Capturing complex processes of human performance

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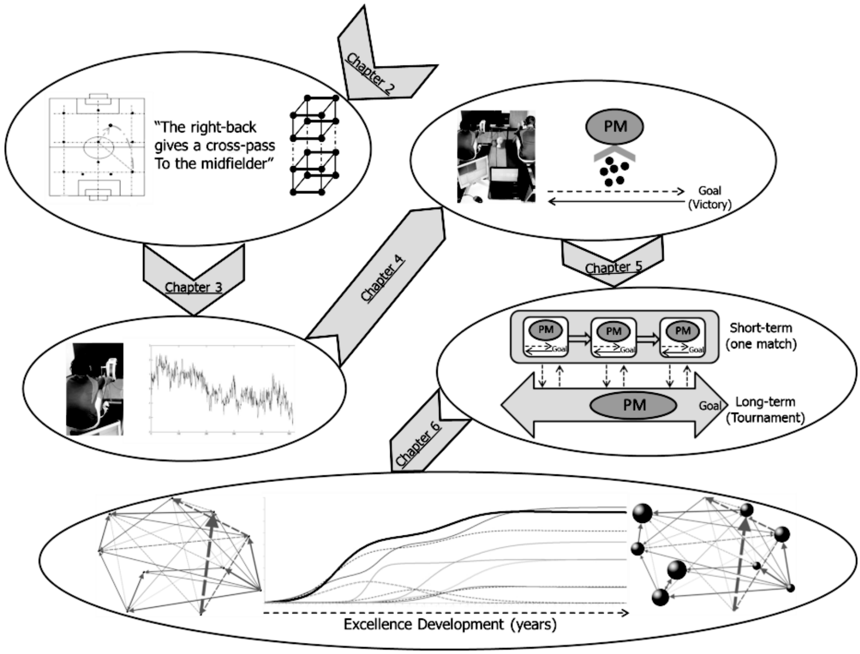
Chapter 7: Summary and General Discussion



7.1 Introduction

In this thesis a diversity of topics related to human performance processes has been discussed in light of one common denominator: Complexity (see Table 1 in the Introduction section). More specifically, the main focus was on the emergence of coherent states or patterns out of the interactions between lower-order components. These processes were primarily studied in sports, a typical context in which ongoing psychological and performance processes take place that can relatively easy be observed and measured (Day et al., 2012). We proposed that complex processes could be captured using specific research designs and methods inspired by the theory of complex dynamical systems (e.g., Davids et al., 2014; Kelso, 1995; Nowak & Vallacher, 1998; Van Geert, 1994).

Although the complexity approach differs from the conventional reductionist paradigm to the study of human behavior—in which explanations for behavior can be reduced to some underlying causal components—, the complexity perspective touches on fundamental theoretical assumptions already proposed in the previous century. For instance, Lewin (1935) emphasized that individual and environmental factors do not operate independently; they interact. Moreover, he stated that the relationships between these factors change over time, which is why we may characterize them as complex dynamical processes. In general, researchers will probably not deny that behavior takes place in a context of many interacting personal and environmental factors that undergo change. Most researchers, however, would argue that this complexity makes precise prediction of behavior nearly impossible (Gill & Williams, 2008). Therefore, in order to explain and predict human psychological and performance states as accurately as possible, most studies examine a selection of potential determinants in isolation, either at one moment or across a few time points. That is, the conventional approach is to untangle the complicatedness of a certain state by reducing the explanation of that state to the additive influences of (isolated) causal components (see Introduction).

Rather than studying (potential) determinants in isolation, this dissertation proceeded from the viewpoint that individual and environmental factors continuously interact and change over time, which results in particular psychological and behavioral patterns. That is, we assumed that the underlying mechanism that explains human performance processes is complex. Chapter 2 started with a study on the complexity of cognitive skills, embedded in verbalizations while watching video clips of game plays. In Chapter 3 we proceeded with a study on the underlying dynamic organization while athletes are performing an actual sports task. In the Chapters 2 and 3, we thus extracted a complexity measure of two different kinds of processes, and we examined how these were related to expertise. In Chapter 4 and 5 we proceeded from the assumption that psychological momentum (PM) is a complex phenomenon emerging during goal striving. We examined patterns in collective psychological and behavioral performance variables that are characteristic of PM, during periods in which athletes progressed or regressed in relation to their goal. Finally, in Chapter 6 we focused on macro-level patterns, that is, developmental trajectories of excellence, and on the specific underlying dynamics in the form of mathematical equations. In this way we tested our assumption that excellent human performance emerges out of complexity, that is, ongoing interactions between multiple performance-related variables (e.g., motivation, practice, family support). Together, the different chapters thus shed light on the complexity of performance-related processes across different levels and time scales (from bodily processes during a single sports task to ability development over the course of a career). The next section provides a brief overview of the findings of each chapter.

