2005. Recurrence quantification analysis of nonlinear dynamical systems. In M. A. Riley, G. C. Van Orden (Eds.), *Tutorials in contemporary nonlinear methods for the behavioral sciences* (pp. 26-96). Retrieved June 26, 2020, from https://www.nsf.gov/pubs/2005/nsf05057/nmbs/nmbs.pdf

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

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