7.2 What Did We Find?

Chapter 2

We started with an empirical study on the complexity of representations as they are constructed in real-time by soccer players, who were exposed to offensive game plays. Such representations are assumed to emerge from the integration of pieces of information, such as the positions and movements of other players on the soccer field (e.g., Helsen & Starkes, 1999), or details of the actions carried out (e.g., McPherson, 2000). Previous research found that expert soccer players generate a greater number of verbal report statements, evaluate the situation more often, and look at informative locations on the field (e.g., scanning elements or areas surrounding the player having the ball). Hence, previous research primarily focused on specific components that expert players notice, and which potentially explain their superior perceptual-cognitive skills (e.g., Roca et al., 2011). Yet, how soccer players integrate the components at particular levels of complexity has remained unknown and may shed a new light on cognitive skills, and their relation with expertise.

We used Skill Theory (Fischer, 1980; Fischer & Bidell, 2006) to construct a coding system (De Meij, Van der Steen, & Den Hartigh, 2012), so that we could reliably determine the complexity levels of the representations that were formed by soccer players with different levels of expertise: Experts (professionals), near-experts (high amateurs), and non-experts (low amateurs). Based on verbalizations that soccer provided while watching soccer game plays, we were able to assess players' short-term representations. We found that players with higher levels of expertise constructed their representations at higher complexity levels. In addition, when constructing their representations, players with more expertise described information excluding the player with the ball (off-the-ball movements, defending actions) relatively more often at high complexity levels.

Thus, Chapter 2 illustrated how the complexity of athletes' cognitive skills can be measured and evaluated in terms of the higher-order structure, rather than the specific content of these representations. Our findings suggests that the skill to perceive game information—the players, the ongoing actions, etc.—in a more complex way, is characteristic for players with higher expertise levels. This suggestion fits with Fischer's (1980) notion that cognitive skills become more complex over the course of human (cognitive) development.

Chapter 3

In Chapter 3 we shifted our focus from a task that targeted cognitive skills to a task in which athletes actually had to perform a sports task. More specifically, we examined the temporal structure of variation in ergometer rowing performance, in order to draw inferences about the complexity of the underlying dynamic (motor) organization. The central limit theorem implies that when a large amount of measures are independently collected in a sample, and each of these measures consists of the sum of independent components, we would observe a normal distribution of these measured values (see Kello et al., 2010). In time series of actual task performance, this would mean that successive measurements are independent of previous measurements, that is, the temporal structure of variation would consist of random fluctuations around some mean value (i.e., white noise). However, we assumed that sport performance emerges from complexity, that is, rather than being determined by independent component effects, it emerges from the ongoing interactions between components across multiple time scales throughout the system. Such a complex dynamic organization would typically result in a more structured pattern of variation (i.e., pink noise) (e.g., Kello et al., 2010; Van Orden et al., 2003).

In order to test our assumption, we asked rowers to perform 550 strokes at their preferred rowing rhythm. Then, we examined the temporal structures of variation of the rowers' force peak intervals between stroke 18 and 530, in order to assure a sufficiently long time series to analyze. The structure in the time series was assessed based on a specific nonlinear time series technique: Detrended fluctuation analysis (DFA; Peng et al., 1993). As expected, for each rower the temporal structure deviated from white noise, and was close to pink noise. In addition, time series of rowers who were members of a first-year's team that was ranked among the best 16.67% nationally, revealed more pink noise than the time series of rowers who were members of a team ranked below-average (i.e., ranked between 50% and 67% nationally).

Taken together, the findings of Chapter 3 make it likely that motor performance in sport, specifically ergometer rowing, emerges from complexity. Indeed, pink noise in human behavior is assumed to be an expression of self-organizing system-components across multiple time scales, rather than the activation of components operating independently, or in a serial manner (e.g., Diniz et al., 2011; Gilden, 2001; Van Orden et al., 2003; Wijnants, 2014). In addition, more prominent patterns of pink noise were associated with higher rowing expertise in terms of recent team-results in (on-water) rowing competitions. The complexity of the dynamic organization underlying the generation of rowing strokes may thus be a reflection of rowing expertise, or more specifically of rowers' ability to continuously and functionally adapt their behavior to satisfy task constraints (see Seifert et al., 2013).

Chapter 4

The previous chapters provided insights into the (measurement of) complexity in situations in which we aimed to keep perturbing, outside influences to the minimum. These studies revealed that complexity at the level of cognitive skills, as well as the entire motor system underlying sport performance, is likely related to athletes' expertise levels. In Chapter 4, we shifted the focus to a complex phenomenon—*Psychological momentum* (PM)—, which is observed in various achievement contexts in which people are striving for specific goals. Positive and negative PM can emerge through interactions among a variety of precipitating events (e.g., scoring, referee decision, crowd behaviors, opponent behavior, etc., see Taylor & Demick, 1994), provided that they give rise to the perception that one is progressing or regressing in relation to a desired goal or outcome (Gernigon et al., 2010). In order to obtain the first insights into the emergence of positive and negative PM in teams, we studied the evolvement of a few collective psychological and behavioral variables (i.e., collective efficacy, task cohesion, exerted efforts, and interpersonal coordination). We did so by directly manipulating the position (progress or regress) in relation to the team goal, in order to examine how PM moves from its positive to its negative state, and the other way around. This strategy is in accordance with the guidelines defined by the HKB method (Haken et al., 1985).

In our study we made pairs of rowers, who formed a team. We placed them in a performance context (i.e., ergometer competition), and provided them with a clear goal to pursue: Beating the opponent by taking an 8-second lead. In the negative momentum race, we let the team take a lead of 6 seconds at the start, after which the team gradually moved toward a lag of 6 seconds. This scenario was the exact opposite in the positive momentum race. During the races we measured collective efficacy and task cohesion at fixed intervals of one minute, while we continuously measured the exerted efforts and interpersonal coordination. We found decreases in collective efficacy and task cohesion in the negative momentum scenario, which were relatively stronger than the increases in collective efficacy and task cohesion in the positive momentum scenario. It thus seems that, psychologically, teams converge more rapidly to a negative PM state than to a positive PM state. However, note that the pattern we found does not correspond to a typical hysteresis pattern, according to which we should have observed a resistance to change from positive to negative PM and vice versa (e.g., Bardy, Oullier, Bootsma, & Stoffregen, 2002; Hock, Kelso, & Schöner, 1993). We found asymmetrical dynamics, in which teams reacted more strongly to a scenario in which they start to lose seconds while they almost won. This is in line with Kahneman and Tversky's (1979) prospect theory according to which losses hurt more than gains feel good. Related to this, in our study exerted efforts decreased more rapidly in the negative momentum scenario than in the positive momentum scenario, while the interpersonal coordination was better in the positive momentum scenario.

In Chapter 4, we thus demonstrated an asymmetry between positive and negative PM in teams. Given our research setup, involving two exactly symmetrical (manipulated) scenarios, we may conclude that team PM is not only determined by some independent variable (e.g., the team's position in the race). If this were the case, we should have observed symmetrical linear increases and decreases in the variables under study during positive and negative momentum. The fact that we found significant differences between the scenarios suggests that team PM is a dynamical phenomenon demonstrating properties that are also found in complex dynamical systems, history-dependence in particular.

Chapter 5

While past studies on PM dynamics, including Chapter 4, have focused on psychological and behavioral changes within a race or match, athletes' PM may extend over a single match and develop over the course of a tournament or longer (Adler, 1981). The theory of complex dynamical systems postulates that processes taking place at different time scales are interconnected and mutually influence each other (e.g., Newell et al., 2001; Thelen & Smith, 1994). Given the evidence that PM is a complex and dynamical phenomenon (Briki et al., 2013; Briki, Den Hartigh et al., 2014; Gernigon et al., 2010; see also Chapter 4), we experimentally tested the property of interconnected time scales in PM processes.

The participants in this study were involved in a tournament, in which they competed in three (manipulated) races against a direct opponent on rowing ergometers. During the tournament, participants thought they could win a money prize by getting three points, which could be accomplished by winning three races (i.e., gaining 9 seconds on the opponent in each race). The races were manipulated, so that one group of participants lost the first two races (negative momentum condition), whereas the other group won the first two races (positive momentum condition). Before each subsequent race we assessed participants' perceptions of momentum and self-efficacy, to determine the influence of the previous race(s) on their long term PM development. Overall, on the long term, we found that perceptions of momentum and self-efficacy increased in the positive momentum condition and decreased in the negative momentum condition.

In the third race, the scenario was similar for all participants: From an almost victory—a lead of 6 seconds—they moved toward the defeat (i.e., losing 9 seconds on the opponent). To assess the PM dynamics, we measured the participants' perceptions of momentum and self-efficacy at fixed intervals of one minute, while we continuously collected their exerted efforts. We found that momentum and self-efficacy perceptions decreased less rapidly in the third race for participants who won the previous races (i.e., who developed positive long-term PM), than for participants who lost the previous races (i.e., who developed negative long-term PM). Furthermore, exerted efforts were higher for the participants in the positive momentum condition than for those in the negative momentum condition.

The finding that long-term PM was shaped by (short-term) races, and that the long-term PM seemed to shape the dynamics of short-term (within race) PM, supports the proposed interconnection between long- and short-term PM processes that is typical for complex dynamical systems. More specifically, PM dynamics within a task (i.e., race) seem to be constrained by the PM process on the long term, in a way that an athlete's state within a task converges less rapidly to negative PM when experiencing positive PM on a longer time scale.

Chapter 6

In the previous chapters we provided insights into complex processes taking place in relatively standardized situations, in which psychological and behavioral processes could directly be observed. Processes that take place across longer periods of time (e.g., years), and are distributed over a range of situational contexts, are more difficult to observe directly. One of the most debated long-term processes with regard to human performance, is the development of talent and excellence. So far, the debate has primarily focused on the nature of the underlying (causal) mechanisms of ultimate excellent performance, and its early indicators. While this discussion started in the 19th century (De Candolle, 1873; Galton, 1869), it is still ongoing (for hot recent debates on the roles of heritability and deliberate practice, see for instance Ackerman, 2014; Ericsson, 2014; Ericsson, 2013; Ericsson et al., 2013; Gagné, 2013; Hambrick et al., 2014; Plomin, Shakeshaft, McMillan, & TrzasKowski, 2014). Rather than focusing on specific components that may explain why some reach excellence, whereas others do not, Chapter 6 took a complexity approach. We aimed to construct a plausible model that predicts some typical properties of talent and excellence development across the domains of business, arts, science, and sports. Simonton (2001) has defined these properties as follows: (a) In different individuals a similar ability can emerge at different ages, (b) the underlying constituents of a particular ability can change during an individual's life span or career, (c) an individual's ability development over time can take a variety of forms, and (d) early indicators of later excellence are often absent. Another typical finding in the literature on talent and excellence is that the distribution of performance in terms of individuals' ultimate productivity is highly right-skewed across the population in virtually any performance domain (e.g., O'Boyle & Aguinis, 2012). To illustrate this, consider the following: In total, 404 professional tennis players have won *at least* one ATP tournament, 74 of them won only one tournament, whereas three exceptional players were able to win more than 80 tournaments: Federer, Lendl, and Connors (www.atpworldtour.com, accessed at 5 November 2014).

In order to discover the kind of model that reveals the typical properties of excellence, we simulated different kinds of models on a computer (cf. Nowak et al., 1990; 2000; Van Geert, 1991). We proceeded from the idea that excellence develops over time—from a beginner level up to the level at which excellent performance is demonstrated—and that a variety of factors are involved that influence, or are influenced by the changing ability level, such as practice, family support, coaching, etc. (e.g., Abbott et al., 2005; Phillips et al., 2010). In line with this idea, we simulated networks consisting of sparsely connected components. We found that the resulting trajectories corresponded to the typical developmental properties proposed in the literature (Simonton, 2001). Furthermore, the network model generated highly skewed productivity distributions across populations of performers, which has been consistently found across achievement domains (e.g., O'Boyle & Aguinis, 2012). While the network model produced highly plausible results in light of the current literature on talent and excellence development, the null-hypothesis model did not. More specifically, we were unable to detect the properties of talent and excellence when we simulated models in which abilities were normally distributed across the population, and were supported by the additive effects of all supporting factors.

Taken together, the results of our simulations suggest that excellence emerges from dynamic network structures. More broadly we showed that talent and excellence likely develop out of complexity—the ongoing interactions between sparsely connected components—rather than complicatedness—the additive influences of ability-related components.

7.3 How Do Our Findings Advance Insights in Human Performance Processes?

In this thesis, we assumed that performance-related states cannot be explained by linear relationships with specific underlying components, because such states are generated by a complex underlying process involving ongoing interactions between continuously changing components. This assumption had to be taken into account in our choice of methods, which should be able to draw inferences about the complexity of human performance processes.

As noted earlier, the processes we studied took place across different levels and time scales (from motor processes during a rowing ergometer session to person-environment interactions during excellence development). However, in all studies we found emergent patterns at a higher level, out of the underlying, dynamically interacting components at the lower level. The most comprehensive demonstration was provided in Chapter 6 on the development of excellence across a career. In this chapter we demonstrated higher-order patterns emerging out of specified (coupled) mathematical equations. Based on the network model we proposed, we could explain a) intra-individual trajectories from a beginner's level up to an excellent performance level, and b) inter-individual differences in the output, in terms of productivity, of excellent performers. Apart from Chapter 6, the findings of the other chapters also suggest that networks of interacting components are at work that a) form the basis for the ongoing representations that soccer players construct during game plays (Chapter 2), b) underlie the coordination of rowers' rowing strokes (Chapter 3), and c) move toward positive or negative PM during goal pursuit (Chapter 4 and 5); see Figure 21 for a schematic presentation. However, some elaboration may be needed about what our findings specifically mean in terms of the causality of human behavior, and performance processes in particular.

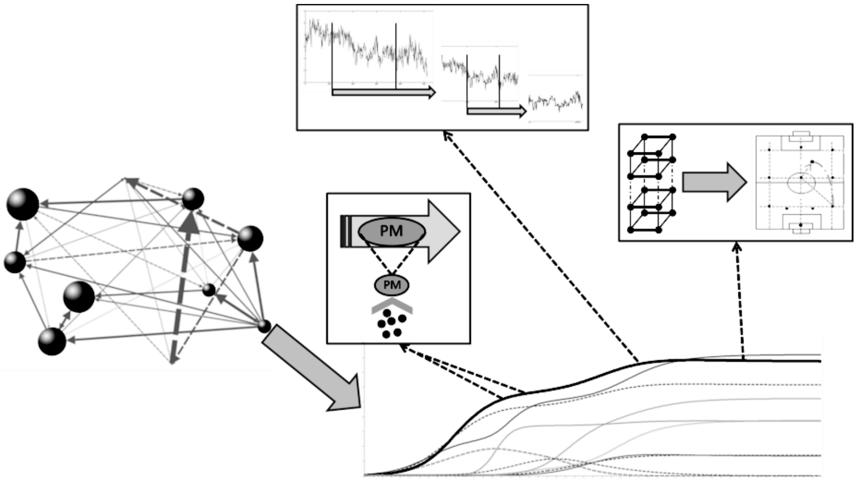


Figure 21. Schematic representation of the complexity at work in the different chapters. The numbers correspond to the numbers of the different chapters, and the processes take place across the time scale of excellence development to which the studies are connected.

7.4 What Do the Findings Suggest about Causality?

Given that none of the studies answered questions related to *which* components cause a particular psychological or performance state, one may conclude that none of the studies in this thesis identified the specific causal mechanisms underlying human performance. Yet, this does not entail that our studies, and the findings derived from them, hold no explanatory power. More specifically, based on the kinds of patterns we observed in the studies, we can provide plausible explanations on the kinds of processes (rather than the kinds of components) underlying the patterns (cf. Beek, Peper, & Stegeman, 1995). Below I will briefly clarify what our conclusions in terms of the underlying complex processes imply for the explanation of psychological and performance states.

For example, Chapter 3 focused on patterns of peak-to-peak interval series of rowing strokes. While debate has existed on the exact meaning of pink noise, or long-range correlations in time series (Diniz et al., 2011), researchers seem to have reached a general agreement that pink noise reflects the complexity of the system, in terms of the flexible and adaptive coordination between multiple components (Delignières & Marmelat, 2013; Delignières, Marmelat, & Torre, 2011). Because only knowing the output of the system, that is, the temporal structures of performance, could be considered as indirect evidence for the nature of the underlying system, Delignieres and colleagues recently performed computer simulations of different kinds of systems. The authors showed that pink noise time series are generated when distinct networks of components are simultaneously involved in the generation of performance (Delignières & Marmelat, 2013; Delignières et al., 2011). This interaction-dominant model is at odds with models that assume localized central pattern generators (e.g., Dimitrijevic, Gerasimenko, & Pinter, 1998). This pleads for a model that explains performance based on simultaneously interacting components, rather than a causal chain involving a control mechanism (e.g., the brain) that activates the actions to be performed.

In the Chapters 4 and 5 we proceeded from the assumption that PM is a dynamical and complex process, evidence for which has been provided in different recent studies (Briki, Den Hartigh, Bakker, & Gernigon, 2012; Briki et al., 2012; 2013; Briki, Den Hartigh et al., 2014; Gernigon et al., 2010). With this assumption in mind, the main focus in these studies was to examine *how* the dynamics of PM can be characterized, by scaling a control parameter that moves PM from its positive to its negative state. In other words, we focused on the properties of the patterns in PM-related variables when athletes undergo progress and regress in relation to their desired goal, which is in line with the HKB method (Haken et al., 1985). Our finding in Chapter 4 that team members' psychological and behavioral states converge more rapidly on a negative PM than a positive PM, suggests that positive PM is a weaker kind of equilibrium state than negative PM (i.e., negative PM would be a stronger attractor than positive

PM; see also Briki et al., 2013). Subsequently, Chapter 5 demonstrated a higher resistance to enter a negative PM when having experienced successes in previous competitions compared to having experienced losses in previous competitions. An additive model involving independent variables to explain PM at a certain moment is therefore unlikely to provide an explanation for the PM process. More specifically, the rate at which our thoughts, perceptions, and behaviors converge to a positive or negative PM state, is embedded in a performance history that takes place within a competition (Chapter 4), but also across multiple competition rounds (Chapter 5). To date, an actual dynamic systems (mathematical) model of PM has not been proposed, this remains a challenge for future research. One possibility might be to use the HKB-model, which allows the modeling of attractor dynamics and has already been successfully applied to the domains of postural coordination (Bardy et al., 2002), human locomotion (Diedrich & Warren, 1995), economics (Barnett & He, 1999), and speech categorization (Tuller, Case, Ding, & Kelso, 1994).

One chapter in which we explicitly modeled the emergence of performance processes, was chapter 6. Based on a coupled logistic growth equation, we simulated networks consisting of sparsely connected components, and we found that the patterns of ability growth corresponded to typical characteristics of talent and excellence development according to previous literature. In this study we also manipulated the network in a way that we removed the links between the components, thereby simulating a model in which ability development is influenced by the *sum of* —rather than the *interactions among*—the components. Because this latter model did not reveal patterns resembling characteristics of excellence according to the literature, our approach provides a new, and plausible notion of the process underlying talent and excellence development, based on a comparison of earlier literature and archival data with model simulation results.

Taken together, theoretically, findings of this dissertation do have explanatory power in terms of revealing the *kind of model* that can explain the emergence of psychological and performance states, and/or how psychological and performance patterns converge towards another pattern when being perturbed (i.e., from positive to negative PM and vice versa; see Chapters 4 and 5). Given that our findings suggest that the principle explanation of human performance processes may lie in the ongoing interactions between (causal) components, to which specific dynamical models apply (e.g., dynamic network models), the future research agenda can be adapted accordingly. In other words, instead of trying to fit additive linear models involving sets of determinants, we should (also) explore alternative models that account for the interaction-dominant processes in which the components are involved. I therefore recommend a three-pronged research strategy consisting of theory development, computer simulations, and empirical studies, each of which should inform the other two and lead to the improvement of the dynamic model explaining complex human performance processes across different levels and time scales (cf. McGrath et al., 2000).

7.5 Implications for Practice

Although this thesis was of a fundamental nature, and we have not investigated practical applications in this thesis, suggestions can be made that are specifically focused on positively altering psychological and performance patterns in terms of complexity or stability. For instance, with regard to Chapter 2, particularly expert soccer players seem to have the skill to construct complex representations of the actions taking place, which means that they are superior in extracting higher order *patterns* of information from the game plays. This is in line with Savelsbergh and colleagues, who stipulated that it is not so much a matter of gaze behavior per se (i.e., the kinds of information players look at, such as the ball or players on the field), but rather of *how* soccer players are able to use the information they perceive that distinguishes the elite adult players (Savelsbergh, Haans, Kooijman, & Van Kampen, 2010; Savelsbergh, Onrust, Rouwenhorst, & Van der Kamp, 2006). Although we have not examined the actual actions and decision making of the soccer players during an actual game, it is plausible that the skill to integrate information during game plays at higher complexity levels goes hand-in-hand with successful actions and decision making. For example, perceiving that a player ‘chooses position’ probably affords the action to chase or cover that player, whereas perceiving that same action as a player who ‘sprints’ may not afford such actions. In order to monitor or evaluate players’ ability to integrate the information on the field at high complexity levels (i.e., perceive patterns during ongoing game plays), coaches could apply the user-friendly coding system that we constructed (De Meij et al., 2012).

Chapter 3 showed that elite athletes display a pattern of variation suggesting that the motor system finds itself in a critical state allowing different modes of behavior (Van Orden et al., 2003). This is in line with the assumption that athletes should be flexible yet stable in their behaviors, in order to execute coordinated movements, while at the same time adjust in an ongoing athlete-environment interaction (e.g., Davids et al., 2003; Seifert et al., 2013). In the specific case of rowing, we may therefore cast doubt on a training practice in which athletes have to learn to repeatedly reproduce the exact same or ideal movement, and to minimize the variation from stroke-to-stroke. Following the results we found, another strategy could be considered, namely to let rowers practice at “the edge” or in a pink noise rhythm in order to stimulate complexity (cf. Chow et al., 2010; Marmelat, Torre, Beek, & Daffertshofer, 2014). Marmelat et al. (2014) have recently provided gait training to participants, which consisted of walking in line with an auditory metronome. The authors varied the pattern of interval variation of the metronome and found that (only) a pink noise pattern of variation elicited a pink noise gait pattern. Hence, to improve (coordination in) cyclical performance, which includes rowing, training according to a pink noise pattern could be a potential strategy.

If we take the above-mentioned idea one step further, we might speculate that adaptive behavior could be facilitated when coaches help athletes to explore the meta-stable regions of their performance landscape (e.g., Chow et al., 2011). In order to do so, rather than prescribing an athlete to practice the same movements repeatedly, a coach could place an athlete in a situation in which different (creative) performance solutions are available. For instance, Hristovski, Davids, Araújo, and Button (2006) showed that boxers were able to perform a diversity of actions (hooks, jabs, uppercuts) when they were at a certain (medium) distance from their target, thereby minimizing “mode-locked” behaviors and maximizing the possibility to learn different action patterns. Taken together, in order to stimulate the coordinated, yet flexible behaviors that elite athletes should develop, and which are typical for complex dynamic systems, practitioners such as coaches could attempt to introduce adaptive noise (i.e., functional variability) in the practice regimen (Chow et al., 2011).

Regarding PM (Chapters 4 and 5), practical implications could be focused on the (in)stability of PM. Findings from different studies, including Chapter 4, suggest that negative PM is triggered relatively easy compared to positive PM (Briki, Den Hartigh, Hauw et al., 2012; Briki et al., 2013; Gernigon et al., 2010). Strategies or interventions should thus attempt to improve the stability of a positive PM pattern in order to delay the emergence of negative PM. One strategy that can be applied within a sports match is to ask for a time out when one starts moving away from the victory. This time out may interrupt the formation of a (strong) negative PM attractor and provide the time and opportunity to recover a positive state (cf. Briki, Doron et al., 2014). Another strategy within and outside sports may be to endorse Mastery-approach (MAp) goals, that is, aiming to do better than before, or performing a task well (Elliot & Church, 1997; Van Yperen, 2003). A recent qualitative study on PM showed that MAp goal endorsement helped athletes to maintain positive PM, but also to overcome negative PM during a table tennis match or swimming race (Briki, Den Hartigh, Hauw et al., 2012). This is in line with general findings across sports, business, and education that MAp goals promote self-regulation, the maintenance of efforts, and the immersion in task (e.g., Elliot & Church, 1997; Elliot & McGregor, 2001; Van Yperen, 2006; Van Yperen, Blaga, & Postmes, 2014, in press).

Finally, considering talent and excellence development, the practical implications should focus on the structure of the individual ability networks rather than the components that generally relate to excellence across the population[6]. More specifically, the potential interactions between the components should be a principal focus of attention, which means that the probability of establishing positive feedback-loops between various ability-supporting components should be enhanced. This could be attained if the 'supporters' of talent in the child's environment (coach, family, teacher) recognize their role as being (just) one component in the network, and if they stimulate 'complexity' rather than a mono-disciplinary life-style and/or training practice. This means that a coach or teacher, but also parents, should be sensitive

[6] According to recent advances in network science, specific components (driver nodes) may guide the dynamics of the network. Importantly, in these cases the controlling influence of driver nodes is embedded in, and dependent on, the structure of the dynamic network (Liu, Slotine, & Barabási, 2011). A discussion of the potential role of driver nodes in an individual's ability-network is beyond the scope of this dissertation, but can be a fruitful avenue for future research.

to the child and its environment (e.g., the enthusiasm, engagement in school or sports) that signal supportive or competing influences for excellence to develop. In other words, the coach or teacher should be adaptive, because he or she is situated in an idiosyncratic and changing network that is typical for a particular athlete, artist, or scientist, and which involves mutual interactions between components.

The positive consequences of establishing a complex and rich ability network can be twofold. First, a network involving multiple (sparsely) coupled components may increase resilience. Although this speculation was not tested as such in Chapter 6, it follows from recent advances in network sciences that the higher the degree of a node, the less responsive it is to perturbations, or to changes in other nodes to which it is connected (Barzel & Barabási, 2013). Indirect support for this idea is also provided in earlier literature, showing that psychological and environmental variables, such as goal commitment, coping skills, parental support, and adequate coaching, influence the development of excellence, and more specifically that parental support may act as a buffer to alleviate performance-related stress and deal with setbacks (e.g., Baker et al., 2003; Côté, 1999; Van Yperen, 1995a, 1998, 2009). A second argument is that excellence development may generally benefit from hobbies and interests outside the performance domain in which the performer wants to excel (Simonton, 2014). Examples of this idea include Galileo, who was fascinated by arts, literature, and music (Simonton, 2012), the finding that the most creative scientists pursue a large number of different (and loosely-related) projects (Gruber, 1989), and the proposition that children would benefit from sampling different sports and activities in order to facilitate excellence development in a specific sports domain at a later age (e.g., Abbott & Collins, 2004; Baker, 2003; Côté, Lidor, & Hackfort, 2009).

Finally, note that the above-mentioned propositions with regard to the development of excellence do not correspond to the idea that, primarily, deliberate practice should be accumulated in order to develop excellence (Ericsson et al., 1993). To date, the talent development policies of some countries (e.g., the China policy on developing gymnastics talent) still proceed from the idea that children's ability development benefits most from stimulating the ability-development with much deliberate practice in environments that are deprived from many other components. That is, in these programs children are often (temporarily) cut from their family and friends, and there seems to be less care for the general psychological well-being of the child. Because the network model assumes that excellence can be “fed” by multiplicative relationships between a variety of components, we may cast doubt on a policy that emphasizes just one, or very few, links (e.g., only between ability, coach, and practice). However, new empirical studies and simulation studies should be conducted to more explicitly test the consequences of different kinds of network structures with regard to the development of excellence.

7.6 Concluding Remarks

“Everything is related to everything else, but near things are more related than distant things” (Tobler, 1970, p. 236). This quote reflects Tobler’s first law of geography, which entails that at the level of the globe, patterns of change are a function of (in)directly interrelated components, such as climate, population, land use, industries, which are in an ongoing interaction across multiple scales of time and space. Tobler’s (1970) law also seems to apply to the relatively small scale of human performance. In this thesis we found that (a) ongoing representations formed by soccer players involve the structuring of directly observable components (e.g., the player with the ball), but also more distant and not directly observable components, in particular for expert soccer players; (b) components of the human motor system, spanning multiple scales (e.g., processes at the levels of cells, muscles, limbs), are in continuous interaction, and the interactions are better coordinated for elite rowers; (c) in a performance context PM is characterized by ongoing psychological and behavioral changes that are shaped by the history of events within and across performances (i.e., competitions); and (d) excellence develops over a career or life span through ongoing interactions between proximal (directly connected) and more distal (indirectly connected) components pertaining to different personal and environmental factors.

The idea that everything is related to everything else fits with the premise we started from, namely, that the principal mechanism to explain human performance processes lies in the underlying complexity. In this thesis we have shown that complex performance processes, involving ongoing interactions between multiple components, can be captured by applying a complex dynamical systems approach, ranging from empirical studies zooming in on temporal processes during specific sport tasks to life-span simulation and archival research across sports, arts, business, and science. In all studies we came to the conclusion that the patterns we found are likely generated by a set (or network) of interacting components, which sheds a new light on the way we should explain performance-related processes in real-time and on longer time scales (e.g., during excellence development over years). Therefore, I hope that the methods and results derived from this thesis open up new lines of research and ultimately lead to practical interventions focused on developing and adjusting the dynamical structures that shape human performance.